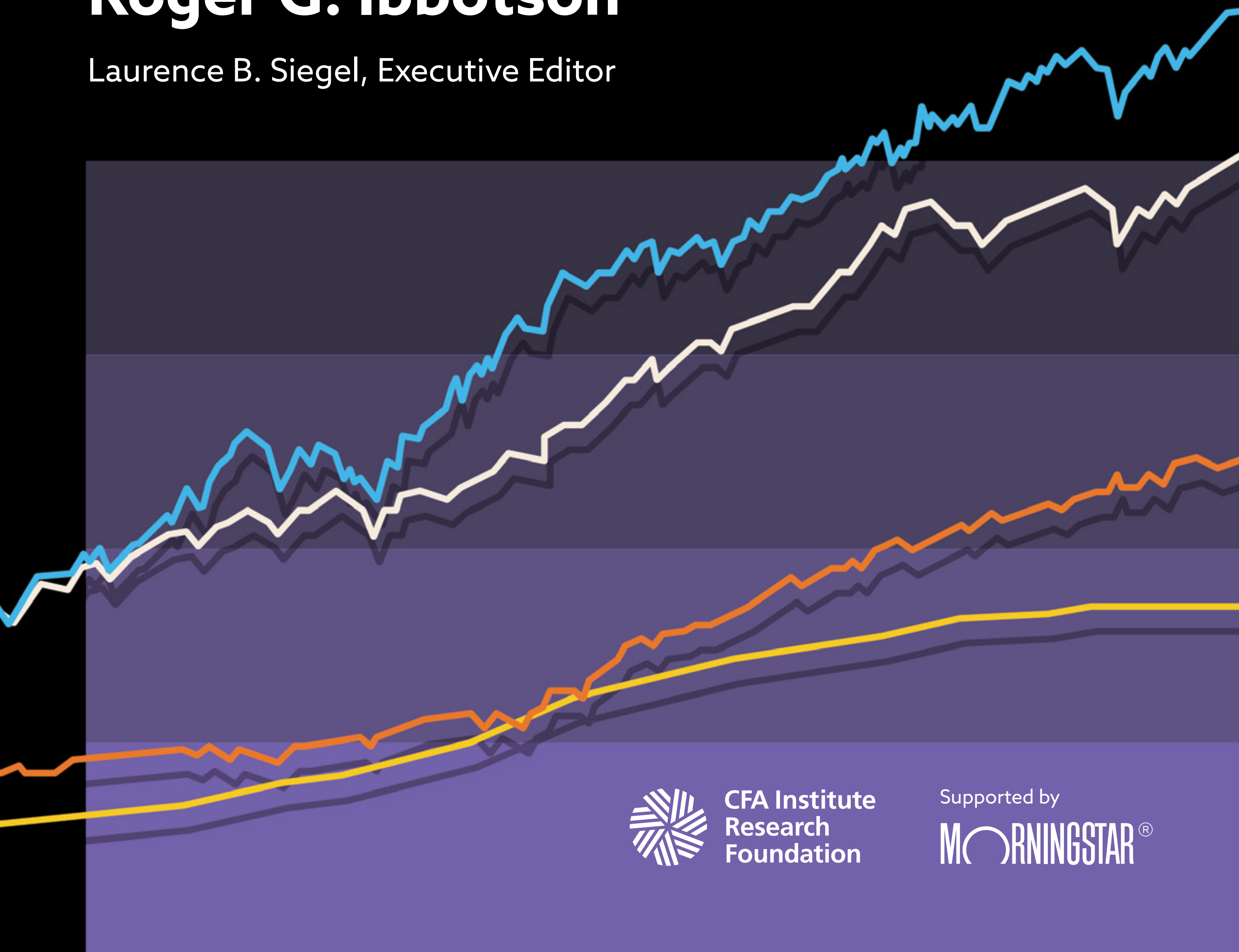
Exponential Wealth: Centuries of Stock and Bond Returns

Roger G. Ibbotson

Laurence B. Siegel, Executive Editor



CFA Institute Research Foundation

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CFA Institute
Research
Foundation

Statement of Purpose

The CFA Institute Research Foundation is a not-for-profit organization established to promote the development and dissemination of relevant research for investment practitioners worldwide.

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The New Datasets

The new Ibbotson® Indices include both equity and bond indices. Ibbotson® is a trademark owned by Morningstar, Inc. The information contained in the indices has not been prepared by Morningstar, and Morningstar is not responsible for any damages or losses arising from any use of this information. Past performance is no guarantee of future results. These indices may also be referred to as Ibbotson Equity and Bond Indices, Ibbotson Equity Indices, or Coleman Fisher Ibbotson (CFI) Bond Indices.

The Center for Research in Security Prices, LLC (CRSP) is the underlying data source of the Ibbotson Equity and the Coleman Fisher Ibbotson (CFI) Bond Indices used in this book, with permission. CRSP was previously affiliated with the University of Chicago Booth School of Business, but was acquired by Morningstar, Inc, with the transaction completed in February 2026.

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A NOTE FROM THE INTERIM PRESIDENT AND CEO OF CFA INSTITUTE

History provides essential context for the financial markets, helping us understand the present and think more clearly about what may lie ahead.

New technologies, evolving asset classes, and changing market structures and geopolitical conditions can seem incredibly disruptive. Understanding their significance requires us to look beyond the immediate to understand what came before, question what we think we know, and continue building on the knowledge accumulated over time.

That is part of what makes *Exponential Wealth: Centuries of Stock and Bond Returns* such an important contribution to investment research.

This monograph brings together an extraordinary breadth of historical data, spanning different periods, countries, and market conditions. In doing so, it offers something valuable: perspective. It reminds us that today's markets are part of a much longer story and that our understanding continues to evolve as the evidence itself becomes richer.

For more than six decades, CFA Institute Research Foundation has created a bridge between rigorous inquiry and investment practice, bringing together researchers and practitioners to advance investment knowledge. *Exponential Wealth* continues that tradition while also carrying forward a body of research that has helped shape investment thinking over generations.

That commitment to advancing knowledge strengthens the profession. The investment profession will continue to change, sometimes in ways we can anticipate and often in ways we cannot. What should remain constant is our willingness to examine evidence carefully, challenge established thinking, learn from different perspectives, and remain curious about what we do not know—and what we think we know.

I would like to thank the authors and contributors who brought this remarkable body of work together and my wonderful former colleagues at Morningstar for their longstanding support of the Research Foundation and this publication. I hope *Exponential Wealth* prompts discussion, further inquiry, and new thinking for many years to come.

Tricia Rothschild, CFA
Interim President and CEO
CFA Institute

A LETTER FROM MORNINGSTAR

It is an honor for Morningstar to help mark the 100th anniversary of the dataset at the heart of this book and the 50th anniversary of the research that first brought it to light.

In 1976, Roger Ibbotson and Rex Sinquefield published "Stocks, Bonds, Bills, and Inflation: Year-by-Year Historical Returns (1926–1974)" in the *Journal of Business*. What began as an academic paper became one of the most widely used bodies of capital market data in the world. When Morningstar acquired Ibbotson Associates in 2006, we also took on a role in carrying that work forward.

Morningstar and Ibbotson Associates have supported CFA Institute and CFA Institute Research Foundation for decades because rigorous, independent research makes markets more transparent and helps more investors find the long-term success they deserve. This book—and Morningstar's support of it—continues that conviction.

The timing matters for Morningstar, too. We recently acquired and rebranded the Center for Research in Security Prices (CRSP), whose stock market data and indexes underpin much of the research in these pages, as well as many of the most widely used investment products. I am grateful to Roger Ibbotson, Laurence Siegel, my colleague Thomas Idzorek, and the many coauthors who have helped this dataset remain useful as it enters its second century.

This book is about what long-term market data can teach us. It measures, with a century of evidence, the returns and risks investors have actually experienced. That same need for better data and clearer understanding is growing in private markets, where data are harder to find, products can be more complex, and returns are often less transparent. Chapter 18, "Popularity and Premiums," offers one way to think about that connection, especially through liquidity and other premiums. I expect the next century of this research will have as much to say about private markets as it does public ones. Morningstar—with our private market intelligence from PitchBook—will make sure of it.

The book reminds us how liquid, well-measured capital markets have created wealth for patient investors and how much we owe to the researchers who have helped investors understand why.

I hope readers come away with the same respect for the data, the same appreciation for the research behind the data, and the same sense of possibility for what the next century can teach us.

Kunal Kapoor, CFA
Chief Executive Officer
Morningstar

AUTHOR BIOS

David Chambers, PhD, is the Invesco Professor of Financial History and co-founder and co-director of the Centre for Endowment Asset Management at the University of Cambridge Judge Business School, where he is a member of the Finance subject group. He is also a Research Fellow at the Centre for Economic Policy Research (CEPR) and a Fellow of Clare College, Cambridge.

Chambers' research interests include financial history and asset management, in particular, long horizon investing. He is well known for his research on the investing of John Maynard Keynes, in particular, "Retrospectives: John Maynard Keynes, Investment Innovator" (with Elroy Dimson, *Journal of Economic Perspectives* 2013) and "The British Origins of the US Endowment Model" (with Elroy Dimson, *Financial Analysts Journal* 2015). His other notable publications for practitioners include *Financial Market History* (editor, with Elroy Dimson; CFA Institute Research Foundation 2016) and "How the Norway Model Evolved" (with Elroy Dimson and Antti Ilmanen; in *The Bernstein Fabozzi/Jacobs Levy Awards Volume 3*, Institutional Investor 2015).

Chambers received his bachelor's degree from the University of Oxford, MSc from the London Business School, and his MSc and PhD from the London School of Economics.

Peng Chen, PhD, currently serves as non-executive chair of Morningstar China, as well as director on the boards of iFAST Corp (Singapore), Income Insurance Limited (Singapore), and Fullerton Fund Management (Singapore). Chen is senior adviser to Morningstar and Deutsche Bank–DWS on their business strategies, and he is also an adjunct finance professor at the Chinese University of Hong Kong and at Harbin Institute of Technology. Chen was the founding chair and CEO of Dimensional Fund Advisors (Asia ex-Japan) from 2012–2020. He was responsible for Dimensional's overall investment and business activities in the region, leading its Singapore and Hong Kong office establishment as well as its expansion in Asia. Chen was also a member of Dimensional's Investment Policy Committee and chaired the Dimensional Global Defined Contribution Committee.

Before joining Dimensional, Chen served as president of Morningstar's global investment management division, which consists of Morningstar's investment consulting, retirement advice, and investment management operations in North America, Europe, Asia, and Australia. From 1997 to 2006, he was president and chief investment officer at Ibbotson Associates, providing innovative investment solutions to more than 200 institutions globally.

Chen was named to the *Investment Advisor* list of the "25 Most Influential Individuals" in 2008 and won the prestigious Graham and Dodd Scroll Award from the *Financial Analysts Journal* three times (2003, 2007, and 2011). In addition, he won the Retirement Income Industry Association's 2012 Academic Thought Leadership Award. He is co-inventor of two US patents.

Chen holds an MS and a PhD in consumer economics from The Ohio State University.

Thomas S. Coleman, PhD, is senior lecturer and executive director of the Center for Economic Policy at the University of Chicago Harris School of Public Policy. In the late 1980s and early 1990s, Coleman and Roger Ibbotson worked with the late Lawrence Fisher to build yield curves using Fisher's newly constructed CRSP US Treasury bond files. Together, they developed the CFI indices that have been expanded in Chapters 7 and 8 of this book. In 2012, Coleman returned to the University of Chicago, first as executive director and senior adviser at the Becker Friedman Institute for Economics and then in 2015 as a lecturer at Harris.

Prior to returning to the university, Coleman worked in the finance industry for more than 20 years, with considerable experience in trading, risk management, and quantitative modeling. His positions included head of quantitative analysis and risk control at Moore Capital Management, LLC; a director and founding member of Aequilibrium Investments, Ltd., a London-based hedge fund manager; and roles on the sell side in fixed-income derivatives research and trading at TMG Financial Products, Lehman Brothers, and S.G. Warburg & Co. in London.

Coleman is author of *Quantitative Risk Management*, published by Wiley, and *A Practical Guide to Risk Management*, published by the CFA Institute Research Foundation. Before entering the financial industry, he taught graduate and undergraduate economics and finance at the State University of New York at Stony Brook.

Coleman earned his BA in physics from Harvard and his PhD in economics from the University of Chicago.

Elroy Dimson, PhD, is a professor of finance, director of research, and co-founder and chair of the Centre for Endowment Asset Management at the University of Cambridge Judge Business School, where he is a member of the Finance subject group. Dimson is also a Research Member of the European Corporate Governance Institute.

With Paul Marsh and Mike Staunton, he co-wrote the influential investment book *Triumph of the Optimists* (Princeton University Press 2002). They have coauthored the *Global Investment Returns Yearbook* annually since 2000 and distribute the Yearbook's underlying dataset, the DMS Dataset. The authors also edit and produce the *Risk Measurement Service*, which London Business School has published since 1979. Dimson and his coauthors have become well known for their global research on the investment performance since 1900 of all the main asset categories.

Dimson's research and consultancy focus on active ownership and on investing for the long term, with a particular interest in endowment asset management. He formerly chaired the Strategy Council for Norway's sovereign wealth fund, as well as the Policy and Advisory Boards of FTSE Russell.

Dimson earned his bachelor's degree from Newcastle University, his MCom from Birmingham University, and his PhD from London Business School.

William N. Goetzmann, PhD, is the Edwin J. Beinecke Professor of Finance and Management Studies and Faculty Director of the International Center for Finance at the Yale School of Management. He is an expert on a diverse range of investments.

Goetzmann's past work includes studies of stock market predictability, hedge funds, and survival biases in performance measurement. His current research focuses on alternative investing, factor investing, behavioral finance, and the art market. Goetzmann has written and coauthored a number of books, including *Modern Portfolio Theory and Investment Analysis* (Wiley 2014, 9th ed.); *The Origins of Value: The Financial Innovations That Created Modern Capital Markets* (Oxford 2005); *The Great Mirror of Folly: Finance, Culture, and the Crash of 1720* (Yale 2013); and *Money Changes Everything: How Finance Made Civilization Possible* (Princeton 2016).

Goetzmann teaches portfolio management, alternative investments, real estate, and financial history at the Yale School of Management. He earned his BA, MBA, and PhD from Yale.

James P. Harrington is a director in Kroll's Digital Valuation Solutions practice, based in Chicago. He provides technical support on client engagements involving cost of capital and business valuation matters and is a leading contributor to Kroll's efforts in the development of studies, surveys, online content, and tools and firmwide valuation models.

Previously, Harrington was director of valuation research in Morningstar's Financial Communications business, where he led the group that produced the Ibbotson Stocks, Bonds, Bills, and Inflation® (SBBI®) Valuation Yearbook; Ibbotson Stocks, Bonds, Bills, and Inflation® (SBBI®) Classic Yearbook; Ibbotson Cost of Capital Yearbook; and various international cost of capital reports. Harrington is a coauthor of the *Valuation Handbook* series along with former Kroll colleague Carla Nunes and Roger Grabowski. He is a contributing author to the *Cost of Capital: Applications and Examples*, 5th ed., and is a Kroll contributor to the Stocks, Bonds, Bills, and Inflation® (SBBI®) Yearbook.

Harrington holds a BS in business administration from The Ohio State University and an MBA in finance and economics from the University of Illinois at Chicago.

Roger G. Ibbotson, PhD, is Professor in the Practice Emeritus of Finance at Yale School of Management. He is also chair of Zebra Capital Management, LLC, an equity investment, index, and hedge fund manager. He is founder, adviser, and former chair of Ibbotson Associates, now a Morningstar Company.

Ibbotson has written numerous books and articles, including *Stocks, Bonds, Bills, and Inflation* with Rex Sinquefield, which serves as a standard reference for information and capital market returns. He conducts research on a broad range of financial topics, including popularity, liquidity, investment returns, mutual funds, international markets, portfolio management, and valuation. Ibbotson is coauthor of several CFA Institute Research Foundation monographs, including *Popularity: A Bridge Between Classical and Behavioral Finance* (2018) and *Lifetime Financial Advice* (2007). He also coauthored *The Equity Risk Premium* with William Goetzmann and two books with Gary Brinson, *Global Investing* and *Investment Markets*.

Ibbotson formerly served on numerous boards, including those of the CFA Institute Research Foundation and Dimensional Fund Advisors. He received a bachelor's degree in mathematics from Purdue University, an MBA from Indiana University, and a PhD from the University of Chicago, where he taught for more than 10 years and served as executive director of the Center for Research in Security Prices.

Thomas M. Idzorek, CFA, is chief investment officer, retirement, for Morningstar Investment Management LLC. He also serves as a member of Morningstar's 401(k) committee and the Public Policy Council. Idzorek chairs Morningstar's overall Research Council and serves on the editorial boards of Morningstar magazine and the *Financial Analysts Journal*.

Idzorek was president of Morningstar's global investment management division from 2012 to 2015, where he oversaw the firm's global investment advice, consulting, retirement solutions, broker dealer, index, and financial wellness businesses. Additionally, he has served as president of Ibbotson Associates, president of Morningstar Associates, board member/responsible officer for a number of Investment Management's subsidiaries, global chief investment officer for Investment Management, chief investment officer for Ibbotson Associates, and director of research and product development for Ibbotson. Most recently, Idzorek served as head of investment methodology and economic research for Morningstar.

Before joining Ibbotson (which Morningstar acquired in 2006), Idzorek was a senior quantitative researcher for Zephyr Associates. An expert on multi-asset-class strategic asset allocation, the Black–Litterman model, target-date funds, retirement income solutions, fund-of-funds optimization, risk budgeting, and performance analysis, Idzorek is the key methodological creator of Morningstar's target-date and retirement managed account (robo-advice) solution.

Idzorek earned a bachelor's degree in marketing from Arizona State University and a master's degree in business administration from Thunderbird School of Global Management.

Antti Ilmanen, PhD, is a principal and global co-head of the Portfolio Solutions Group at AQR Capital Management. In this role, he manages the team responsible for advising institutional investors and sovereign wealth funds and develops the firm's broad investment ideas. Prior to joining AQR, Ilmanen spent seven years as a senior portfolio manager at Brevan Howard and a decade in a variety of roles at Salomon Brothers/Citigroup. He began his career as a central bank portfolio manager in Finland.

Over the years, Ilmanen has advised many institutional investors, including Norway's Government Pension Fund Global and the Government of Singapore Investment Corporation. He has published extensively in finance and investment journals and has received a Graham and Dodd Award, the Harry M. Markowitz special distinction award, and multiple Bernstein Fabozzi/Jacobs Levy awards for his articles. He is the author of two books, *Expected Returns* (2011) and *Investing Amid Low Expected Returns* (2022). He also received the CFA Institute 2017 Leadership in Global Investment Award.

Ilmanen earned MSc degrees in economics and law from the University of Helsinki and a PhD in finance from the University of Chicago.

Rajkumar Janardanan is a managing director at SummerHaven Investment Management. His research on commodities and financial markets has been published in the *Financial Analysts Journal* and the *Journal of Futures Markets*, among others.

Janardanan holds an undergraduate degree from the Indian Institute of Technology, Madras, and an MBA from Yale University.

Paul D. Kaplan, PhD, CFA, now retired, was director of research for Morningstar Canada and a senior member of Morningstar's global research team. He led the development of many of the quantitative methodologies behind Morningstar's fund analysis, indices, adviser tools, and other services.

Previously, he served as quantitative research director for Morningstar Europe in London, director of quantitative research in the United States, and chief investment officer of Morningstar Associates, LLC. Before that, Kaplan was a vice president of Ibbotson Associates and served as the firm's chief economist and director of research. Prior to that, he served on the economics faculty of Northwestern University.

Kaplan's research has been published in professional books and publications, including the *Financial Analysts Journal* and CFA Institute Research Foundation monographs. He has served on the editorial board of the *Financial Analysts Journal* and currently serves on the editorial board of *Financial Planning Review*.

Kaplan has received a Graham and Dodd Award, a Graham and Dodd Award of Excellence, and a Harry M. Markowitz Award. He also is the lead co-creator of the popularity asset pricing model (PAPM).

Kaplan holds a bachelor's degree in mathematics, economics, and computer science from New York University and a PhD in economics from Northwestern University.

Tadaaki Komatsubara is co-founder and chief investment officer at Ibbotson Associates Japan, Inc., a registered investment adviser and subsidiary of Morningstar, Inc. (former Ibbotson Associates, Inc.). He has been with Ibbotson Associates Japan for 25 years, assuming a key role in the development of investment consulting and investment advisory services.

Prior to joining Ibbotson Associates Japan, Komatsubara worked as a portfolio manager for UBS Asset Management and LTCB Investment Management. He managed Japanese equity portfolios and developed asset allocation models and asset liability management for pension fund sponsors.

Komatsubara's work has appeared in the proceedings of the Nippon Finance Association and the Japanese Association of Financial Econometrics and Engineering. He won the Securities Analysts Journal Prize in 2008 for his article "The Explanatory Power of Policy Asset Allocation."

Komatsubara received a bachelor's degree in administration engineering from Keio University.

Otto S. Manninen is an incoming PhD candidate at Yale University School of Management, where he has assisted with research for the Yale Finance Faculty and Yale International Center for Finance, including for coauthors in this book Roger Ibbotson and Will Goetzmann.

Since August 2024, he has worked on substantive projects with a range of topics, including model-free and model-based learning with Professor Nick Barberis, diversification and trading costs with Professor Toby Moskowitz, and Shiller survey indices with Professor Will Goetzmann. After Stocks, Bonds, Bills, and Inflation® (SBBI®) indices were sold to Morningstar and then discontinued, Manninen helped to recreate the new Ibbotson indices using Finaeon, CRSP, and Federal Reserve datasets.

Manninen is a graduate of the University of Jyväskylä.

Paul Marsh, PhD, is Emeritus Professor of Finance at London Business School. He has published articles in *Journal of Business, Journal of Finance, Journal of Financial Economics, Journal of Portfolio Management, Financial Analysts Journal*, and *Harvard Business Review*, among others.

Together with Elroy Dimson and Mike Staunton, he wrote the influential investment book *Triumph of the Optimists*, published by Princeton University Press. Since 2000, this same team has produced the annual Global Investment Returns Yearbook, documenting global asset returns since 1900.

Marsh has held senior roles at London Business School, including Deputy Principal, Faculty Dean, elected Governor, and chair of the finance area. He was part of the team that designed the FTSE 100 Index and, with Elroy Dimson, co-designed the Deutsche Numis UK Index Series.

Marsh has advised on several public enquiries and was previously chair of Aberforth Smaller Companies Trust and a non-executive director of M&G Group and Majedie Investments. He has acted as a consultant to many financial institutions and corporations.

Marsh has a BSc from the London School of Economics and received his PhD from London Business School.

Edward F. McQuarrie, PhD, is a Professor Emeritus in the Leavey School of Business at Santa Clara University. McQuarrie has published in three broad areas: consumer response to advertising, with a focus on rhetoric and narrative; qualitative research techniques and market research appropriate to technology products; and emergent online consumer behaviors.

McQuarrie has written four books: *Customer Visits: Building a Better Market Focus; The Market Research Toolbox: A Concise Guide for Beginners; The New Consumer Online: A Sociology of Taste, Audience, and Publics*; and *Visual Branding: A Rhetorical and Historical Analysis* (with Barbara J. Phillips). His work has appeared in the *Journal of Consumer Research*, *Journal of Consumer Psychology*, *Journal of Advertising Research*, *Journal of Advertising*, *Marketing Theory*, and elsewhere. He previously served as Faculty Director for Assessment at the Leavey School, responsible for the assessment of learning outcomes and the evaluation of teaching. He also served as Associate Dean for Graduate Studies, responsible for the MBA and Executive MBA programs.

McQuarrie received his PhD in social psychology from the University of Cincinnati.

Carla S. Nunes, CFA, is managing director and head of Valuation Research Corporation's (VRC) Capital Markets Research group, where she focuses on advancing the firm's market data, research analytics, and cost of capital frameworks. Prior to joining VRC, she held senior roles at Kroll (formerly Duff & Phelps), most recently in the Office of Professional Practice. She also served as the global leader of Kroll's Valuation Digital Solutions group, overseeing the development of cost of capital thought leadership and data-driven valuation tools, including the Cost of Capital Navigator, an online platform she co-created.

Nunes is a member of the Financial Reporting Committee of the Institute of Management Accountants, the Education Committee of the International Institute of Business Valuers, and the International Valuation Standards Council (IVSC) Standards Review Board (SRB) Environmental, Social, and Governance (ESG) and Sustainability Working Group. She is also an inaugural member of the Business Valuation Resources (BVR) Leadership Council.

Nunes earned an MBA in finance from the University of Rochester's Simon School and an honors degree in business administration from the School of Economics and Management at the University of Lisbon (ISEG Lisbon). She completed coursework toward a master of taxation from Villanova University School of Law. She also holds the Accredited in Business Valuation (ABV) credential.

Fernando Reyes De La Luz has served as a research associate at the International Center for Finance at the Yale School of Management, where he conducted research at the intersection of asset pricing, econometrics, and machine learning. Throughout his studies, he mentored students as a teaching assistant, most notably under the guidance of Osman Nalbantoglu, renowned for his role as a Partner Director at Bridgewater.

Building on his background in physics, finance, and machine learning, Reyes develops quantitative methods to better understand financial markets and design robust investment strategies. His research bridges academic theory and real-world financial applications.

Reyes holds a BS in engineering physics from Universidad Iberoamericana and an MMS in asset management from the Yale School of Management.

Paul Rintamäki is assistant professor of finance at Frankfurt School of Finance and Management, where his current research focuses on the behavior of different types of financial intermediaries, both banks and nonbanks. His research interests also include monetary policy transmission, financial intermediation, and long-run asset returns.

Rintamäki's publications include "Long-Run Asset Returns," with David Chambers, Elroy Dimson, and Antti Ilmanen (*Annual Review of Financial Economics* 2024). He earned his BSc, MSc, and DSc in economics and business administration from Aalto University School of Business in Finland.

K. Geert Rouwenhorst, PhD, Robert B. and Candice J. Haas Professor of Corporate Finance and Deputy Director of the International Center for Finance at the Yale School of Management, specializes in empirical finance and asset pricing. His research interests include international finance, commodity markets, and financial history. Rouwenhorst is also a founding partner of SummerHaven Investment Management, an asset management firm that focuses on commodities. He has held visiting positions at MIT and the IMF. His book *The Origins of Value: The Financial Innovations that Created Modern Capital Markets*, co-edited with Will Goetzmann, was named a book of the year in 2005 by Barron's and *The Economist*. Rouwenhorst holds an MS and PhD from the University of Rochester, as well as a BLaw and MS from Erasmus University, Rotterdam, The Netherlands.

Laurence B. Siegel is the Gary P. Brinson Research Director Emeritus at the CFA Institute Research Foundation. Active with the Research Foundation since 2000, he has written, coauthored, or edited numerous CFA Institute Research Foundation monographs, literature reviews, and briefs, in addition to contributing to several CFA Institute publications. He is a four-time winner of the Graham and Dodd Award for Excellence from *the Financial Analysts Journal*, and until recently, he was also a member of its editorial board.

Siegel retired in 2009 from The Ford Foundation, where he served as director of research in the Investment Division. Previously, he was a managing director at Ibbotson Associates. As an external adviser, he was responsible for a substantial portion of the research output of Barclays Global Investors from 1998 to 2009. He has also been a member of the board of directors of Ibbotson Associates, Oberweis Emerging Growth Fund, and the Dow Jones Hedge Fund Index committee.

Siegel is the author of *Fewer, Richer, Greener: Prospects for Humanity in an Age of Abundance* (Wiley 2019), *Unknown Knowns: On Economics, Investing, Progress, and Folly* (Montesquieu Press 2021), and *On Progress and Prosperity: Essays 2019–2024* (Montesquieu Press 2025). He is currently a member of the editorial boards of the *Journal of Portfolio Management* and the *Journal of Investing*. He serves on the board of directors of the Q Group (Institute for Quantitative Research in Finance) and the American Business History Center.

Siegel earned his bachelor's and MBA degrees from the University of Chicago.

Mike Staunton, PhD, was Emeritus Professor of Finance and director of the London Share Price Database at London Business School. As *Exponential Wealth* was being finalized, he unexpectedly passed away in early August 2026: a huge loss for friends and family, the London Business School, and the economic data community worldwide. He was a frequent coauthor with Elroy Dimson and Paul Marsh on works including the recent book *Triumph of the Optimists*. He taught at universities in the United Kingdom, Hong Kong, and Switzerland.

Staunton was coauthor with Mary Jackson of *Advanced Modelling in Finance Using Excel and VBA* (Wiley 2001) and wrote a regular quant finance column for *Wilmott* magazine. He published articles in *Journal of Banking & Finance, Financial Analysts Journal, Journal of the Operations Research Society*, and *Quantitative Finance*. With Elroy Dimson and Paul Marsh, he coauthored the influential investment book *Triumph of the Optimists*, published by Princeton University Press, which underpins the Credit Suisse Global Investment Returns Sourcebook and associated Yearbook.

Staunton held a PhD in finance from London Business School.

Bryan Taylor, PhD, is the founder, president, and chief economist of Finaeon, Inc., a unique historical finance company that has manually transcribed financial data from printed publications back to the 1300s. Taylor began his career as an assistant professor at California State Polytechnic University, Pomona, in 1986, where he remained for 15 years. He then joined California State University, Los Angeles, as an assistant professor until 2005. In 1992, he took on the role of chief economist at Global Financial Data, a position he still holds to this day. Taylor earned a BA in economics from Rhodes College and an MA (in international relations) and PhD (in economics) from the University of South Carolina.

James Tyler is currently an investment associate at Bridgewater Associates in New York. He completed his BS in computer science and mathematics at Yale University in 2025. While at Yale, he worked as a qualitative trading intern at Jane Street and as a data science intern at Outseer, an anti-fraud software company. As a research assistant at the International Center for Finance at the Yale School of Management, he worked with Will Goetzmann on projects using both structured and unstructured data to analyze financial history.

Xiao Qiao, PhD, is an assistant professor in the Department of Data Science at City University of Hong Kong and a member of the editorial board of the *Journal of Portfolio Management*. His research bridges financial economics and data science, with a focus on fintech, commodities, and investment management. Qiao's work has been published in leading academic journals and conferences, cited by the US Senate, and featured by outlets such as *Forbes*, *Institutional Investor*, and CFA Institute. Prior to academia, Xiao worked in the investment management industry, where he contributed to the development of several award-winning investment products, three of which were listed on the New York Stock Exchange. He has held roles at Morgan Stanley, hedge funds, and a proprietary trading firm. Qiao holds dual bachelor's degrees in economics and engineering from the University of Pennsylvania's Wharton School and School of Engineering and Applied Science. He earned his PhD in finance from the University of Chicago Booth School of Business.

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SECTION 1

Overview of Stock and Bond Returns

FOREWORD

Why aren't we all rich?

The stunning capital market returns documented in *Exponential Wealth: Centuries of Stock and Bond Returns* seem to provide a pathway for anyone with even a little extra income to accumulate a large sum over a lifetime, providing for, at the very least, a comfortable retirement—and perhaps a head start for the kids, a big donation to a favorite charity, some unexpected luxuries.

Usually, it doesn't happen. Why?

Most of the literature on this question blames costs, portrayed as a wedge between investment returns and investor returns. The most burdensome costs are taxes and management fees. There's also inflation, which bites us all hard.

And some people don't have enough money available for investing to make them rich no matter how generous the capital markets are, or they have the money available but spend it all instead of investing. Those problems are beyond the ken of this book.

But taxes and other costs can be managed. Although we can't do much about inflation, equity markets have provided a total return (capital gain plus dividends) far in excess of inflation. Because of the bounty of capital markets, exponential wealth is available to more people than ever before in human history.

How to Miss the Greatest Money-Making Opportunity in the World

Most people try to make money by working. That is right and just, and it is where everyone should start. But it is hard to really get ahead that way. Even as one's skills expand and paychecks grow larger, so do needs and wants, with the result that there isn't much surplus.

Yet, right alongside the path to riches (or at least security and then comfort) represented by working harder and, especially, working smarter is another path that *does not involve working*. It's *easy*. That parallel path consists of putting some of one's money to work in the capital markets, where the users of the capital provided invent things, build factories, design software, mine for raw materials, sell merchandise, and do a myriad of other things that are intended to produce a profit. When they do, a proportionate share of the profit is returned to you in the form of capital market returns. This path can best be understood as a way to get *other people* to do some of the work required to make you rich, instead of your doing it all yourself.

The basic requirement for participating in the marvelous rates of return presented in this book is to invest as much as you can as soon as you can and then stay invested. But this is more difficult than it sounds—and not just because most young people are broke, which I'll get to.

The nonobvious reason that it's difficult is *procyclicality*. This is a fancy way of saying that people have little money to invest at the best times and are flush with cash at the worst times.

The best times in history to invest have been when stock prices are low because the economy is bad and people are short of money. And people being short of money is the reason the market is cheap at such times—it's all very circular—so it's hard to put much money to work at bargain-basement prices. At the other extreme, the worst time to invest is when people are feeling flush because there has been an extended economic boom, but that is also when stock prices are high and expected returns are limited.

Looking at the human life cycle instead of the economic one, the best time to invest is when you're young. The data in *Exponential Wealth* suggest a much higher probability of getting rich if you can leave your money in the market for 50 years than for 10 or 20 years. But most people are poor when they're young. Actually, it's worse than that. Paul Samuelson said that everyone is born short a roof over their heads. That's a big hole to dig out of. You have to not only cover that short position but build a long one—at a time when your income is likely the lowest it will ever be. That's just one of many reasons why we're not all rich.

Can We Fix the Problem?

Is it possible to fix these problems? Yes and no. Anyone with available funds can climb on the exponential wealth ladder: Just buy the broad market, and hold it forever.

I wish it were that simple. First of all, few investors have (or should have) the stomach for the 100% equity allocation that in the absence of taxes, management fees, and other costs would have produced the 14,751-to-1 nominal wealth gain (which inflation reduced to a still impressive 814-to-1 real wealth gain) over the last 100 years.

Second, few people have a 100-year investment horizon. You may think you're investing for your great-grandchildren, but between now and the time they show up to collect the money, life happens and money gets spent. Also, with fertility rates at the lowest level in history, your great-grandchildren may never be born.

Third, taxes bite and bite hard if no action is taken to minimize them. Tax-preferred investment vehicles such as IRAs and 401(k)s help, but it is impossible for individual investors to avoid all taxation. Investors should minimize taxes as much as possible because of their profound effect on long-term returns.

Finally, inflation grinds away at the real value of all investments. The $14,751 nominal wealth gain today (per $1 invested at year-end 1925) becomes $814 after inflation. It's a big comedown, but it's nevertheless fair to call this result exponential wealth. There's no other way to make more than 800 times your money in a century at manageable levels of risk.

A Fallacy of Aggregation

But the outcome for an individual who buys the market (whether through an index fund or diversified active management) and holds it forever doesn't scale to the whole population! *We can't all earn these rates of return* by imitating the person described in my example.

Why not? The reason is subtle and counterintuitive and results from a fallacy of aggregation—that is, what is possible for one investor is not possible for all. Although not everyone holds or should hold index funds, this point is made clearest by using such funds as an illustration.

As this book shows, most of the return from long-term investment in stocks results from reinvestment of dividends into the rising market. And as I wrote in the foreword to a CFA Institute Research Foundation brief by Paul McCaffrey,

> For the investor to realize the index total return, dividends would need to be reinvested in the fund, and if everyone is an indexer, there are no spare shares of the fund to buy. Investors would have to buy the shares from another indexer who already owned them. Any attempt to pursue this ultimately fruitless plan would drive the fund share prices up and expected returns down—*way* down.[1]

In other words, an indexer's attempt to earn the market's total return by buying index fund shares from another indexer with the money received as dividends prevents that other indexer from earning the market's total return! Sad but, when you think carefully about it, obviously true. And the principle applies to active management in almost exactly the same way that it does to indexing.

Thus, my half-serious exhortation to just buy the market and hold it forever can't work for everybody because of the fallacy of aggregation. But don't worry! It is almost impossible to imagine this simple rule being followed by enough people to ruin the prospects of equities.[2] Exponential wealth will continue to be offered to investors who are disciplined in their savings and very patient and who have a global rather than local view of what their investment opportunities are.

Squirrels

When Roger Ibbotson asked me to write this foreword—a sequel to my first published piece of writing, the foreword to the 1982 edition of Ibbotson and Sinquefield's *Stocks, Bonds, Bills, and Inflation*—he reminded me that in that old foreword, I wrote about squirrels. He was hoping I wouldn't do it twice. Surprise! Here I am writing about squirrels again.

"An investment is an asset that we do not consume," wrote the distinguished investment manager and author Mark Kritzman.[3] This seeming oversimplification contains an important truth: Most resources are consumed; otherwise, one wouldn't have bothered to gather or produce them in the first place. Most creatures on Earth are constantly hungry and are in almost immediate danger of starving. For them, it isn't a priority to store resources for a future that may not occur.

In 1982, I wrote:

> Squirrels hoard. Knowing that they must have food in the winter, they willingly forego present (certain) consumption in exchange for future consumption which is also more or less certain. . . .

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[1] Paul McCaffrey (foreword by Laurence B. Siegel), *Stocks for the Long Run Revisited: Dividends and "The Return Nobody Got"* (Charlottesville, VA: CFA Institute Research Foundation, 2026), p. 2.

[2] Some worry that the current high level of the stock market is, at least in part, the result of excessive fund flows into equities by personal investors, especially in retirement portfolios. I don't give this argument much credence because markets "work"—they usually discover the right price for capital assets. Any equity investor is free to sell at any time, rebalancing into bonds and cash, which currently have quite respectable yields (unlike in the recent past). The ability to reallocate assets in response to price changes is what keeps asset prices within a reasonable range of fair value.

[3] Mark P. Kritzman, *Puzzles of Finance: Six Practical Problems and Their Remarkable Solutions* (Hoboken, NJ: John Wiley & Sons, 2000), p. 130.

> Yet squirrels do not build wealth over time. The offspring of particularly industrious squirrels do not find their lives made richer by their parents' past efforts; squirrels as a species are not better off than they were a hundred years ago. Clearly, hoarding or storage (the exchange of present for future consumption, both under certainty) is not a sufficient condition for building wealth.[4]

I was slightly off. Acorn stashes are wealth, but they're not *exponential* wealth. They don't make life for each generation easier than for the one before, resulting eventually in an affluent society of squirrels.

The Greatest Social Invention in History

Squirrels, then, discovered the virtue of saving but did not invent investing or markets or capitalism. Nor has any other living creature except human beings—and human beings did it only in the last few thousand years, out of the tens or hundreds of thousands of years that we've existed. Investing, markets, and capitalism have existed for only an instant in geologic and biologic time. We are sublimely lucky to live within that instant.

Even though individual and group enterprise flourished in many societies in ancient and medieval times and made quite a few people rich, it still didn't create exponential wealth. According to the late economic historian Angus Maddison, global GDP per capita was stuck in a range of roughly \$1,000 to \$1,500 from AD 1 until the middle 1800s.[5] Some countries did better for a while, but the prosperity didn't last: Italy soared to double that level in the Renaissance but never grew significantly after that until the 1870s! The Netherlands, the United Kingdom, and the United States did better once the Industrial Revolution began, but growth was painfully slow even then, with only a 50% rise in incomes between the American Revolution and the 1840s.

The Takeoff into Self-Sustaining Economic Growth

Then, beginning in the West and extending eventually to almost every corner of the world, economic growth went wild. Those living in the United States today enjoy per capita incomes about 20 times the 1840s level (after adjusting for inflation). In Western Europe, the situation is about the same. Unlucky China and India didn't achieve rapid growth until the last quarter of the twentieth century, but once liberated from the shackles imposed by their political systems, the growth rates exceeded anything seen in the West or anywhere else. We are moving rapidly toward a middle-income world.[6]

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[4] Roger G. Ibbotson and Rex A. Sinquefield (foreword by Laurence B. Siegel), *Stocks, Bonds, Bills, and Inflation: The Past and the Future (1982 Edition)* (Charlottesville, VA: Financial Analysts Research Foundation, 1982), p. viii.

[5] Following Maddison, all money amounts in this section are in US dollars at 2011 prices. Multiply by 1.5 for 2026 prices. See www.rug.nl/ggdc/historicaldevelopment/maddison/?lang=en.

[6] According to a commentary piece published by the Brookings Institution, as of 2018, half the world's population was middle class or better. The authors' definition of middle class may not match American or Western European expectations, but it sure beats poverty: "Those in the middle class have some discretionary income that can be used to buy consumer durables like motorcycles, refrigerators, or washing machines. They can afford to go to movies or indulge in other forms of entertainment. They may take vacations. And they . . . can weather an economic shock . . . without falling back into extreme poverty." See Homi Kharas and Kristofer Hamel, "A Global Tipping Point: Half the World Is Now Middle Class or Wealthier," Brookings Institution (27 September 2018), www.brookings.edu/articles/a-global-tipping-point-half-the-world-is-now-middle-class-or-wealthier/.

To what do we attribute this sudden change in fortunes? Economic historians may never agree on the answer—even though at least one Nobel Prize has been awarded for work on the topic—but the emergence of relatively free markets in labor, goods, and capital is almost universally regarded as a key element of the "great enrichment" (the economist Deirdre McCloskey's phrase). Because this book is about capital markets, let's focus on the capital component.

The Purpose and Magic Ingredients of Capital Markets

Big enterprises—those that create a lot of wealth, employ a lot of people, and produce big paychecks—require a lot of capital, all gathered in one place and deployed by entrepreneurs long before any profits have materialized. How might one raise such risk capital, with everyone concerned knowing that the enterprise might fail?

The answer turns out to be complicated. The best, perhaps only, way to raise large amounts of capital systematically and reliably is by selling identical, divisible shares in the enterprise to a great many people, all of whom can diversify their investments so they need not fear a total loss in one of them. This is the stock market.

The two nearly miraculous inventions required to make this happen are thus *divisibility* and *limited liability*. Divisibility (of ownership of a business) means that one share is as good as another, so they can be traded with confidence. Even more important, limited liability prevents losses in one investment from eating the rest of the investor's portfolio—an absolute requirement for raising capital from far-flung, quasi-anonymous investors who have positions in many different companies. Adam Smith was the first to notice that these are the key components of joint-stock capitalism. Two centuries later, the Nobel Prize–winning economic historian Douglass North expanded on the idea.

The first stirrings of these innovations took place in Toulouse, France, in the late 1300s, as documented by Will Goetzmann, a coauthor of several of the chapters in this book.[7] But it wasn't until more than two centuries later, with the establishment of the Dutch and British East India companies in the early 1600s, that joint-stock companies with tradable shares and limited liability began to catch on. After that, it was "only" another two centuries or so—good things take time—before stock markets became the prevailing mechanism for raising large amounts of capital.

To sum up, the takeoff into self-sustaining economic growth, in the West at first and then globally, was closely correlated with the use of the stock market to raise capital for businesses. Correlation may not mean causation, but it sure can be a hint.

The Democratization of Exponential Wealth

The unexpected side effect of this development was that participation in the growth engine became *democratized*. The opportunity for (although obviously not the guarantee of) exponential wealth was available to anyone with a little money. The modern world was emerging. This book follows the blossoming of capital markets through the centuries and

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[7] Goetzmann's magisterial book, *Money Changes Everything: How Finance Made Civilization Possible* (Princeton University Press, 2016) documents the history and evolution of capital markets in an accessible and entertaining manner. I highly recommend it.

across countries, examining the returns of these markets as they experienced bubbles, crashes, and periods of stability, retrenchment, and steady increase. Adding all these types of events together, we see a picture of inexorable growth over time, as long as one remained diversified across companies and, most importantly, across countries because investments in some countries failed completely as a result of war, revolution, or other calamities.

This book is about creating stock and bond indices to measure these results in the past and to help us place future outcomes in context as they unfold. Capital markets accessible to everyone are highly beneficial, but we need well-constructed indices of the various asset classes so we can be better informed when we decide how to invest.

The last few centuries of human history have seen the emergence of widespread, shared prosperity because of capitalism, freedom, and—most importantly in the context of this book—liquid and efficient capital markets. This trio constitutes the most important social invention of all time.

The fruits of this social invention are a prize beyond measure. Let's nurture it, not tear it down. Our descendants, near and far, and our brothers and sisters living in every corner of the world deserve the chance to earn exponential wealth in the markets.

Laurence B. Siegel
Wilmette, Illinois, and Del Mar, California
April 2026

CHAPTER 1. INTRODUCTION

Roger G. Ibbotson, PhD
Professor in the Practice Emeritus of Finance, Yale School of Management
Chair, Zebra Capital Management, LLC

Today, we have an array of technological financial tools at our fingertips, making it almost impossible to look back and fully understand the impact of Rex Sinquefield's and my 1976 article "Stocks, Bonds, Bills, and Inflation: Year-by-Year Historical Returns (1926–1974)" (Ibbotson and Sinquefield 1976a). First published in the University of Chicago's *Journal of Business*, the article on the topic of Stocks, Bonds, Bills, and Inflation®, known as SBBI®,[1] was written during a revolution in the field of academic economics and finance in the early 1970s. Rex and I were surrounded by a panoply of future Nobel Prize winners at the University of Chicago's Graduate School of Business. Brilliant minds were rapidly developing economic theories around us on that campus, and we were in the right place at the right time. SBBI provided the risk and return measures that helped put these theories into practice.

Although diversification had long been a principle of investing, Harry Markowitz, finishing his doctorate at the University of Chicago in 1952, developed the mathematics and theory behind diversification. During the 1950s and 1960s, there was considerable work on the random walk hypothesis, asserting that stock price fluctuations are independent, random, and unforeseeable. By the 1960s, William Sharpe (1964) and John Lintner (1965) had independently developed the capital asset pricing model (CAPM), which explained the relationship between risk and return and demonstrated that in perfect capital markets with common beliefs, everyone would hold the market portfolio, with cash or leverage.

Shortly after I arrived at the University of Chicago, Eugene Fama (1965, 1970) developed the efficient market hypothesis, which asserted that prices of securities were fair and reflected all available information, making it impossible to consistently "beat the market" or achieve superior returns without taking higher risks. In an efficient market, prices adjust instantly to new information, aligning market value with intrinsic value, suggesting that neither technical nor fundamental analysis is capable of consistently outperforming the market.

In the late 1960s, I decided to earn a PhD after failing in two post-MBA jobs. My interest in finance had been sparked early: I was investing in stocks as a teenager, so a career in finance was appealing. The approaches being developed at the University of Chicago, however, were totally different from the bottom-up security analysis with which I had been familiar. Because markets were relatively efficient, what really mattered was "modern portfolio theory," with expected returns related to risk, fair prices, diversified portfolios, and the start of index funds. Even as a PhD student, I was given an opportunity to manage the bond portfolio at the university investment office and soon after to consult on equity index funds, all the while participating with top-tier theorists—a perfect storm. Eugene Fama was chair of my dissertation committee, and my close colleagues at the university included Fischer Black, Myron Scholes, and Merton Miller.

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[1] SBBI® and Stocks, Bonds, Bills, and Inflation® are registered trademarks of Precision Information, LLC, DBA Financial Fitness Group. Any mentions of SBBI and Stocks, Bonds, Bills, and Inflation in this book are nominative, are made for the purpose of providing historical context, and do not imply any ownership of the relevant marks, or endorsement by or affiliation with Precision Information, LLC, DBA Financial Fitness Group or any entity affiliated with same.

Not only was the university a great place for theory; it was also a major repository of financial data. James H. Lorie and Lawrence Fisher had set up the Center for Research in Security Prices (CRSP) at the University of Chicago in 1960, and 10 years later, computers were in widespread use on campus. Things began to heat up: CRSP had the data, and we were armed with the knowledge to use the data.

Enter SBBI

The CAPM had already provided a formal theory of how the risk–return relationship might work. Rex Sinquefield and I took 50 years of data from the stock market and compared stock returns with the yields on riskless bonds to measure the equity risk premium. Economists had talked about risk premiums long before SBBI, but SBBI gave us a measure of it. Indices are really important: They give you the long-term history and tell you collectively how stocks and bonds have performed.

Rex went on to cofound Dimensional Fund Advisors (DFA), which is now one of the world's largest investment managers, with one of my former University of Chicago roommates, David Booth. For more than 40 years, I was on the board that oversaw DFA's funds, which use efficient market concepts to manage the assets.

By including both stock and bond data, we could measure a number of different risk premiums: the equity risk premium, the horizon or interest rate term premium, the default risk premium, and all the inflation-adjusted real returns, including the short-term real riskless rate of interest. As with the Fisher and Lorie (1964, 1968) studies, we started our data in 1926, and suddenly, with our dataset, market participants could understand the payoffs for risks.

Timing is often critical; our results came out just after the 1973–74 recession and the corresponding market crashes. In contrast, the historical 50-year returns that we had measured were high. We also extrapolated the high achieved risk premiums for another 25 years out to the end of the century. Because the numbers were high, the realized and forecasted stock market returns were very reassuring to the financial press. Our studies quickly became famous.

The returns we measured were "total returns," which included both the income return and the capital gains or losses. This was not the common practice at the time; price-only returns were typically reported along with a separate income yield. For decades, our total return stock and bond data were the go-to source when an analyst, adviser, financial trivia seeker, or teacher needed detailed information on the historical total returns, expected returns, and risks of a variety of asset classes.

Our work might have had more practical appeal than academic appeal. Creating stock and bond market total return indices had a tremendous impact on the business world. Investors were interested to know what kind of long-term return to expect from the stock market, and they were just beginning to realize the enormous impact of compounding, which, as we know, leads to exponential growth of wealth. It seems obvious 50 years later, but, for example, with a 10% return compounded over 50 years, $1 grows to more than $117. This concept astounded investors and made them realize that simply investing in an overall stock market index could create tremendous wealth over a long period.

The original stock and bond data were published in the *Journal of Business*. In the second of these articles, "Stocks, Bonds, Bills, and Inflation: Simulations of the Future (1976–2000)"

(Ibbotson and Sinquefield 1976b), we used the historical data as the starting point for modeling inflation, real interest rates, and various risk premiums to simulate long-term stock and bond probability distributions of future returns. Although the forecasts were bootstrapped a quarter-century forward, the simulations out to 2000 turned out to be remarkably accurate, including nominal stock market returns. In the latter sections of this book, we will be using current financial markets to predict the future. One of the prediction chapters in this book, coauthored by Will Goetzmann, Otto Manninen, and me, uses methods similar to those in the original article (Ibbotson and Sinquefield 1976b) to predict asset returns from 2026 through 2050.

History of Creating Stocks, Bonds, Bills, and Inflation Indices

In the years after the original SBBI series was published, we continued to update the series, which included our first CFA Institute Research Foundation (formerly named Financial Analysts Research Foundation) publications (Ibbotson and Sinquefield 1977, 1979, 1982). In 1977, I founded Ibbotson Associates (IA), which eventually took over the updating and publication activities, publishing the first *Stocks, Bonds, Bills, and Inflation Yearbook* in 1983. The Yearbooks continued to be published by Ibbotson Associates every year from 1983 through 2006, when Morningstar, Inc., purchased Ibbotson Associates. Starting in 1999, Ibbotson Associates also published Valuation Editions of the *Stocks, Bonds, Bills, and Inflation Yearbook*.

After it purchased Ibbotson Associates in 2006, Morningstar continued to produce the SBBI data and the Yearbooks. Morningstar discontinued the Valuation Editions of the Yearbooks in 2013. In 2016, it discontinued the remaining Classic Editions of the Yearbooks, transferring the publication rights to Duff & Phelps, Inc., which also spun off this activity in 2021 to Kroll Inc. Kroll continued to publish the Yearbook until the last one was published in 2023. Morningstar had sold off the SBBI trademark, and in the recent past only charts and tables have been produced under the SBBI trademark. Morningstar continued to publish the underlying stock and bond indices through 2024 but publicly announced it was discontinuing the indices in early 2025.

Back to the Future

Flash forward 50 years, and we are now celebrating the 50th anniversary of the original publication of "Stocks, Bonds, Bills, and Inflation: Year-by-Year Historical Returns (1926–1974)." Because the data we collected for this flagship tool started in 1926, it is also the 100th anniversary of the dataset. The original SBBI data are being discontinued, but the purpose of this project, which includes this book, is to continue with a replacement dataset that incorporates the original US markets, with some additional detail. The replacement data are now called Ibbotson®[2] Equity and Bond Indices, and we are using CRSP data to create the new indices.

[2] Ibbotson® is a trademark owned by Morningstar, Inc. The information contained in the indices has not been prepared by Morningstar, and Morningstar is not responsible for any damages or losses arising from any use of this information. Past performance is no guarantee of future results. These indices may also be referred to as Ibbotson Equity and Bond Indices, Ibbotson Equity Indices, or Coleman Fisher Ibbotson (CFI) Bond Indices.

The primary purpose of this book is to promote and analyze the new replacement stock and bond return indices, as well as to take a look back. These Ibbotson Indices start in 1926, as the prior series did. Of course, the US markets started before 1926, and they are not the only important stock and bond markets in the world, nor is the most recent 100 years the only period that matters. Thus, although I am the primary editor of this book, I rely on a host of coauthors, many of whom are friends and colleagues around the world, who help contextualize the last 100 years of US data.

Although I have continued over the years to straddle business and academia, I have partnered with many of the coauthors of this book from both worlds to make their academic work more clear to laypeople and finance experts. Collectively, these coauthors are many of the top researchers in creating the historical data that have become so useful in understanding our financial markets.

The Voices in This Book

Gathered in these pages are some of the seminal voices in finance and economics over the last 50 years. Many of these experts "grew up together" in this field, and we have relied on each other as sounding boards, reviewers, contrarians, and, for the most part, friends.

Larry Siegel, a student of mine at the University of Chicago, became my first employee at Ibbotson Associates. He was a consultant, writer, editor, and media spokesperson. The financial press flocked to IA for comments, and Larry was accessible, smart, and accurately quotable. Ibbotson Associates became a household word in the finance community, partly because of SBBI but also because Larry knew how to communicate its relevance. Although Larry and I have not worked together in decades, we remained friends and have reunited for this book. Larry serves as executive editor of this book, coauthoring several chapters, writing the foreword, and closely editing every chapter. One of the chapters Larry coauthored is Chapter 9, written with Carla Nunes, until recently a managing director at Kroll (formerly Duff & Phelps), on "The Equity Risk Premium."

IA hired Tom Coleman when he was a PhD student at the University of Chicago in the early 1980s. In 1984, I became a faculty member at the Yale School of Management, and Tom was at Stony Brook University. In the late 1980s and early 1990s, we worked with the late Lawrence Fisher to build yield curves using his newly constructed CRSP US Treasury bond files. The three of us were dynamic: I organized and funded the project, Lawrence provided much of the expertise and datasets, and Tom worked on the programming and implementation. Tom and I have extended and updated our Coleman Fisher Ibbotson (CFI) indices in Chapters 7 and 8.

James Harrington, another Ibbotson Associate from the early 2000s, took over producing the SBBI Yearbook after it was sold to Morningstar. When Morningstar discontinued SBBI, Jim followed the Yearbook to Duff & Phelps and later to Kroll, producing it until 2023. More than anyone, he understands the background of the formulas, so we asked him to co-write Chapter 3 on index construction. Jim has been a lifelong supporter of SBBI. His writing is brilliant and fluid, and his formulas are accurate.

When Worlds Collide: Academia and Business

We would have made a grave mistake to produce a book on the history of stocks, bonds, bills, and inflation without including a historian in the mix. Financial historian and Yale professor William Goetzmann, author of *Money Changes Everything: How Finance Made Civilization Possible* (Goetzmann 2016), has worked on several chapters, including "The London Market, 1870–1929" (Chapter 12), with Geert Rouwenhorst and Fernando Reyes De La Luz. Will is currently a professor and the faculty director of the International Center for Finance at the Yale School of Management. He takes great interest in bootstrapping, working with Otto Manninen and me on "Forecasting Equity and Bond Returns" (Chapter 20).

Yale University has been highly supportive of me, for which I express deep appreciation. Many chapters of this book were written by or coauthored with my Yale colleagues.

Will and I met when he was an MBA and doctoral student at Yale. He left to teach at Columbia University, and I worked to hire him back at Yale, where he founded the International Center for Finance. Will and I published our separate and coauthored research papers related to the equity risk premium into a volume, *The Equity Risk Premium: Essays and Explorations* (Goetzmann and Ibbotson 2006), and he brings his expertise to coauthoring Chapters 5 and 6, "Statistical Analysis of Equity Returns" and "Bubbles, Booms, and Crashes, 1792–2024."

Another former Ibbotson Associate, Thomas Idzorek, moved from IA to Morningstar in 2006, when the latter firm bought the former. Tom is a good example of the "bridge" between academia and business. He thinks like an academic in the corporate world. Tom, along with Larry Siegel, helped me write Chapter 2, "Highlights of the Past 100 Years." Paul Kaplan, another IA alumnus, recently retired from Morningstar, and Tom, Paul, and I have coauthored many papers and monographs over the years, several of them on popularity. (Spoiler alert! See Chapter 18, "Popularity and Premiums.") Perhaps the most influential publication the three of us cowrote (along with James X. Xiong) was *Popularity: A Bridge Between Classical and Behavioral Finance* (Ibbotson, Idzorek, Kaplan, and Xiong 2019), which includes a foreword by Larry Siegel.

With the ability to produce the math behind the concepts, Paul Kaplan has been my reliable "go-to" brain for quantitative thinking over the last several decades. He was able to recast an earlier paper I had written on equilibrium theory with the popularity asset pricing model as the result. Paul was a director of research at Morningstar, responsible for the quantitative methodologies behind Morningstar's fund analysis, stock analysis, advice, adviser tools, and other services. His chapter on "Parametric Forecasting" (Chapter 19) perfectly reflects his ability to express data and forecasts quantitatively.

Geert Rouwenhorst and I have been in the same academic circles at Yale for 25 years but have never coauthored a publication. He created a suite of new commodity indices and founded a US commodities investment management firm in 2009. Geert is able to communicate difficult concepts about commodities gracefully, bridging the gap between the corporate and the academic worlds. His chapter, "An Index of Commodity Futures Returns Since 1871" (Chapter 13), written with Rajkumar Janardanan and Xiao Qiao, offers good insights on a complex topic.

My work with the staff of Zebra Capital, where I am chair, has also been helpful in constructing the stock and bond indices. I am particularly grateful to Michael Holmgren for analyzing and refining data and finding ways to display the data effectively.

Across Space and Time

Although the book focuses primarily on SBBI and its impact in the United States over the past 100 years, we are fortunate to have a section that summarizes market returns that are not covered by the Ibbotson Indices. We start in Chapter 10 with Edward McQuarrie's "US Stocks and Bonds Before 1926." Although Will Goetzmann, Liang Peng, and I collected the NYSE stock data over 1815–2025, we were unable to include much dividend or capitalization data. Ed came along several years ago and was able to fill in many of the gaps, using various sources from the internet.

Bryan Taylor, chief economist at Finaeon, collected an incredible trove of data to examine global markets in previous centuries. He begins his story (Chapter 16) way back in 1601, when only one stock traded on the Amsterdam stock exchange; by 1914, thousands of stocks and bonds traded on dozens of stock exchanges throughout the world.

The well-known work of Elroy Dimson, Paul Marsh, and Mike Staunton is summarized in Chapter 11, "Global Markets over the Last 126 Years." Elroy and I have known each other for more than 25 years. While I was compiling US data for stock and bond indices starting in 1926, Elroy was putting together indices from every country in the world. Our work is complementary and synergistic. Elroy also worked with David Chambers, Antti Ilmanen, and Paul Rintamäki on evaluating and critiquing index construction (Chapter 17).

Asian equity and bond markets were added to the mix more recently, and both Chinese and Japanese stock markets have been influenced strongly by historical and political forces. Tadaaki Komatsubara and Peng Chen present their new Japanese and Chinese market indices in Chapters 14 and 15, respectively.

Tadaaki cofounded Ibbotson Associates Japan in 2000 and has served as its chief investment officer for more than 25 years, working as a leading provider of investment consulting services to institutional investors in Japan. Although it was acquired by Morningstar in 2006, the firm is still known as Ibbotson Associates Japan. Tadaaki calls himself the "Last Samurai," still feeling connected to the Ibbotson brand. Peng Chen was chief investment officer of IA and later served as president of Morningstar Investments, before heading up Dimensional Fund Advisors in Asia for many years. He is now a consultant to Morningstar, Inc., and several other organizations.

Otto Manninen is responsible for compiling much of the US data and writing several chapters. A new member of the Ibbotson galaxy, Otto received his master's degree at the Yale School of Management in 2024 and stayed on to assist Will Goetzmann, me, and other faculty with our work, including coauthoring Chapters 4, 5, and 20. His contributions to the development of the book are too numerous to mention, and his intellectual capabilities bode well as an example of his rising generation's contributions to the fields of economics and finance.

As can be seen from this description, this book represents a reunion of the many years all of us have worked together, as well as a reunion of the project. The original two SBBI papers are now (in 2026) celebrating their 50th anniversary, and the dataset now covers 100 years. A data and book project of this complexity requires special organization, and Katherine Hinds has served as an exceptional project manager, both organizing and editing this book.

The Outline of This Book

The book is divided into four sections. It starts with an overview. The second section features a discussion of the past 100 years in US markets using the new Ibbotson Equity and Bond dataset. The next section is a presentation of US data prior to 1926 and data from global markets over multiple centuries. The final section focuses on using historical data to help predict the future.

We hope you learn from it, enjoy it, and pass it on.

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CHAPTER 2. HIGHLIGHTS OF THE PAST 100 YEARS

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Introduction

Fifty years ago, in 1976, the publication of Roger Ibbotson and Rex Sinquefield's "Stocks, Bonds, Bills, and Inflation" (SBBI®) in the *Journal of Business* (Ibbotson and Sinquefield 1976a) marked the first time that data on the total returns and associated exponential wealth indices of the major asset classes were compiled. This research allowed investors to study the historical returns, understand the distributions of returns, and see how each of these asset classes interacted with each other. Their study used data beginning in 1926. Now, in 2026, we celebrate the highlights of the past 100 years!

Within the past several years the SBBI indices in their original form were discontinued, but the SBBI trademark continues to be used in connection with the publication of charts and tables. The authors of and contributors to this book, however, have replaced, renamed, updated, and expanded the stock and bond series. The new indices are generated from Center for Research in Security Prices (CRSP) datasets.[1] The new stock and bond indices presented here cover the 100-year period 1926–2025.

100 Years of Stock and Bond Returns

The Ibbotson® Equity and Bond Indices (Ibbotson Indices) are monthly total return indices that start in 1926 and now cover a full century.[2] Following Ibbotson and Sinquefield (1976a, 1976b), the Ibbotson Indices cover US large-capitalization stocks, US small-cap stocks, US long-term

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[1] CRSP was created in 1960 at the University of Chicago Graduate School of Business (now Chicago Booth), becoming a wholly owned LLC subsidiary of the University of Chicago in 2020. In 2026, it was acquired by Morningstar, Inc.

[2] Ibbotson® is a registered trademark of Morningstar, Inc. The information contained in the Ibbotson Equity and Bond Indices has not been prepared by Morningstar, and Morningstar is not responsible for any damages or losses arising from the use of the information. Past performance is no guarantee of future results. Morningstar is not responsible for this content and has no liability for its use.

Treasury bonds, "cash" (US 30-day Treasury bills), and US inflation, along with several additional size categories of US stock markets and maturity categories of US Treasury bonds.

The names of all individual and composite indices in the Ibbotson® Equity Indices and selected indices in the Coleman Fisher Ibbotson® Bond Indices[3] are displayed in the sidebar below.

Ibbotson Equity and Bond Indices: List of Index Names

Ibbotson Equity Indices*

Base Indices

Ibbotson 25
Ibbotson Large Cap (includes Ibbotson 25)
Ibbotson Mid Cap
Ibbotson Small Cap
Ibbotson Micro Cap

Composite Indices

Ibbotson Large Cap Composite (Large Cap + Mid Cap)
Ibbotson SMID Composite (Mid Cap + Small Cap + Micro Cap)
Ibbotson Small Cap Composite (Small Cap + Micro Cap)
Ibbotson All Cap Composite

Coleman Fisher Ibbotson (CFI) US Treasury Par Bond Yield and Return Indices**

CFI 30 Day Treasury Bills (T Bills)
CFI 3 Month T Bills
CFI 6 Month T Bills
CFI 1 Year T Bills
CFI 2 Year T Notes
CFI 3 Year T Notes
CFI 5 Year T Notes
CFI 7 Year T Bonds
CFI 10 Year T Bonds
CFI 20 Year T Bonds
CFI Long Term T Bonds

*All equity indices include total return, income, and capital gain series.

**All bond indices include annualized yields, monthly yield returns, returns in excess of yield, and total returns.

[3]For more information, see Thomas S. Coleman, Lawrence Fisher, and Roger G. Ibbotson, *US Treasury Yield Curves 1926–1988* (Moody's Investors Service, 1989).

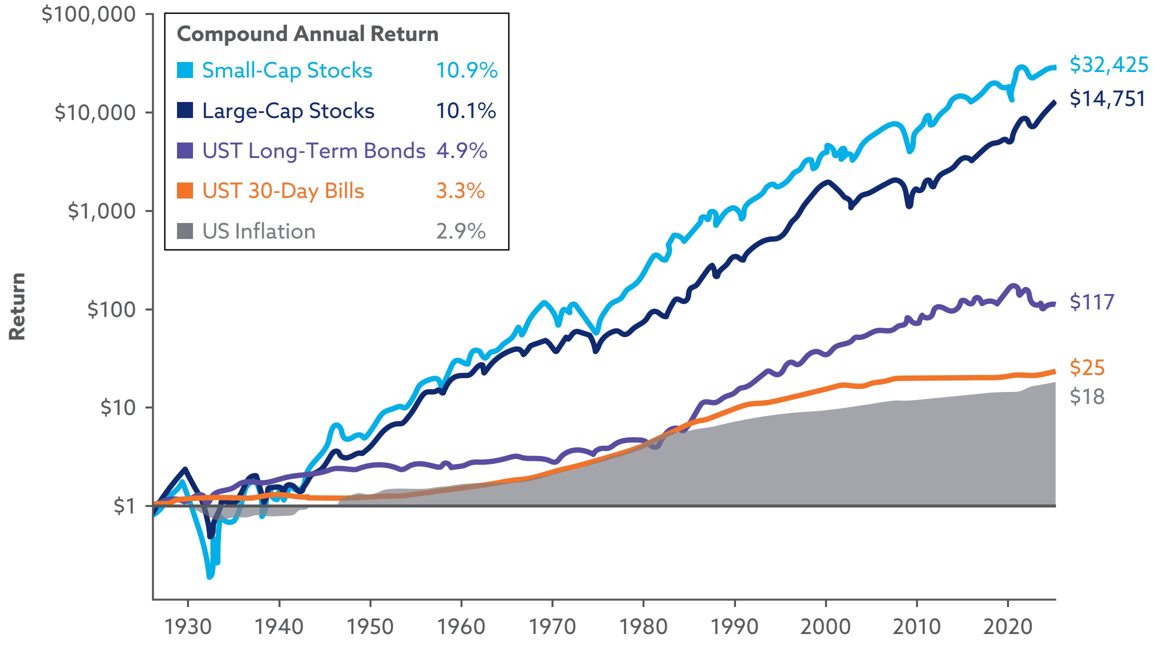
The Growth of a Dollar over the 100 Years

In **Exhibit 2.1**, we show what happened to the stock and bond markets over the last 100 years. If we invested $1 at the beginning of 1926 and reinvested all the dividends and income, holding these indices over the entire 100-year period ending in 2025, we can see how much wealth is created.[4] Exhibit 2.1 is drawn in log scale, so on the vertical axis, the difference between $1 and $10 is the same as that between $10 and $100, as is the difference between $100 and $1,000. Thus, the slope on the graph represents the rate of return over time, no matter how much is invested at any one time and no matter what time interval in the 100-year time period is examined.

Starting with US large-cap stocks, which represent the bulk of the US stock market, $1 invested in 1926 grew to almost $15,000 over the 100-year period, providing a compound annual return or geometric mean return of 10.1%. US small caps did even better, with a 10.9% compound return, causing $1 invested in these stocks in 1926 to grow to more than $30,000!

The bond market returns are nowhere near as high. US long-term Treasury bonds earned a 4.9% return, and US Treasury bills delivered a 3.3% return, growing to around $117 and $25,

Exhibit 2.1. Ibbotson Equity and Bond Total Return and Wealth Indices, 1926–2025



Source: Ibbotson Equity and Bond Indices, derived from CRSP data.

Note: UST stands for US Treasury.

[4] This result assumes the investor incurred no costs, such as management fees, transaction fees, or taxes.

respectively, over the 100-year period. We will look at the impact of inflation shortly, but a key highlight is that equity markets produced an incredible amount of wealth, in both nominal and real (inflation-adjusted) terms, during the 100 years of exponential growth.

These returns were not realized in a vacuum. The last 100 years were filled with events that, in many cases, directly impacted capital markets. At times, the causality was in the opposite direction, with market events impacting the economy.

In Chapter 3, we explain how we calculate annual arithmetic mean returns, compound annual (geometric mean) returns, and the standard deviations of the return series.

The Stock Market

The period we study begins with the Roaring Twenties. That decade ended with the Great Crash of October 1929, which ushered in the Great Depression of the 1930s. The Great Depression was associated with the worst stock market returns of the 100-year period. After a partial recovery in the mid-1930s, the late 1930s ended with another large decline. By 1940, the market index (including total returns) was above its level at the beginning of 1926 but still well below its early September 1929 highs.

World War II started in 1939 and was initially not good for US stocks. The stock market dramatically improved by mid-1942, however, with strong returns as the prospects of the Allies improved. As World War II ended, the stock market was initially weak but soon recovered because the US economy was largely undamaged by the war. This expansion continued through the 1950s and 1960s, with only a few minor recessions. The Korean War and the Vietnam War were not as harmful to US capital markets as previous wars had been.

The long bull market that followed World War II ended with the severe recession of 1973 and 1974. The stock market had its largest major fall since the 1930s, with a total return of about –44% from monthly peak to trough. The market continued to advance through the 1980s, apart from the recession of 1981, with a positive total return even in 1987, when the largest one-day decline in history occurred in October of that year.

Although the 1990s started with a recession, returns throughout the decade were spectacular, especially for technology stocks. This expansion finally ended with the bursting of the tech bubble and the recession of 2000–2001, resulting in a three-year drop in stock prices with a total return of almost –50%. But the stock market recovered again until the global financial crisis of 2008. This latter drop was just as severe, again with a total return of almost –50% from peak to trough on a month-end basis, a drop exceeding those that accompanied the 1973–74 and 2000–01 recessions.

The stock market recovered again, however, and then more recently moved to new highs. Since 2009, we have had only a few bad periods. One occurred during the COVID-19 pandemic, which led to a large drop in March 2020, but after this decline, the move to new highs was relatively quick in coming and large in magnitude. After three years of double-digit increases, the market fell in 2022. But as our century of data comes to an end in 2025, the stock market was once again at an all-time monthly high, the result of three more double-digit up years.

The Bond Market

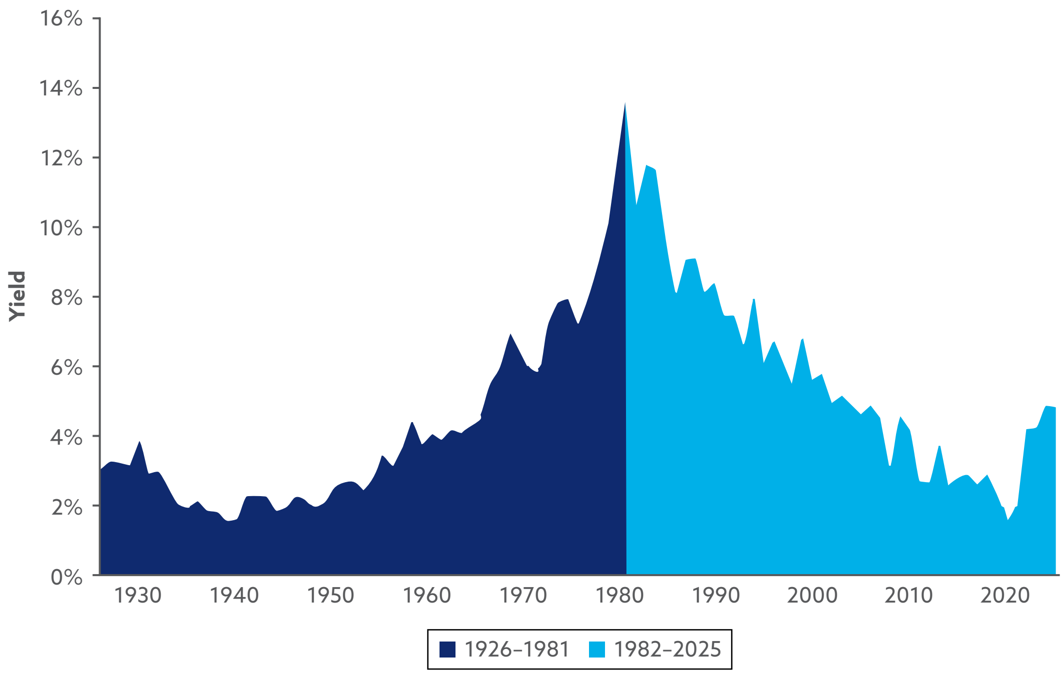
The fixed-income side contains a remarkable long-term event, which in other work we have called the "bond mountain." When bond yields rise, bond prices fall. When bond yields fall, bond prices rise. The return on a bond is the bond's initial yield plus the *return in excess of yield*. This latter quantity, arising from changes in the bond's price, is approximated by the duration of the bond multiplied by the negative change in the yield of the bond.

Yields mostly fell from 1926 until the middle of World War II, when they hit their bottom because of price controls. After that, bond yields rose, as if climbing a mountain, to levels that were unprecedented except in wartime. The peak was reached in 1980–1981, when long-term US Treasury yields exceeded 15%, reflecting the double-digit inflation rates of the time.

After the 1981 peak, bond yields fell sharply and continued to fall in a more or less continuous decline for the next four decades on the way to yields below 1% in 2021. The decline in yields meant that bond *prices* rose dramatically—so much so that the total returns of long-term US Treasury bonds almost matched the total return of stocks during the long bull markets that started in the early 1980s.

Exhibit 2.2 shows bond yields over 1926–2025. The bond mountain is by far the most prominent feature of the exhibit.

Exhibit 2.2. Year-End Yields on Coleman Fisher Ibbotson US Treasury 20-Year Bonds, 1926–2025



Source: Coleman Fisher Ibbotson US Treasury Indices.

Summary Statistics

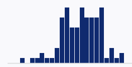
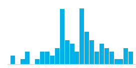
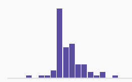
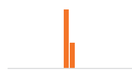
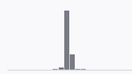
Exhibit 2.3 summarizes the data. We show the compound annual return and the arithmetic mean return along with the standard deviation, which is a measure of the risk of the asset. We also include, in the last column, bar graphs showing the distributions of the corresponding 100 annual returns, all on the same scale; this is another way of showing that the risk of stocks is much higher than the risk of bonds.

The Negative Impact of Inflation

Thus far, we have focused on investment returns without adjusting them for inflation. Inflation is a decline in the purchasing power of money. For investors, it is particularly harmful because it causes them to be paid back in dollars that are worth less than those they originally invested.

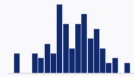
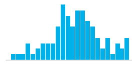
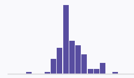
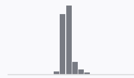
Inflation can be deceptive. During inflationary periods, nominal asset prices (those that are observed) can increase even while their economic value declines. People can feel wealthier even though they are able to purchase less with their money. Inflation thus contributes to nominal growth but not to actual growth. To address this issue, economists calculate "real" returns—that is, the nominal return is adjusted for inflation, reflecting the fact that inflation drags down the purchasing power of a dollar.

Exhibit 2.3. Ibbotson Equity and Bond Returns and Risk, 1926–2025

	Compound Annual Return	Arithmetic Annual Return	Risk (standard deviation)	Return Distribution
Large-Cap Stocks	10.1%	11.8%	18.9%	
Small-Cap Stocks	10.9%	14.4%	27.5%	
UST Long-Term Bonds	4.9%	5.4%	10.6%	
UST 30-Day Bills	3.3%	3.3%	3.1%	
US Inflation	2.9%	3.0%	3.9%	
				–90 ← 0 → 90

Source: Ibbotson Equity and Bond Indices, derived from CRSP data.

Exhibit 2.4. Inflation-Adjusted Stock, Bond, and Bill Returns and Risk, 1926–2025

	Compound Annual Return	Arithmetic Annual Return	Risk (standard deviation)	Return Distribution
Large-Cap Stocks	6.9%	8.7%	18.9%	
Small-Cap Stocks	7.8%	11.2%	27.1%	
UST Long-Term Bonds	1.9%	2.5%	11.5%	
UST 30-Day Bills	0.3%	0.4%	3.9%	
US Inflation	2.9%	3.0%	3.9%	
				–90 ← 0 → 90

Source: Ibbotson Equity and Bond Indices, derived from CRSP data.

As shown at the bottom of Exhibit 2.1, consumer prices went up 18-fold—a 2.9% rate of inflation—over the 100-year period. Stated differently, at the end of 2025, you would need $18 to purchase what $1 could have purchased at the beginning of 1926. In **Exhibit 2.4**, we show the evolving inflation series and adjust the stock and bond series to show the real or inflation-adjusted exponential growth of $1.

By comparing the real returns in Exhibit 2.4 with the nominal returns in Exhibit 2.1, we can see the significant negative impact of inflation on real growth. Nevertheless, the *real* returns that the stock market provided were generous indeed: We could have made more than 800 times our money even *after* inflation. We would not have made that kind of money in the bond markets. After inflation over the last 100 years, we would have made less than eight times our original investment in long-term US Treasury bonds and less than twice our money in Treasury bills.

Is Exponential Wealth Attainable?

Some commentators have argued that creating wealth indices by linking total returns produces an illusion of very large returns, which, some assert, are unattainable by investors. This critique points out that a wealth index constructed from total returns is not macro-consistent—that is, not everybody can earn these returns because dividends are mostly consumed rather than being reinvested in markets.[5] However, we are measuring what is possible for those who *do* reinvest, even if not everybody can do so. Total returns are the relevant measure of performance.

We have already indicated in the discussion accompanying Exhibit 2.4 that real (inflation-adjusted) returns are more relevant than nominal returns. Investors also have costs, including management fees, transaction costs, and, most importantly, taxes. Thus, in practice, one cannot earn exactly the exponential wealth numbers that we present. The total returns that we present, however, are mostly for indices that can be matched closely with index funds. With their very low fees and transaction costs, such funds earn before-tax returns close to those documented here. Indexing also results in substantially less realization of gains subject to tax than traditional active management.

Some critics also argue that during a substantial part of the period studied, it would have been very difficult for investors to construct portfolios that match the indices provided here. This assertion is undoubtedly true during the first 50 years of our sample, but by 1976, when the original Ibbotson and Sinquefield (1976a, 1976b) articles were written, equity index funds—with their low fees, limited trading, and low tax impacts—already existed.

A Volatile and Sometimes Painful Journey

By any reasonable assessment, it has been a wonderful 100 years for investors, especially for equity investors, as demonstrated by the high rates of return and levels of terminal wealth shown in the foregoing sections. With such favorable long-term results, it is easy to overlook the volatility of the journey and the periods of pain—times when the market went down and stayed down—associated with that volatility.

Drawdowns: Periods of Pain

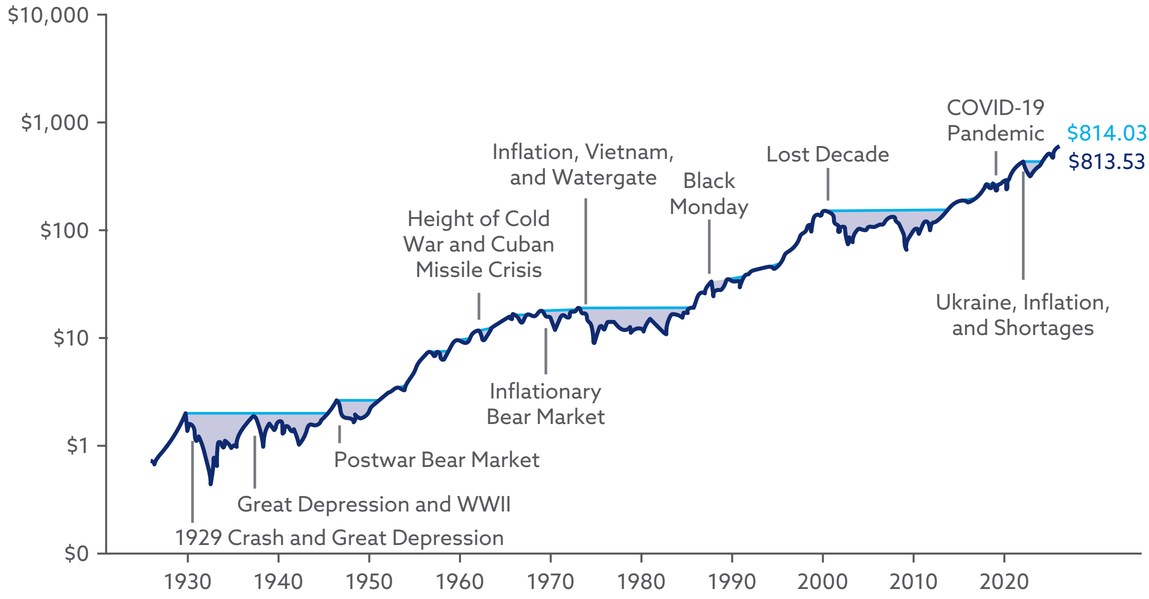
Looking back at Exhibit 2.4 and focusing on US large-cap stocks, we can see that these stocks produced a lot of *real* wealth—"real" both in the sense that the wealth measure is inflation adjusted and in that the amount of wealth created is economically significant.

Yet this journey had at least three periods of 10 years or longer—accounting for about one-third of the 100-year history—in which investors felt extended periods of pain.

In **Exhibit 2.5**, the "pain pools" are shown as shaded areas. These are periods when the value of the inflation-adjusted total return index remains below its previous high-water mark. The length of the pool represents the amount of time it took to return to the previous high-water mark on an inflation-adjusted basis. The volume of the pain pool—a measure of investor pain—depends on the depth and the length of the pool. The "fluid" in these pools is inflation-adjusted dollars.

[5] If everybody tried to be a total return investor, when they received a dividend they would be attempting to invest it in shares of the index. But because (in this hypothetical world) everyone is an index investor, all shares of the index are already held by other investors. Thus, if the would-be total return investor managed to buy shares of the index, she would be buying them from another investor who, as a result of the transaction, could not earn the index total return. This is why it is impossible for *everyone* to earn the total return, even though *any given investor* can do it.

Exhibit 2.5. Real Growth of $1 in US Large-Cap Stocks Showing Pain Periods (logarithmic scale), 1926–2025



Source: Ibbotson Large Cap stock index, adjusted for inflation.

Note: The dark blue value ($813.53) is the ending real (inflation-adjusted) value as of 31 December 2025, which is slightly below the previous high-water mark ($814.03) shown in light blue.

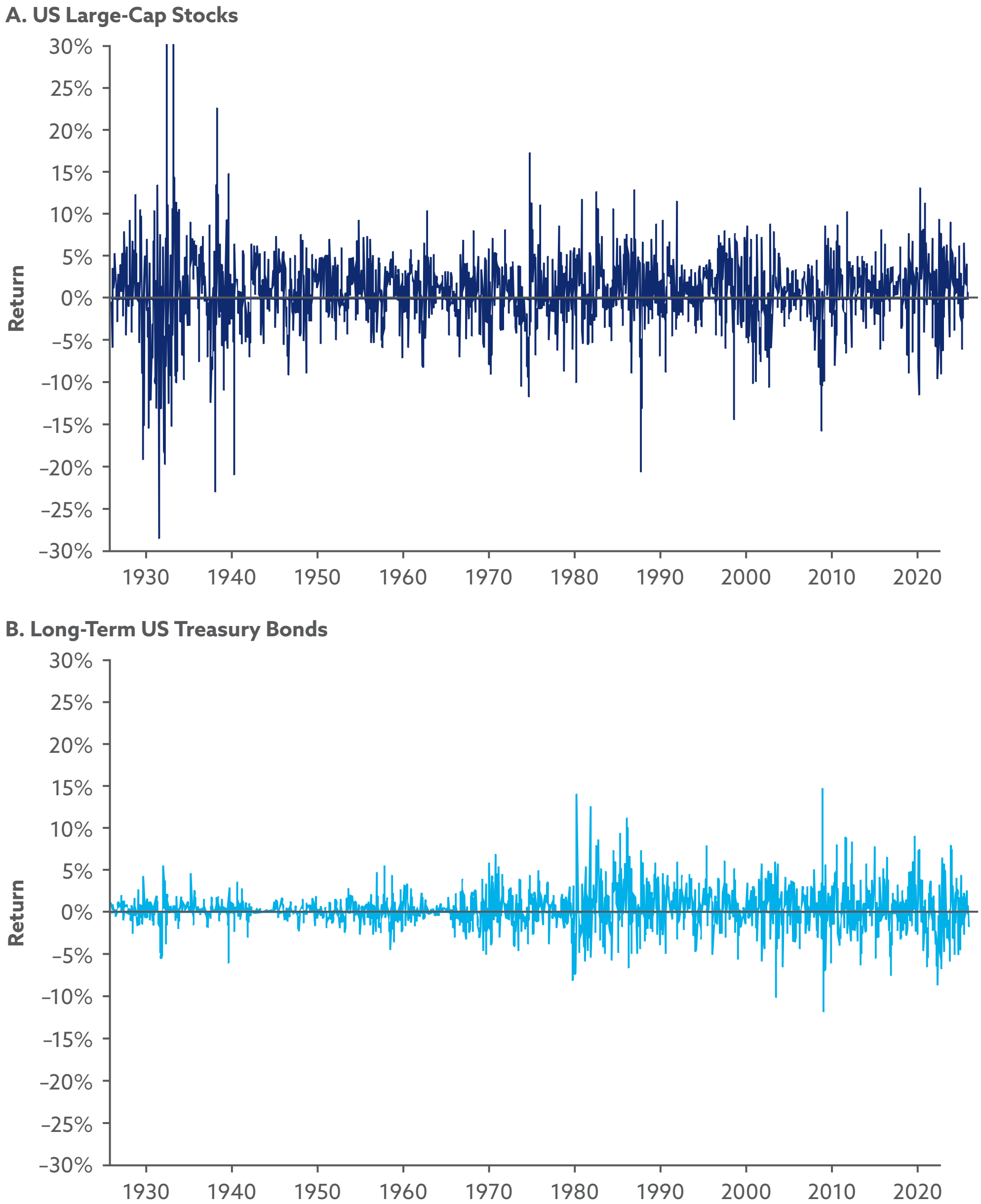
The trifecta of the 1929 crash and Great Depression, World War II, and the post–World War II recession represent a particularly painful two-decade stretch for equity investors in both real and nominal terms. Likewise, the 16-year period from 1966 to 1982 saw almost no growth in real terms. Moving to the twenty-first century, the period from the dot-com bubble through the 2008–09 global financial crisis is frequently referred to as the lost decade. The more recent COVID-19 pandemic–related downturn in the first quarter of 2020 is hardly visible.

Volatility and Risk

Another way to think about pain and risk is volatility. By looking at a graph of realized monthly returns, one can see and compare the volatility of the different asset classes. **Exhibit 2.6** shows the monthly returns of US large-cap stocks and US long-term government bonds. We use the same scale for all series.

Volatility is one of the most important components, if not the dominant component, of risk. As such, stocks are much riskier than bonds. Likewise, US small-cap stocks are riskier than US large-cap stocks, and long-term US Treasury bonds are riskier than Treasury bills. Investors have to be compensated in expectation for taking this extra risk; otherwise, no one would want to invest in the riskier asset classes.

Exhibit 2.6. Monthly Returns on Stocks and Bonds Shown on a Common Scale, 1926–2025



Source: Ibbotson Equity and Bond Indices, derived from CRSP data.

Risk Premiums as Compensation for Risk: The Building Block Approach

Investors are risk averse—that is, to induce investors to hold risky assets (stocks) instead of safer ones (bonds or bills), the risky assets must be priced to offer a higher expected return. We have seen that on average over long periods of time, this expectation has been realized. This difference in returns—realized or expected—between stocks (represented by a cap-weighted market index) and bonds or bills is called the equity risk premium (for more information, see Chapter 9).

In this section, we provide some detail on the premiums that exist in the market. Later, in Chapter 18, we explain why premiums, or return differentials, may result not only from risk but because of other factors as well.

By breaking total returns into their component parts, we can gain a better idea of how inflation and the various premiums sum to the total returns. The building block approach starts with inflation and the real interest rate; these components are embedded in the total return of all the asset classes. When inflation is high, nominal asset returns have to be high enough to offset the degradation of real returns from inflation. Because we are typically measuring risk premiums, asset returns must also attempt to recoup the real interest rate. The real interest rate plus inflation equals the short-term nominal riskless rate, or essentially the return on riskless cash invested in US Treasury bills.

Exhibit 2.7 presents a building block approach to understanding the total return on equities. We start with the return on cash—the sum of inflation and the real interest rate—to give us a

Exhibit 2.7. Building Blocks of Equity Return Premiums

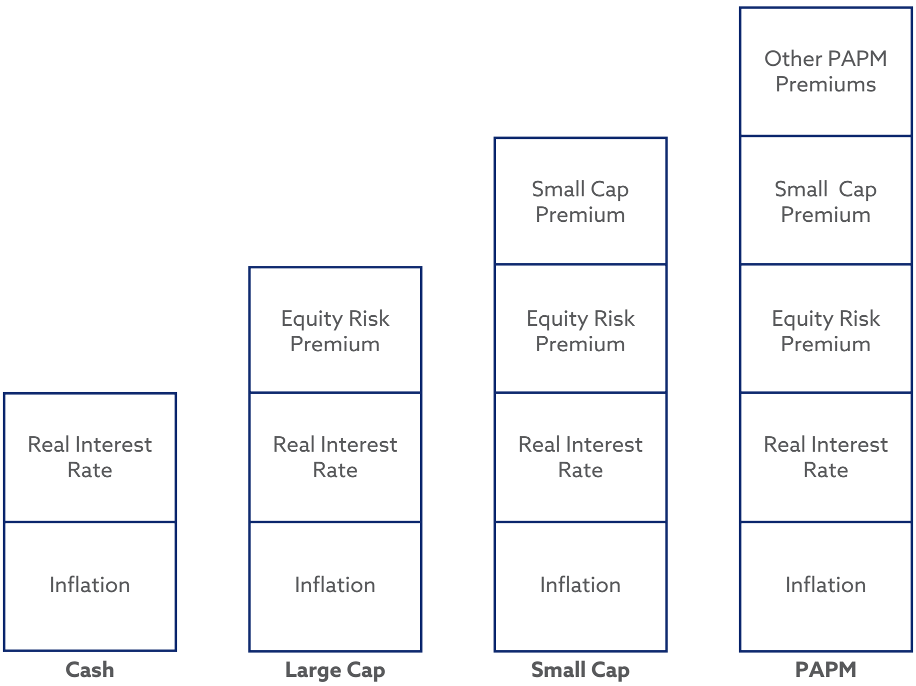
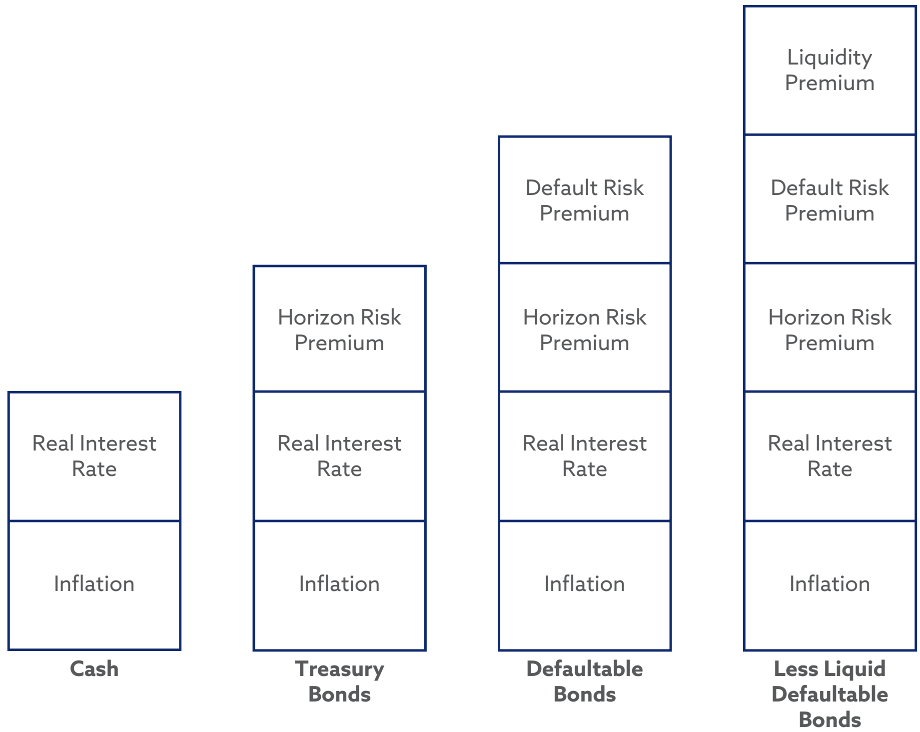


Exhibit 2.8. Building Blocks of Bond Return Premiums



riskless rate. For large-cap equities, we add in the equity risk premium. The historically higher return on small-cap stocks reflects a small-cap premium, which we add to the total return on large caps. We can also add in other premiums as well, including those suggested by the popularity asset pricing model (PAPM), described in Chapter 18.

Moving to fixed income in **Exhibit 2.8**, we also start with inflation and the real interest rate. This sum is merely the US Treasury bill yield, which is directly observable. Adding in the bond horizon premium gives us the US Treasury bond yield. These yields are also observable. The US Treasury yield curve is usually considered to be free of default risk, which means the yield on a US Treasury bond is also the expected return of the bond over the lifetime of that bond.

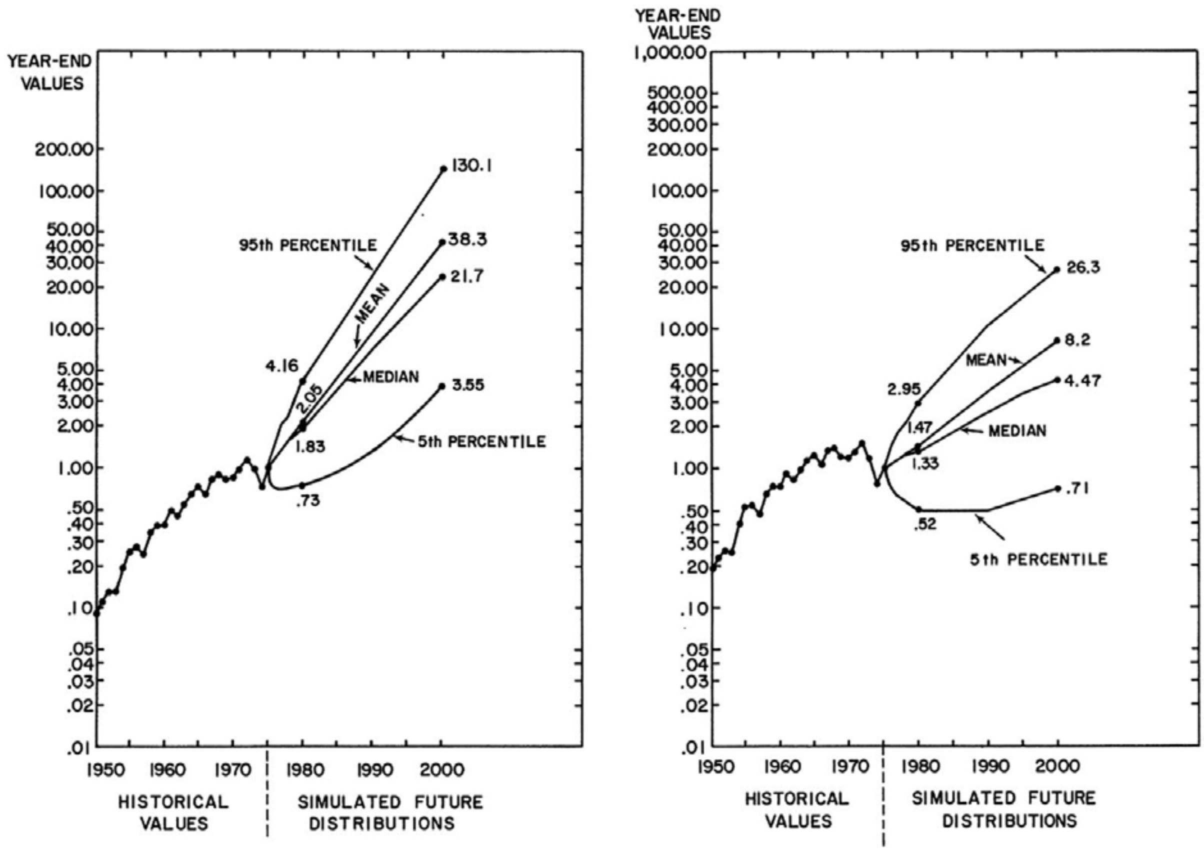
Most other bonds can default. Defaultable bonds have yield spreads over and above the US Treasury yield curve. These yields have to be high enough to compensate investors for any expected defaults and, in addition, high enough to include a default risk premium that investors expect to keep, net of defaults. Thus, investors anticipate realizing higher returns from defaultable bonds than from US Treasury bonds—but not as high as their yields, because they anticipate losing some of their returns to defaults.

Exhibit 2.8 shows the return that investors expect from the various types of bonds. They expect the return from US Treasury bills to cover inflation and the real interest rate. They expect an additional return from buying longer-term US Treasuries because many investors have short-term time horizons, whereas bond issuers prefer to lock in capital over longer periods. Thus, investors prefer shorter-term bonds and have to be compensated for the extra interest rate risk from locking their money up over time; this is the horizon risk premium. Investors also require and expect a default premium for taking on default risk. Finally, investors need to be compensated with a higher yield for holding less liquid bonds.

Forecasting

The "stacks" in Exhibits 2.7 and 2.8 can be used to analyze the past or the future. When an investor is establishing future expectations, yields currently observable in the bill or bond markets, rather than historical average returns, should be used for the parts of the stacks where market yields exist. These include inflation and the real interest rate in Exhibit 2.7 and inflation, the real interest rate, and the horizon premium in Exhibit 2.8. Chapter 9 presents historical averages for each of the risk premiums in these exhibits.

Exhibit 2.9. Original Figures 2 and 4 from Ibbotson and Sinquefield (1976b): Simulated Growth of $1, Nominal and Real, 1976–2020



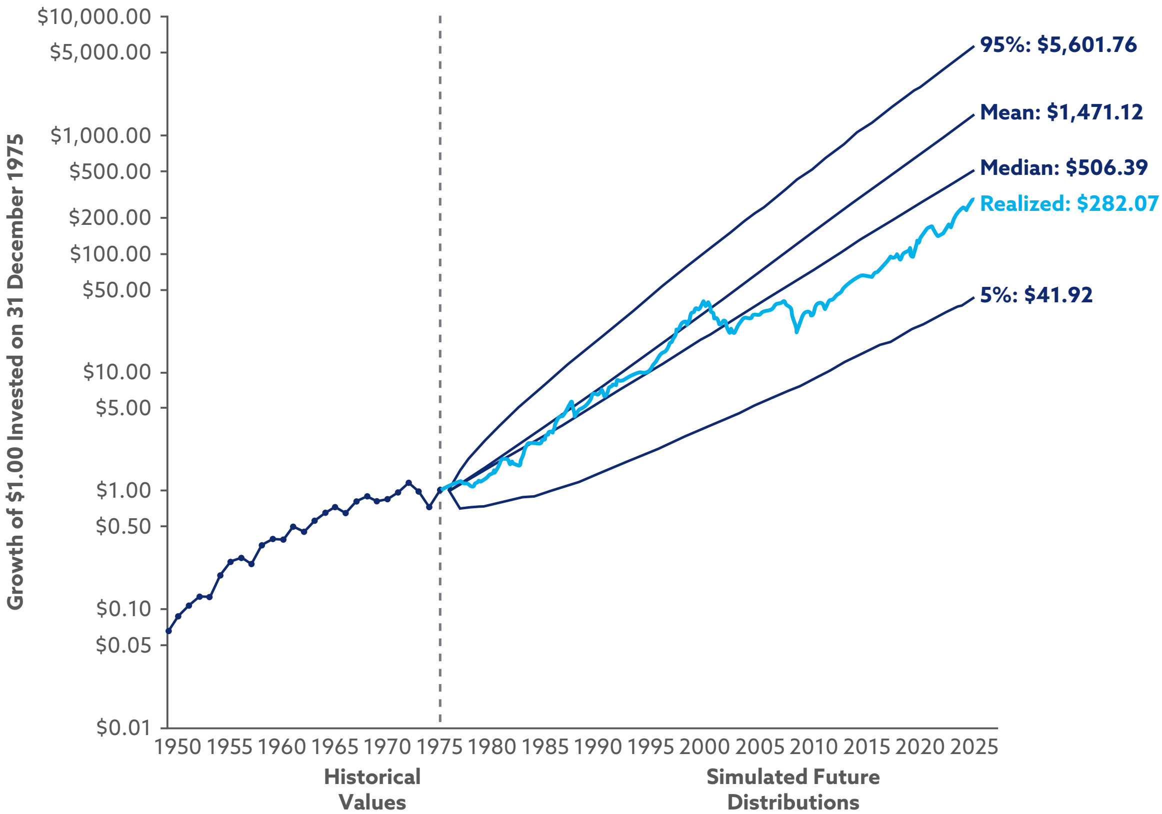
Source: Ibbotson and Sinquefield (1976b).

Note: Year-end values are dollars per dollar invested on 31 December 1975 (left panel shows nominal dollars; right panel shows real or inflation-adjusted dollars).

In "Stocks, Bonds, Bills, and Inflation: Simulations of the Future (1976–2000)," Ibbotson and Sinquefield (1976b) used the various premiums or "building block" approach to simulate future returns—the future at that time being 1976–2000. Now that we have experienced 50 years of returns "out of sample"—that is, after the 1976 forecasts were made—we can assess the accuracy of those forecasts. We perform that assessment next; in Chapters 19 and 20, we return to the topic of forecasting and present two separate ways to forecast future returns and distributions, looking forward from today.

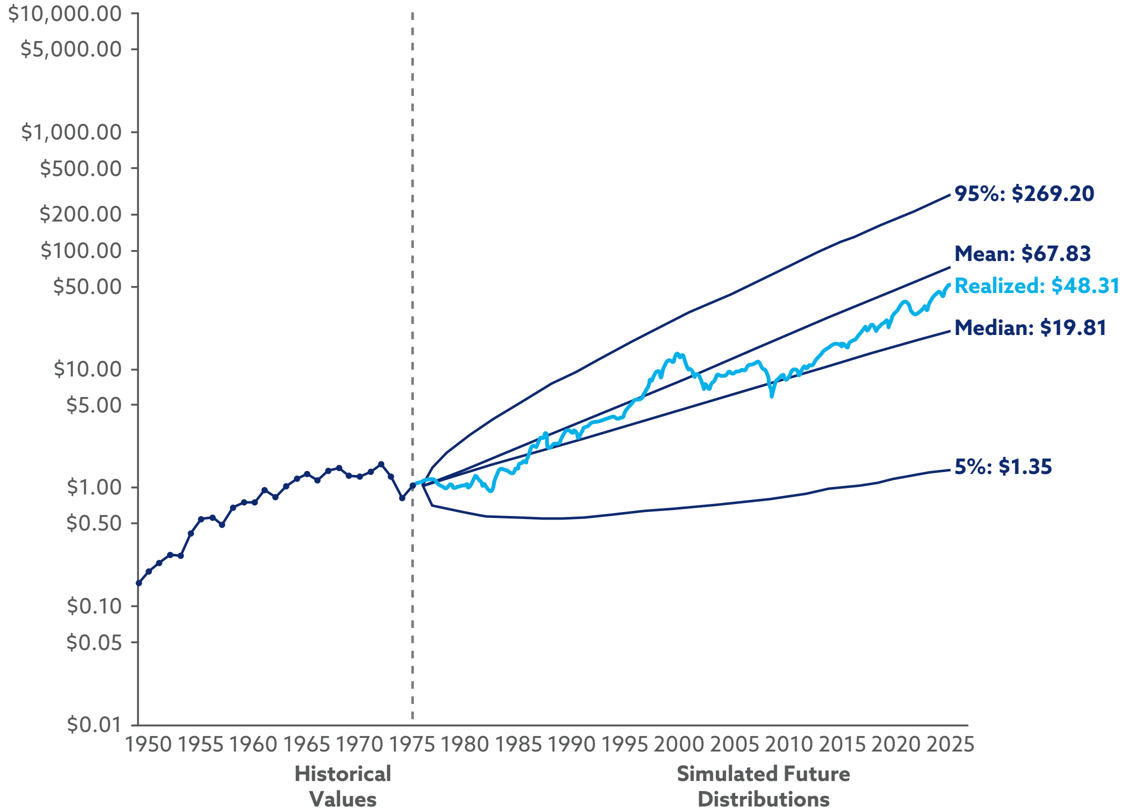
The left and right panels in **Exhibit 2.9** are direct copies of Figure 2 and Figure 4, respectively, from Ibbotson and Sinquefield (1976b). The left panel (originally Figure 2) shows forecast *nominal* returns, and the right panel (originally Figure 4) shows the forecast *real* (inflation-adjusted) returns from 1976 to 2000. Both panels display the forecast mean and median values, along with the values associated with the 95th percentile (approximately the best case) and 5th percentile (approximately the worst case) outcomes using the lognormal simulation method.

Exhibit 2.10. Forecast and Realized Wealth Indices of Common Stocks, 1976–2025, Based on Ibbotson and Sinquefield (1976b)



Source: Ibbotson Equity and Bond Indices.

Exhibit 2.11. Real Forecast and Realized Wealth Indices of Common Stocks, 1976–2025, Based on Ibbotson and Sinquefield (1976b)



Source: Ibbotson Equity and Bond Indices.

In **Exhibit 2.10**, we now apply the 1976 forecasting methodology, using the data and parameters from 1976 (that is, using only information that was available in 1976), to simulate the return distribution over the subsequent 50 years (1976–2025). We also overlay *realized* US large-cap stock returns.

Starting with *nominal* returns, Exhibit 2.10 shows the mean, median, 95th percentile, and 5th percentile growth of $1 in US large-cap stocks. The light blue line shows the actual, or realized, returns on the Ibbotson Large Cap stock index. For the first half of the forecast period (1976–2000), realized returns mostly hovered between the mean and median of the forecast. Then, in the second half of the period (2001–2025), with lower inflation and interest rates, realized returns fell somewhat below the forecast median.

Moving to *real* returns, **Exhibit 2.11** shows the mean, median, 95th percentile, and 5th percentile growth of $1 invested in US large-cap stocks in inflation-adjusted terms. As before, the light blue line shows the realized returns—in this case, real returns—corresponding to the Ibbotson Large Cap stock index. In real terms, the simulation based on the 1976 methodology and parameters does an exceptional job of forecasting the subsequent 50 years' real returns.

Key Takeaways

- We measure the total returns of stocks and bonds. For stocks, total returns consist of capital gains plus reinvested dividends. For US Treasury bonds, total returns consist of the bond's yield plus the return in excess of yield.
- The compound annual total return on US common stocks was 10.1% and on US Treasury bonds was 4.9% during the 100-year period 1926–2025.
- We link (compound) the annual returns to create wealth indices illustrating the creation of exponential wealth through long-term investing. Most of the return represented by these indices is attainable by investors who keep their costs low and reinvest income instead of consuming it.
- Equity returns were approximately the same in both halves of the period. Bonds, however, did poorly because of rising yields until 1981 and then did very well because of falling rates afterward.
- Equities outperformed bonds but with higher risk, providing a high realized equity risk premium.

References

Ibbotson, Roger G., and Rex A. Sinquefield. 1976a. "Stocks, Bonds, Bills, and Inflation: Year-by-Year Historical Returns (1926–1974)." *Journal of Business* 49 (1): 11–47. doi:10.1086/295803.

———. 1976b. "Stocks, Bonds, Bills, and Inflation: Simulations of the Future (1976–2000)." *Journal of Business* 49 (3): 313–38. doi:10.1086/295854.

CHAPTER 3. INDEX CONSTRUCTION: PRINCIPLES AND MODERN DEVELOPMENTS

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Introduction

In the preceding chapter, we examined the historical performance of major asset classes over the past century. We observed how $1 invested at the beginning of 1926 in the Ibbotson Large Cap stock total return index grew to $14,751 by the end of 2025 (100 years) and had a compound annualized return of 10.1%. These remarkable results raise an important question: How exactly do we construct the indices that measure such performance?

The answer is far from trivial. The methodology underlying index construction has profound implications for both performance measurement and investment strategy. This chapter builds on the foundations laid in Chapter 2 by exploring the mechanics of index construction, the evolution of index methodologies, and recent innovations that have transformed how we measure market performance. The choice of index methodology can materially affect measured returns and, consequently, investment decisions affecting trillions of dollars globally.

What Indices Measure

When we track the performance of asset classes, we use indices to represent their cumulative wealth creation. At their core, indices serve three fundamental purposes: They provide the list of portfolio constituents and weights for index funds, supply a benchmark for evaluating the performance of non-index investments, and quantify the returns available to investors who hold a diversified portfolio within an asset class.

First, indices provide the portfolio list for index funds. Conventional index funds and exchange-traded funds are designed to replicate the performance of a specific index by mirroring its composition. The fund manager's primary goal is to minimize tracking error—the difference between the index's return and the fund's return—and the portfolio changes only when the underlying index rebalances.

Second, active managers use the index as a benchmark to evaluate their ability to add value. They might overweight certain stocks or sectors they believe will outperform or underweight those they believe will underperform. In essence, index funds use the index as a strict roadmap, whereas active managers use it as a base map from which they *intentionally* deviate to seek higher returns.

The distinction between index levels and index returns is crucial. An index level represents the cumulative level of wealth resulting from an initial investment, typically normalized to \$1.00 at a base date. Returns represent the percentage change in wealth over a specific period. Applying the compound annual return of large-cap stocks (10.1%) to all 100 years over the 1926–2025 period results in the same \$14,751 terminal index level:[1]

$$\$1 \times (1 + 10.1\%)^{100} = \$14{,}751. \tag{3.1}$$

Weighting Schemes: A Critical Choice

A fundamental decision in index construction is how to weight the constituent securities. This choice determines which securities have greater influence on index performance and shapes the risk–return characteristics of the index.

Price Weighting: Theoretically Weak

First published in 1896, the oldest major US equity index, the Dow Jones Industrial Average (DJIA), is price weighted. Under this scheme, a stock's influence on the index is proportional to its share price, not its market capitalization. A \$200 stock receives twice the weight of a \$100 stock, regardless of the company's relative economic importance.

Consider a two-stock index consisting of Company A (share price of \$100, market capitalization of \$1 billion) and Company B (share price of \$200, market capitalization of \$1 million). Price weighting would give Company B twice the weight of Company A, even though Company B is 1/1,000 the size. This arbitrary scheme persists primarily because of the DJIA's historical prominence and brand recognition. Most modern indices have abandoned this approach in favor of more economically meaningful alternatives.

Market-Capitalization Weighting: The Theoretical Standard

Market-capitalization weighting has become the dominant method to construct modern indices. Each security's weight equals its market capitalization (share price multiplied by shares outstanding) divided by the total market capitalization of all constituents.

This weighting scheme has theoretical support from the capital asset pricing model (CAPM), which implies that the market-cap-weighted portfolio is the optimal portfolio for all investors. Market-cap-weighted indices are also "macro-consistent": The index's composition attempts to match the overall holdings of investors in the market, making it self-rebalancing for ordinary price changes. Corporate actions such as dividend payments, stock splits, and mergers require adjustment, but routine price movements do not.

Nearly all major modern indices use market-cap weighting, including the S&P 500 Index, MSCI World Index, Russell 3000 Index, and FTSE All-World Index.

[1] The precise compound annual return of the Ibbotson Large Cap stock total return index over the 1926–2025 period is 10.07488%; the difference results from rounding.

Creating a Market-Cap-Weighted Index

A market-cap-weighted index consists of the returns of the individual index constituents "weighted" by their respective market capitalizations. Consider a simple two-constituent portfolio consisting of Company A (market cap = \$1 million) and Company B (market cap = \$2 million). The aggregate market cap is \$3 million, so Company A represents 33% and Company B represents 67%. If the returns of Company A and Company B are 7% and –2%, respectively, the overall return of a portfolio consisting of Company A and Company B is calculated as

$$(33\% \times 7\%) + (67\% \times -2\%) = 1\%. \tag{3.2}$$

Note that the overall return (1%) is closer to Company B's return (–2%) than Company A's return (7%). This is because Company B carries more "weight." **Exhibit 3.1** extends this concept to five companies for February 2025.

First, we must understand a critical concept: When weighting by market cap, the market caps are "lagged." This means that the market caps as of the end of the *previous* month are used to weight the returns of the *current* month[2] (e.g., in the example in Exhibit 3.1, the January 2025 market caps are the weights that should be used to calculate the returns of February 2025).

Lagging the weighting component, regardless of what it is, is standard practice in index construction—and for a very good reason: In the case of market-cap weighting, the return of a stock is *embedded* in the market cap.

For example, say Company A in Exhibit 3.1 had a \$1,000,000 market cap at the end of January 2025 and it increased to \$1,045,000 by the end of February 2025 (a 4.5% return). If we used

Exhibit 3.1. Month-End Market Caps and Returns for Companies A, B, C, D, and E

	Month	Market Cap	Percentage of Aggregate Market Cap	Month	Return
Company A	January 2025	\$1,000,000	4.5%	February 2025	7.0%
Company B	January 2025	\$2,000,000	9.1%	February 2025	–2.0%
Company C	January 2025	\$10,000,000	45.5%	February 2025	12.0%
Company D	January 2025	\$7,000,000	31.8%	February 2025	8.0%
Company E	January 2025	\$2,000,000	9.1%	February 2025	2.0%

[2] In this example, a monthly return is calculated. The concept of "lagging" also applies to different time periods (e.g., day, week, quarter).

the February 2025 market cap ($1,045,000), we would be "double counting" the 4.5% return that Company A experienced in February 2025.[3]

The February 2025 return of the index in Exhibit 3.1 can be calculated as follows:[4]

$$(4.5\% \times 7\%) + (9.1\% \times -2\%) + (45.5\% \times 12\%) + (31.8\% \times 8\%) + (9.1\% \times 2\%) = 8.3\%. \qquad (3.3)$$

Float Adjustment: Refining Market-Cap Weighting

A critical refinement to market-cap weighting emerged in the early 2000s: float adjustment (McBride 2000). This methodology recognizes that not all shares are equally available for investment. Closely held shares, cross-holdings, and government stakes are subtracted from total shares outstanding to determine the "free float," the portion available for public trading.

Consider a company with a large market capitalization where 70% of its shares are held by a founding family. Float adjustment ensures that index weights reflect the reality that investors can access only the remaining 30%. Most major index providers have adopted float adjustment as standard practice.

Equal Weighting

In an equal-weighted index, every stock receives the same weight—simply 1/*N*, where *N* is the number of stocks. The S&P 500 Equal Weight Index does exactly this, holding the same 500 companies as the standard S&P 500 but weighting them *equally* at each quarterly rebalance.

This approach reduces concentration in the biggest companies and introduces a built-in contrarian effect: At each rebalance, the index trims stocks that have risen and adds stocks that have fallen. To the extent that stock prices exhibit mean reversion,[5] this discipline can generate a modest rebalancing premium. Equal weighting also tilts the portfolio toward *smaller* companies, which have historically earned slightly higher returns as compensation for higher risk. Together, these effects help explain why the equal-weighted S&P 500 total return index had a compound annual return of 11.1% since 1990 (36 years), slightly ahead of the 10.8% for the cap-weighted version.

The tradeoffs are significant. Price movements constantly push weights away from 1/*N*, requiring frequent rebalancing and generating higher transaction costs. Since 1990, the equal-weighted S&P 500 total return index had an annualized monthly standard deviation of 18.4%, greater than the 16.4% for the cap-weighted version.

Equal-weighted indices are not macro-consistent. They do not reflect how the market is actually held in aggregate, making them more of an active strategy than a neutral benchmark.

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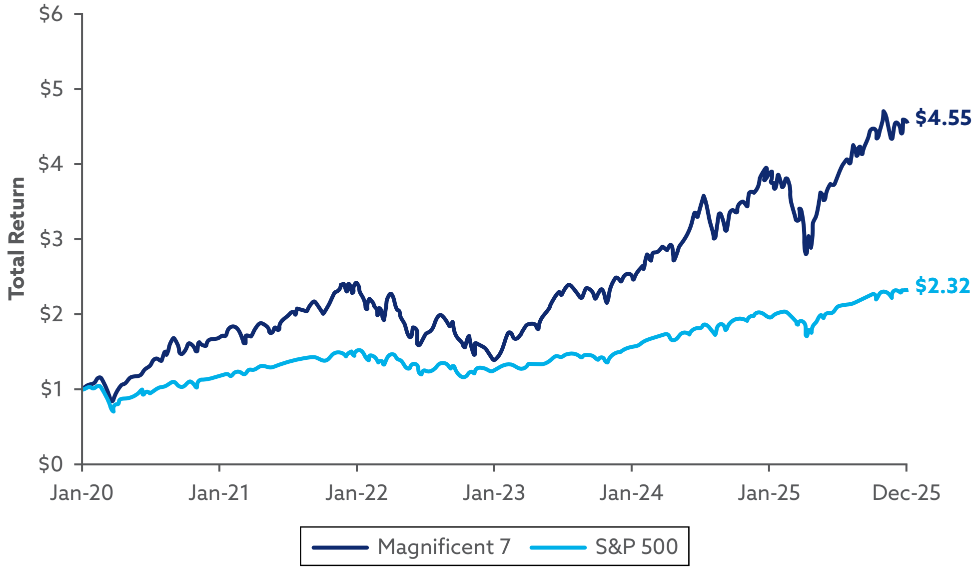
[3] The same argument for "lagging" can be made for most weighting factors to ensure that the weighting factor is independent of returns.

[4] A Microsoft Excel formula can be used to calculate this more easily: SUMPRODUCT(Market Caps, Returns)/Sum(Market Caps).

[5] "Mean reversion" is simply the tendency for assets that have risen above their long-run average to subsequently pull back and for those that have fallen below it to subsequently recover.

Exhibit 3.2. S&P 500 Total Return Index and a Portfolio Consisting of the Magnificent 7, 2020–2025 (year-end 2019 = $1.00)



Sources: Calculations by the authors using data from Datastream and LSEG.

The growing dominance of a handful of mega-cap stocks in cap-weighted indices makes this debate increasingly consequential. When just a few very large companies account for a significant portion of total index weight, such as the so-called Magnificent 7 (Alphabet, Amazon, Apple, Meta, Microsoft, NVIDIA, and Tesla), a cap-weighted index can behave less like a broad market measure and more like a concentrated bet. These seven stocks had an aggregate market capitalization of more than $19 trillion at the end of 2025, accounting for nearly one-third of the approximate $61 trillion aggregate market capitalization of the S&P 500.

Over 2020–2025, a market-cap-weighted portfolio of just the Magnificent 7 compounded at 28.7% annually, compared with 15.1% for the S&P 500 total return index. Stated differently, $1 invested in the S&P 500 at the beginning of 2020 would have grown to $2.32 by the end of 2025, while $1 invested in the Magnificent 7 would have grown to $4.55 (see **Exhibit 3.2**).

Exhibit 3.3 summarizes the key characteristics of the three principal weighting approaches discussed in this section: price-weighted, market-cap-weighted, and equal-weighted indices.

Alternative Weighting Schemes

The past two decades have witnessed an explosion of alternative weighting schemes, marketed under such labels as "smart beta," "strategic beta," and "factor investing." These approaches weight securities based on characteristics other than market capitalization, such as fundamental measures (book value, earnings, sales) or inverse volatility. Although each scheme has its proponents, they share a common trait: They represent active strategies rather than neutral market benchmarks.

Exhibit 3.3. Characteristics of Price-Weighted, Market-Cap-Weighted, and Equal-Weighted Indices

	Price Weighting	Market-Cap Weighting	Equal Weighting
How weights are set	By share price	By market capitalization	Each stock receives 1/*N*
What drives weight differences	Higher-priced stocks receive more weight	Larger companies receive more weight	Nothing—all equal at rebalance
Rebalancing frequency	Only when stocks split or index changes	Minimal—self-adjusting	Frequent (typically quarterly)
Turnover	Low	Low	High
Concentration risk	High—dominated by highest-priced stocks	High—dominated by mega-caps	Low—reduces concentration in largest stocks
Size effect	None—unrelated to company size	Toward larger stocks	Toward smaller stocks
Macro-consistent?	No	Yes	No
Prominent example	Dow Jones Industrial Average	S&P 500	S&P 500 Equal Weight
Key advantage	Simple, long history	Low cost, represents aggregate market	Diversified exposure, rebalancing premium
Key drawback	Arbitrary—a stock split changes the weight	Concentration in largest stocks	High turnover and transaction costs

Fundamental Weighting

Fundamental weighting, introduced by Robert Arnott, Jason Hsu, and Philip Moore (2005) in an influential *Financial Analysts Journal* article, weights constituents by accounting measures, such as book value, earnings, or sales, rather than market price. The key insight is that cap weighting systematically overweights overvalued stocks and underweights undervalued ones because price is embedded in the weight. Fundamental weights, anchored to economic fundamentals rather than price, produce a structural tilt toward value stocks that has historically generated modest return premiums over long periods, although the premium is cyclical and can disappoint for extended stretches, as value investors discovered during the 2010s.

Inverse-Volatility and Minimum-Variance Weighting

Inverse-volatility weighting assigns larger weights to less volatile securities in proportion to the inverse of each stock's historical standard deviation of returns. The intuition is that lower-volatility stocks have historically delivered surprisingly competitive long-run returns relative to their risk—a result that challenges the simple CAPM prediction that higher risk should command a higher reward. Minimum-variance indices extend this idea through portfolio optimization, identifying the combination of weights that minimizes total portfolio variance while accounting for correlations among securities. Both approaches tilt toward defensive sectors (such as utilities and consumer staples) and require regular rebalancing as volatilities and correlations shift, generating higher transaction costs than a cap-weighted index.

Common Tradeoffs

All alternative weighting schemes share several important limitations. First, they are not macro-consistent; investors in aggregate cannot hold a fundamentally or volatility-weighted index the way they can hold the cap-weighted market portfolio. Second, they require active rebalancing, generating turnover, transaction costs, and, in taxable accounts, potential capital gains tax liabilities. Third, their return premiums, to the extent they exist, are generally explainable as compensation for known risk factors or as a mechanical rebalancing premium, not necessarily evidence of market inefficiency.

When Roger Ibbotson and Rex Sinquefield constructed the original SBBI® return series in the 1970s, they chose market-cap weighting precisely because it represents the most neutral, broadly available investment approach—one that any investor could, in principle, replicate. That logic remains sound for the purpose of long-run market measurement. Alternative weighting schemes serve a different purpose and should be evaluated accordingly.

Index Construction Methodology

Beyond weighting, index construction involves numerous methodological choices that collectively determine an index's characteristics and behavior, including security selection criteria, reconstitution frequency, and corporate action treatments.

Company Universe Definition and Security Selection

The first step in index construction is defining the investment universe. For US equity indices, this universe typically includes all securities listed on major exchanges (NYSE, Nasdaq, NYSE American) that meet certain eligibility criteria.[6] Most index providers exclude, for example, American Depositary Receipts, limited partnerships, and closed-end funds.

Index providers differ in how they draw boundaries between market segments. The S&P 500 uses a committee-based approach, considering factors beyond pure market capitalization, including liquidity, financial viability, and sector representation. In contrast, the Russell 3000 uses rule-based criteria to select the 3,000 largest securities, with no committee discretion. These methodological differences can produce meaningful differences in composition and performance, even among indices supposedly measuring the same market segment.

[6] The NYSE American exchange was formerly called NYSE MKT and, prior to that, the American Stock Exchange.

Fixed-Count vs. Percentage-Based Index Construction

An important methodological distinction among index providers is how they define the boundaries between market-capitalization segments. Two principal approaches exist: fixed-count methods and percentage-of-capitalization methods.

Under a fixed-count approach, the index defines its constituents by ranking companies by market capitalization and selecting a predetermined number. The S&P 500 selects approximately 500 large-cap companies; the Russell 1000 Index takes the 1,000 largest; and the Russell 2000 Index takes companies ranked 1,001 through 3,000. This approach is intuitive and produces a stable number of constituents.

Fixed-count methods have a notable limitation, however: The number of publicly listed companies changes substantially over time. According to data from the Center for Research in Security Prices (CRSP), the number of listed US common stocks rose steadily through the 1980s and into the 1990s. It peaked at approximately 7,300 in 1996, before declining sharply as delistings, mergers, and private equity acquisitions of public companies after the dot-com bubble mounted, falling to roughly 4,200 in recent years.[7]

In its first decades, the CRSP database, which initially covered only NYSE-listed stocks, contained far fewer companies. A portfolio defined as the "top 500 stocks" could represent 70% of total market capitalization in one era and 85% in another, depending on how many stocks are listed and how concentrated the market is. The economic exposure of a fixed-count index can shift meaningfully over time even though its count remains constant—a subtle but important limitation for long-run performance measurement.

Two CRSP Index Methodologies

CRSP constructs a variety of stock indices. In this subsection, we focus on its two principal kinds of indices: decile methodology and market ("cap cuts") methodology.

CRSP Decile Methodology

Used for research purposes, CRSP's decile methodology takes a different approach to defining boundaries between market segments. Rather than fixing an absolute number of constituents, CRSP sorts the NYSE universe into 10 equally populated deciles in a way that is economically meaningful and consistent across time.

The foundation of this first (i.e., older) CRSP methodology is its decile framework. CRSP first ranks the eligible NYSE-listed common stocks by total market capitalization and divides them into 10 deciles, each holding an equal number of NYSE stocks. The largest and smallest capitalizations in each decile set its breakpoints. NYSE American- and Nasdaq-listed common stocks are then assigned to those deciles by their own market capitalizations. Decile 1 contains the largest companies; Decile 10 contains the smallest.

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[7] The CRSP US Stock Databases include daily and monthly market data and corporate actions for more than 32,000 active and inactive securities. To learn more, visit www.crsp.org/research/crsp-us-stock-databases/.

In February 2026, Morningstar, Inc., acquired CRSP from the University of Chicago. To learn more, see Morningstar (2026).

Because these breakpoints are set by NYSE stocks alone, not by the combined exchange universe, the decile definitions stay consistent over time. They remain the same even as smaller NYSE American and Nasdaq names crowd into the lower deciles, so that (after 1962 when these smaller stocks were added) the deciles do not have equal populations. This approach has been applied to periods dating back to 1926, enabling genuinely comparable size-based analysis across the full span of US market history.

CRSP Market ("Cap Cuts") Methodology

CRSP's Market Indices, which are used as the basis for a number of index funds, form a separate and newer index family. They segment the market by cumulative capitalization (which we call the "cap cuts" methodology) rather than by number of companies, providing consistent economic exposure to "size" regardless of how many companies are listed at any given time. CRSP's Mega-Cap Index contains companies that collectively represent approximately the top 70% of total US market capitalization. Its Mid-Cap Index captures the next 15%, its Small-Cap Index captures the next 13%, and its Micro-Cap Index captures the remaining 2% (CRSP 2026). Whether the market has 3,000 or 7,000 listed companies, the CRSP Large-Cap Index will always represent approximately the top 85% of market capitalization.

Morningstar, which acquired CRSP in 2026, is renaming the CRSP indices under its own brand (for example, the CRSP US Total Market Index becomes the Morningstar US Total Market Index). The underlying methodology, however, is unchanged.

Compare these approaches with a fixed-count methodology. Suppose an index always holds the 500 largest stocks. In the early 1930s, when fewer than 1,000 common stocks traded publicly, those 500 names might represent well over 90% of total market capitalization. By the late 1990s, when more than 7,000 stocks were listed, the top 500 represented a far smaller fraction. So although the index has the same name and the same count, it measures something quite different in each era. Both CRSP approaches ("deciles" and "cap cuts") sidestep this problem: A "large-cap" stock in 1935 and a "large-cap" stock in 1999 both occupy the same relative position in the size distribution, making the indices comparable across decades.

CRSP further refines its cap cut methodology with transitional "bands" around each breakpoint. Rather than rigidly moving a company from one index to another the moment that company crosses a capitalization threshold, CRSP uses a "packeting" system that allows holdings to be shared between adjacent indices during transitions. This arrangement cushions the movement of companies near breakpoints, reduces unnecessary turnover, and maintains greater style purity—a practical solution to a common problem in rule-based index construction.

The Ibbotson Equity Indices

The Ibbotson Equity Indices presented in this book use a hybrid approach that draws on the CRSP decile framework. For the earlier period (1926–1975), when the total number of securities in the CRSP file was relatively low, the indices are based on CRSP decile portfolios ranked by size. For the later period (1976–2025), the indices transition to fixed numerical counts that produce size-based portfolios with economic exposures broadly consistent with the percentage-based breakpoints used by CRSP's commercial indices.

For example, the Ibbotson Large Cap stock total return index uses CRSP Deciles 1 and 2 through 1975, and then it uses the top 300 stocks from 1976 onward. The correlation between the Ibbotson Large Cap stock total return index and the CRSP S&P 500 replication is approximately 0.99.

Reconstitution and Rebalancing

Indices must periodically update their composition to reflect changes in the investment universe. Reconstitution accounts for companies that go out of business, are acquired, or fail to continue meeting index inclusion criteria. Size-related indices must also be reconstituted periodically to reflect stock price changes that shift companies from one size category to another.

The Russell size indices reconstitute annually each June.[8] The S&P 500 is rebalanced quarterly for reweighting purposes in March, June, September, and December, and its Index Committee meets monthly to review pending corporate actions.[9] More frequent reconstitution keeps the index more current but generates higher transaction costs for index-tracking portfolios. Less frequent reconstitution reduces costs but may allow the index to drift from its intended market representation.

Treatment of Corporate Actions

Index construction requires clear rules for handling corporate actions, including stock splits, spinoffs, mergers, acquisitions, and bankruptcies. For total return indices, such as those presented in Chapter 2, dividend reinvestment is automatic; the index assumes that all cash distributions are immediately reinvested in the index. This approach ensures that total return indices reflect the complete return available to long-term investors. Price return indices, by contrast, ignore dividends and capture only capital appreciation.

The treatment of spinoffs varies across providers. Some immediately add spun-off entities if they meet eligibility criteria, and others wait until the next reconstitution.

Calculating Returns and Index Values

The mathematical relationship between returns and index values is fundamental to understanding long-term wealth accumulation. As illustrated in Chapter 2, the cumulative wealth from holding large-cap stocks grew from $1 to $14,751 over the 1926–2025 time period—a testament to the power of compounding.

Measuring Single-Period Returns

We typically measure the total return of a security or portfolio over a specific period. Equation 3.4 expresses the total return as the sum of two components: the capital gain (or loss)

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[8] Starting in 2026, the Russell size indices (e.g., the Russell 1000 and Russell 2000) will start rebalancing twice per year, on the fourth Friday in June and the second Friday in November. For more information, see Yoshimoto (2025).

[9] For more information, see S&P Dow Jones Indices (2026).

and the income received. The first term captures the percentage change in value from V_{t-1} to V_t, and the second term represents the dividend or income yield, D_t, earned over the period:

$$R_t = \underbrace{\frac{V_t - V_{t-1}}{V_{t-1}}}_{\text{\% Capital gains}} + \underbrace{\frac{D_t}{V_{t-1}}}_{\text{\% Dividends}} . \tag{3.4}$$

Portfolio Returns

Returns across securities can be aggregated into portfolio returns. In Equation 3.5, the return of portfolio p, R_p, is the weighted sum of the returns of the individual securities, R_i, with the weights, W_i, summing to 1:

$$R_p = \sum_{i=1}^{n} W_i R_i . \tag{3.5}$$

From Returns to Index Values

Index values are calculated by linking (compounding) returns over successive periods. We start with an initial value V_0 (typically \$1.00). In Equation 3.6, we compound the single-period returns, R_t, over T multiple periods using the product operator $\prod$, which multiplies the single-period wealth relatives $(1 + R_t)$ to obtain ending wealth V_T:

$$V_T = V_0 \prod_{t=1}^{T} (1 + R_t), \tag{3.6}$$

or, equivalently,

$$V_T = V_0 \times (1 + R_1) \times (1 + R_2) \times \ldots \times (1 + R_T). \tag{3.7}$$

This formulation makes explicit the multiplicative nature of wealth accumulation. A 10% gain followed by a 10% loss does *not* return an investor to the starting point; the ending value is $\$1 \times (1 + 10\%) \times [1 + (-10\%)] = \$0.99$. For larger price changes, the outcome is more dramatic: A 50% decline requires a 100% increase, not 50%, to break even.

Arithmetic and Geometric Mean Returns

We can summarize returns over T periods using two averaging methods. The arithmetic mean return, R_A, is the simple average of single-period returns:

$$R_A = \sum_{t=1}^{T} \frac{R_t}{T}. \tag{3.8}$$

Alternatively, we can calculate the geometric mean return, R_G, by taking the Tth root of the ratio of ending wealth to beginning wealth and subtracting 1:

$$R_G = \left(\frac{V_T}{V_0} \right)^{\frac{1}{T}} - 1. \tag{3.9}$$

Equivalently, we can express the geometric mean as the Tth root of the product of wealth relatives minus 1:

$$R_G = \left[\prod_{t=1}^{T}(1+R_t)\right]^{\frac{1}{T}} - 1. \tag{3.10}$$

The geometric mean, equivalent to the compound annualized return, tells us the constant rate of return that would produce the observed terminal wealth. The arithmetic mean represents the simple average of periodic (e.g., annual) returns.

The difference between the geometric mean and arithmetic mean is related to the variability of returns. The arithmetic mean is always greater than the geometric mean, except in one unique situation: where all the periodic returns are identical and "variability" is absent. The more variable the periodic returns are, the greater the difference between the arithmetic and geometric average.

This relationship can be illustrated with an extreme example. If we invested $1 million in Period 0 and then experienced a return of +50% in Period 1 and a return of –50% in Period 2, our ending wealth (using Equation 3.7) would be

$$V_T = \$1{,}000{,}000 \times (1 + 50\%) \times [1 + (-50\%)] = \$750{,}000. \tag{3.11}$$

This would give an arithmetic mean (using Equation 3.8) of

$$R_A = \frac{[50\% + (-50\%)]}{2} = 0\% \tag{3.12}$$

and a geometric mean (using Equation 3.9) of

$$R_G = \left(\frac{\$750{,}000}{\$1{,}000{,}000}\right)^{\frac{1}{2}} - 1 = -13.4\%. \tag{3.13}$$

Alternatively, the geometric mean can be calculated using Equation 3.10:

$$R_G = \{(1+50\%)\times[1+(-50\%)]\}^{\frac{1}{2}} - 1 = -13.4\%. \tag{3.14}$$

In this example, the volatility of returns was very high (50% swings up and down), creating a large difference between the arithmetic mean (0%) and the geometric mean (–13.4%).

These examples demonstrate that the simple or arithmetic average of returns, R_A, does not provide us with a very clear picture of what has happened. The geometric mean, which summarizes the compounding of returns, does.

The geometric annual return goes by many names: compound annualized return, annualized geometric mean return, compound annual growth rate, and so on. These terms all have the same meaning.[10]

[10] Geometric mean returns can be measured using any base period of time (e.g., daily, monthly, quarterly, annually). Annualized geometric returns are usually the ones we are most interested in.

The Rule of 72

Equations 3.9 and 3.10 provide the exact calculation of how money compounds. It may also be useful to have a simple formula that gives us an approximation of the number of years it takes to double our initial wealth.

The Rule of 72 provides a rough approximation of how many years it takes to double your wealth. It is simple enough to calculate in your head:

$$n \approx \frac{72}{R}, \tag{3.15}$$

where n is the number of years to double your initial wealth and R is the compound annualized return expressed as a percentage. For example, a compound annual return of 12% would double your initial wealth in about six years:[11]

$$n \approx \frac{72}{12} \approx 6 \text{ years.} \tag{3.16}$$

Decomposing Total Returns

Total returns for equity indices can be decomposed into two primary components: (1) capital appreciation return and (2) income return. Income return measures the periodic dividend payment many stocks make, and capital appreciation return captures changes in the price of the stock, typically resulting from earnings growth or market sentiment.

Many investors focus on capital appreciation return. For example, buying a stock at $50 that increases in value to $60 is, after all, quite satisfying. But income (i.e., dividend) return and its reinvestment, rather than capital appreciation return, have historically accounted for the vast majority of long-term equity returns.

We previously saw that an investment of $1 in the Ibbotson Large Cap stock total return index (a "total return" index includes both capital appreciation returns and dividend returns) over the 1926–2025 period would have grown to $14,751 by the end of 2025. But investing $1 over the same period in an equivalent index that measures only capital appreciation returns would have grown to a mere $398, implying that $14,353 ($14,751 – $398)—or an astonishing 97%—of the growth of the total return index can be attributed to dividend returns and their reinvestment.[12] This striking statistic underscores the importance of dividend reinvestment in long-term wealth creation.

For bond indices, the decomposition takes the same form. Income return is defined as the return that would have been realized if the yield had not changed over the period; it is essentially the return attributable to coupon payments. The remainder—the "return in excess of yield"—captures price changes caused by movements in interest rates.

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[11] A more exact formula for the Rule of 72 is $n = \ln(2)/\ln(1 + R)$. Assuming a compound annual return of 12% and using this formula, it would take 6.12 years to double your initial wealth.

[12] The "equivalent index" used in this example is the Ibbotson Large Cap stock capital gain index.

Measuring Risk

The typical way we measure risk or volatility is by using the standard deviation of returns. This starts with the calculation of the variance, which measures the average squared deviation of individual-period returns from their mean. The standard deviation is then the square root of the variance.

Population vs. Sample Standard Deviation

Before presenting the equations, we must address an important question: Should the variance be calculated by dividing by n (the number of observations) or $n - 1$?

Dividing by n produces the *population* standard deviation. It is appropriate when the dataset represents the complete population of interest—for example, if you measured the height of every student in a class and wanted to describe only that class's variability, with no intention of making inferences about a broader set of possible outcomes.

Dividing by $n - 1$ produces the *sample* standard deviation.[13] This incorporates Bessel's correction, used when the true mean of a population is unknowable—that is, when the observations being analyzed are a sample, not the full population.

Returning to the classroom example, if you measured only some of the students and wanted to *estimate* the variability of the entire school, you would use $n - 1$. A sample tends to cluster closer to its own average than the full population does, naturally understating the true spread. Dividing by $n - 1$ slightly inflates the result to compensate.

In finance, we nearly always work with a sample drawn from a theoretically larger population. Even 100 years of annual stock returns represent only a sample of the return-generating process, not the complete universe of returns that could have occurred, that have occurred in other countries, or that will occur in the future. For this reason, the sample standard deviation may be the more appropriate choice.

In the past, the *Stocks, Bonds, Bills, and Inflation® (SBBI®) Yearbook*, published by Ibbotson Associates, then Morningstar, then Kroll, used the sample version of the standard deviation when measuring the standard deviation of returns. We continue that convention in this book. We acknowledge that many practitioners and textbooks use the population formula (dividing by n) for long historical return series, particularly when treating the data as a complete record rather than a sample. Either approach is defensible; what matters is applying it consistently.[14]

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[13] Excel users are familiar with the standard deviation function in Excel (STDEV), which calculates standard deviation using the formula for "sample" (i.e., it uses "$n - 1$" in the variance calculation). Microsoft has replaced the STDEV function with STDEV.S for "sample" calculations and STDEV.P for "population" calculations. For more information, visit https://support.microsoft.com/en-us/office/stdev-function-51fecaaa-231e-4bbb-9230-33650a72c9b0.

[14] For long data series, the practical difference is negligible. For example, when calculating the annual standard deviation of the Ibbotson Large Cap stock total return index over the 1926–2025 period (100 observations), the material impact of dividing by 99 (sample) rather than 100 (population) is negligible (19.04% versus 18.94%, respectively).

Calculating the Variance and Standard Deviation

The variance of a sample of n return observations is

$$\sigma^2 = \frac{1}{n-1}\sum_{t=1}^{n}(R_t - R_A)^2. \tag{3.17}$$

The standard deviation is simply the square root of the variance:

$$\sigma = \sqrt{\sigma^2}. \tag{3.18}$$

Calculating the Standard Deviation of Annual Returns

If we have annual data, we calculate the annual standard deviation of returns. For a three-year period with returns of 10%, –20%, and 40%, the arithmetic mean is

$$R_A = \frac{[10\% + (-20\%) + 40\%]}{3} = 10\%. \tag{3.19}$$

The variance is calculated using Equation 3.17:

$$\sigma^2 = \frac{[(10\% - 10\%)^2 + (-20\% - 10\%)^2 + (40\% - 10\%)^2]}{3-1} = \frac{[(0\%)^2 + (-30\%)^2 + (30\%)^2]}{2} = 9\%. \tag{3.20}$$

The standard deviation can be calculated using Equation 3.18:

$$\sigma = \sqrt{9\%} = 30\%. \tag{3.21}$$

Note that using the population formula (dividing by $T = 3$) would give a variance of 6% and a standard deviation of 24.5%. The difference between the sample (30%) and population (24.5%) standard deviations is substantial in this small sample (three observations). With larger samples, the difference diminishes, but using the sample version consistently ensures internal consistency across all calculations and comparisons.

Annualizing Monthly Standard Deviation

In practice, standard deviation is often calculated using monthly return data, which provide more observations and can make estimates more statistically reliable. A series of *monthly* returns produces a *monthly* standard deviation. The following approximation is often used by analysts to express a monthly standard deviation in annualized terms:

$$\sigma_n = \sigma_1 \times \sqrt{n}, \tag{3.22}$$

where σ_1 is the monthly standard deviation and n is the number of periods—in this case, 12.

Exhibit 3.4 shows monthly returns for January–December 2020—the year in which the COVID-19 pandemic hit, with unusually volatile returns.

Exhibit 3.4. Ibbotson Large Cap Stock Total Return Index, January 2020–December 2020

	Return
January 2020	0.6%
February 2020	–7.9%
March 2020	–11.4%
April 2020	13.3%
May 2020	5.0%
June 2020	2.3%
July 2020	6.1%
August 2020	8.3%
September 2020	–4.0%
October 2020	–2.9%
November 2020	11.5%
December 2020	4.0%

Using Equation 3.8, the arithmetic mean of the monthly returns in Exhibit 3.4 can be calculated as follows:

$$R_A = \frac{\begin{array}{c}[0.6\% + (-7.9\%) + (-11.4\%) + 13.3\% + \\ 5.0\% + 2.3\% + 6.1\% + 8.3\% + \\ (-4.0\%) + (-2.9\%) + 11.5\% + 4.0\%]\end{array}}{12} = 2.1\%. \tag{3.23}$$

The variance is calculated using Equation 3.17:

$$\sigma^2 = \frac{\begin{array}{c}[(0.6\% - 2.1\%)^2 + (-7.9\% - 2.1\%)^2 + (-11.4\% - 2.1\%)^2 + \\ (13.3\% - 2.1\%)^2 + (5.0\% - 2.1\%)^2 + (2.3\% - 2.1\%)^2 + \\ (6.1\% - 2.1\%)^2 + (8.3\% - 2.1\%)^2 + (-4.0\% - 2.1\%)^2 + \\ (-2.9\% - 2.1\%)^2 + (11.5\% - 2.1\%)^2 + (4.0\% - 2.1\%)^2]\end{array}}{12 - 1} = 0.57\%. \tag{3.24}$$

The monthly standard deviation for calendar year 2020 can be calculated using Equation 3.18:

$$\sigma = \sqrt{0.57\%} = 7.5\%. \tag{3.25}$$

The *monthly* standard deviation (7.5%) can be *annualized* using Equation 3.22:

$$\sigma_n = 7.5\% \times \sqrt{12} = 7.5\% \times 3.46 = 26.0\%. \tag{3.26}$$

The average and median annualized monthly standard deviation for *all* calendar years (1926–2025) for the Ibbotson Large Cap stock total return index are approximately 15% and 13%, respectively, demonstrating that market returns in 2020 (the first year of the COVID-19 pandemic) were unusually volatile.

The Relationship Between Geometric and Arithmetic Means

Measuring risk is important because it appears to be the major determinant of the equity risk premium, the difference between stock and bond returns. Risk is also the reason that geometric means are lower than arithmetic means.

The divergence between these measures is proportional to return volatility. The approximate relationship is as follows:[15]

$$R_G \approx R_A - \frac{\sigma^2}{2}. \tag{3.27}$$

This well-known approximation states that the geometric mean is approximately equal to the arithmetic mean minus one-half the variance. It works reasonably well when standard deviations are moderate but becomes less accurate when standard deviations are high.

The standard deviation of the annual returns on the Ibbotson Large Cap stock total return index over the 1926–2025 period is 19%, implying a variance of about 3.6% (because $19\%^2 \approx 3.6\%$). The arithmetic average annual return of the index is 11.8%, so the geometric mean can be estimated using Equation 3.27:

$$R_G \approx 11.8\% - \frac{3.6\%}{2} = 10\%. \tag{3.28}$$

This estimate approximates the previous empirical observation that the Ibbotson Large Cap stock total return index produced a 10.1% compound annualized return over the 1926–2025 period.

The important concept to remember is that the *higher* the standard deviation, the *greater* the difference will be between compound (i.e., geometric) and arithmetic average returns.

The choice between geometric and arithmetic means depends on the purpose. For measuring historical performance and wealth accumulation, the geometric mean is appropriate. For forward-looking expected returns in portfolio optimization, many practitioners prefer arithmetic means.

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[15] Mindlin (2011) provided a more thorough treatment, presenting four approximate relationships between the arithmetic expected return, geometric expected return, and variance and checking their accuracy against historical data. His analysis confirms that the "one-half variance" adjustment in Equation 3.27 is a convenient first approximation but that more precise formulations exist for applications where accuracy is critical.

Modern Developments in Index Construction

The field of index construction has evolved substantially since the inception of the Ibbotson return series in the 1970s. Recent decades have witnessed innovations in methodology and technology, as well as the proliferation of specialized indices targeting specific investment strategies or market segments.

Environmental, Social, and Governance (ESG) Indices

ESG indices emerged in the first decade of the twenty-first century and gained substantial momentum through the 2010s. They screen securities based on nonfinancial criteria such as carbon emissions, labor practices, board diversity, or alignment with sustainable development goals. According to Morningstar, assets in ESG-focused funds reached $3.9 trillion in 2021 (Murugaboopathy and Maan 2021).

ESG investing has since encountered significant headwinds (Furness 2025; Cifrino 2025). Sustainable fund inflows slowed sharply after 2022, amid political and regulatory pressures in certain jurisdictions and widespread concerns about "greenwashing"—the practice of overstating a fund's environmental or social credentials. From an index construction standpoint, ESG indices face a fundamental methodological problem: ESG rating agencies frequently produce divergent assessments of the same company, reflecting the absence of a universally agreed-upon standard. A company rated highly by one provider may rank poorly with another, depending on how each agency weights the underlying criteria. This inconsistency makes it difficult to evaluate ESG indices on equal footing or to know precisely what they are measuring.

Performance results have been mixed. ESG indices are not designed to be neutral market benchmarks; they are, by construction, exclusionary. Excluding entire sectors, such as fossil fuels, defense, or tobacco, introduces sector tilts that can help or hurt performance depending on the market environment. During the ESG boom years of 2019–2021, the exclusion of energy stocks was a tailwind; then, as energy surged in 2022, it became a headwind. ESG indices remain a significant segment of the index landscape, but investors should understand them for what they are: a set of active bets about which companies and sectors society will reward over time.

Factor-Based and Multifactor Indices

The academic literature on factor investing has spawned a proliferation of factor-based indices that tilt portfolios toward such characteristics as value, momentum, quality, low volatility, liquidity, or size. Single-factor indices target one characteristic; multifactor indices combine several, attempting to harvest premiums from multiple sources while diversifying across factor exposures.

Factor indices blur the line between passive and active management. Although they follow rule-based approaches, they make deliberate bets that deviate from market-cap weighting. The implementation of factor indices requires careful consideration of factor definitions, weighting methodologies, and rebalancing frequencies.

Cryptocurrency and Digital Asset Indices

The emergence of cryptocurrencies and digital assets has created an entirely new domain for index construction. These indices face unprecedented methodological challenges: Cryptoassets trade around the clock with extreme volatility, lack traditional corporate structures, and present novel questions about what should be weighted (market capitalization based on fully diluted supply or current circulating supply) and what qualifies as an eligible asset. Several providers have launched cryptocurrency indices using market-cap weighting with minimum liquidity thresholds, equal weighting, or capped weighting. Methodological standards continue to evolve.

Custom and Direct Indexing

Technological advances have enabled "direct indexing," under which investors hold customized portfolios of individual securities rather than pooled index funds. These customized portfolios are intended to replicate the performance and risk of an index while enabling tax-loss harvesting at the individual security level and, if desired, customization to reflect personal values or constraints. Direct indexing represents the logical extension of index methodology, from a single benchmark that serves all investors to personalized portfolios tailored to individual circumstances.

Practical Considerations in Index Selection

For practitioners seeking to measure performance or construct portfolios, choosing appropriate indices requires careful consideration of several factors beyond just historical returns.

Investability

An ideal index represents an investable opportunity. Investors should be able to replicate the index's returns with reasonable effort and cost. Doing so requires adequate liquidity in constituent securities, enough supply, and reasonable transaction costs. The Ibbotson Indices avoid such pitfalls as survivorship bias by focusing on broad, liquid markets with transparent pricing and accessible trading.

Transparency and Replicability

Index methodologies should be transparent and consistently applied so that investors can understand what they are measuring. The S&P 500's committee-based approach introduces an element of discretion that has occasionally generated controversy. Other index families emphasize rule-based methodologies with minimal discretion. Both approaches have merits; the key is that the methodology be clearly documented and consistently applied.

Historical Consistency

For long-term analysis, such as the studies discussed in Chapter 2, historical consistency is paramount. The index methodology should be stable over time, allowing for meaningful comparisons across decades. The transition to float adjustment in the early part of the twenty-first century created a methodological break that index providers handled in different ways, with some reconstructing historical data retroactively and others maintaining values based on full market capitalization. Users of long-term return series must be aware of such shifts when conducting historical analysis.

Conclusion

The indices that form the foundation of Chapter 2's historical performance analysis are far more than neutral scorecards. They embody specific methodological choices about weighting, universe definition, reconstitution, and corporate action treatment—choices that profoundly influence measured returns and our understanding of market behavior.

Market-capitalization weighting has emerged as the dominant approach because of its theoretical foundation in modern portfolio theory and its practical advantages in terms of investability and macro-consistency. The addition of float adjustment refined this methodology to better represent investable opportunities.

The CRSP decile framework offers a powerful solution for long-run market analysis. By defining size segments based on the relative position of companies in the overall capitalization distribution rather than fixed counts, CRSP delivers consistent economic meaning across decades, which is why the Ibbotson Indices rely on CRSP decile portfolios for the pre-1976 period and adopt comparable fixed counts for the modern era.

In recent decades, we have witnessed an explosion of index innovation, from ESG indices and factor-based strategies to cryptocurrency indices and direct indexing. These developments expand the toolkit available to investors but also introduce complexity. Not all innovations represent improvements over traditional market-cap weighting for the core purpose of broad market measurement.

The fundamental principles remain as relevant as ever: broad diversification, transparent methodology, investability, and theoretical soundness. The $14,751 terminal wealth from a $1 investment in the Ibbotson Large Cap stock total return index documented in Chapter 2 was built on indices that maintained methodological consistency over a century. Understanding how they are constructed is inseparable from understanding what they tell us.

Key Takeaways

- Index construction methodology matters. The choices embedded in an index guide the measurement of returns and risk characteristics and influence investment decisions affecting trillions of dollars globally.
- Market-capitalization weighting is the dominant approach because it is grounded in the CAPM, requires minimal rebalancing, and is macro-consistent. Float adjustment refined this methodology by ensuring that index weights reflect shares actually available for public investment.
- Alternative weighting schemes—equal weighting, fundamental weighting, and "smart beta" strategies—offer different perspectives on diversification and concentration risk, but they represent active strategies rather than neutral benchmarks.

- The geometric mean, not the arithmetic mean, tells us what an investor actually earned. The higher the return volatility, the greater the gap between the two.
- When selecting an index, investability, transparency, and historical consistency should guide the decision. A well-constructed index is not just a scorecard—it is the foundation for performance evaluation, risk measurement, and capital allocation.

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SECTION 2

The Past 100 Years in US Markets

CHAPTER 4. A CENTURY OF US EQUITY INDICES

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Introduction

Historical market data have been the statistical foundation for evaluating the risk and return of investing since the emergence of modern portfolio theory. Long-run return series provide the empirical basis for asset allocation, financial planning, capital budgeting, and portfolio construction. For equity investors in particular, understanding how markets have behaved across different economic regimes is essential for forming expectations about the future.

In this chapter, we introduce a new family of US equity indices constructed from security-level data provided by the Center for Research in Security Prices (CRSP). These indices span the full 1926–2025 period and are designed to represent capitalization-weighted portfolios segmented by firm size. The goal is to provide a transparent, consistent, and economically meaningful representation of the US equity market over a full century.

The century from 1926 to 2025 includes extraordinary periods. It spans the Great Depression, World War II, the postwar expansion, the inflationary shocks of the 1970s, the technology boom and bust, the global financial crisis, and the COVID-19 pandemic, while also capturing the beginning of the current AI-driven technology boom. During the course of the century, the structure of the economy evolved dramatically, with regimes ranging from industrial manufacturing dominance to a technology- and services-oriented market. Yet despite these changes and challenges, US equities delivered extraordinary long-run returns, even when compared with the global markets (Dimson, Marsh, and Staunton 2002).

Over the full 100-year sample, the broad composite market portfolio produced a compound average total return of approximately 10.3% per year. Large-cap stocks delivered an average compound return slightly above 10%, while midcap, small-cap, and microcap portfolios generated even higher long-run compound returns, around 11% annually. These differences may appear modest on an annual basis, but over multidecade horizons, they compound into large differences in terminal wealth.

To illustrate, without taxes or other costs, $1 invested in 1926 in the broad market portfolio would have grown to more than $17,000 by the end of 2025, while the smaller size segments compound to roughly double that. Even after accounting for inflation, the real increase in purchasing power remains substantial. The century-long record demonstrates both the resilience and volatility of public equity markets. Severe drawdowns occurred, but recoveries followed, and long-term investors were rewarded for remaining invested.

At the same time, the distribution of returns differs meaningfully across size segments. Smaller-cap portfolios historically delivered higher average returns but also greater volatility. Large-cap portfolios exhibited somewhat lower return dispersion and, in some subperiods, higher risk-adjusted performance. Understanding these differences is central to both strategic asset allocation and portfolio diversification.

The indices presented in this chapter are constructed to facilitate such analysis. They are purely market-cap weighted and use stable, rank-based size definitions. Unlike many modern commercial benchmarks, they do not apply free-float adjustments. This design choice preserves methodological consistency over the full 1926–2025 period and ensures comparability across structural shifts in the market.

In this chapter, we first describe the construction of the Ibbotson Equity Indices, explaining key methodological choices, including capitalization weighting and the distinction between full-cap and float-adjusted approaches. We then examine the century-long behavior of returns across size segments and discuss why long-run data remain essential for estimating expected returns and risk.

Construction of the Ibbotson Equity Indices

The Ibbotson Equity Indices are designed to provide a transparent and consistent representation of the US equity market across the full last century. The construction methodology has been selected to emphasize transparency and replicability, with a key focus on long-run consistency. All portfolios are fully based on market capitalization of the underlying firms.

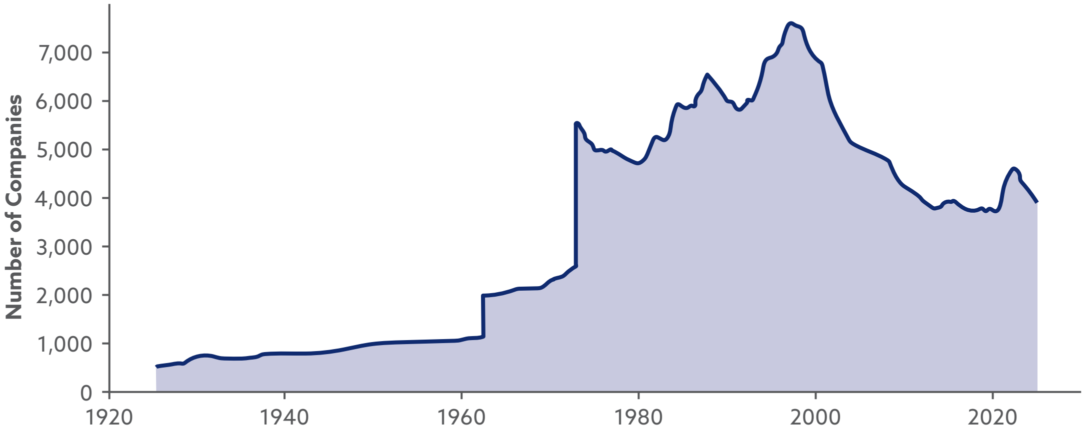
The objective is not to replicate any specific commercial index. Rather, the Equity Indices are constructed to provide economically meaningful size-segmented portfolios that can be used for long-run analysis, benchmarking, and research. The focus is on preserving stable definitions across time so that comparisons across decades reflect economic change rather than methodological revisions.

Underlying Universe

All the Equity Indices are constructed from the CRSP Monthly Stock File, which provides security-level return and market capitalization data beginning in 1926. This dataset offers a comprehensive view of the development of US equity markets and accounts for several biases that can arise in historical return series.

In particular, CRSP data address survivorship bias by tracking firms after delisting and incorporating the last return after delisting, where available. This process ensures that returns reflect the experience of investors holding securities through such corporate events as mergers, liquidations, and bankruptcies. More broadly, CRSP provides comprehensive historical coverage,

Exhibit 4.1. Number of Companies Listed on the NYSE, Nasdaq, and American Exchanges, 1926–2025



Source: Ibbotson Equity Indices, underlying data from CRSP.

Note: The sudden changes in 1962 and 1973 are due to the addition of the American Stock Exchange and Nasdaq, respectively, to the CRSP database and do not reflect changes in the number of US publicly traded firms in existence.

accurate security identifiers, detailed corporate action adjustments, and well-documented methodology. For these reasons and because of the overall depth and quality of the dataset, the CRSP universe is widely regarded as the gold standard in academic research, providing a consistent representation of the US public equity market.

The universe used for index construction includes common stocks listed on the NYSE, Nasdaq, and NYSE American (formerly the American Stock Exchange, widely known as AMEX). We constrain the securities included to the common stocks listed, excluding any exchange-traded funds, REITs, closed-end funds, and American depositary receipts from the final universe used in index construction.

The number of publicly traded firms has changed significantly over time, and these changes have been well documented (Doidge, Karolyi, and Stulz 2017). As shown in **Exhibit 4.1**, the number of stocks in the US equity universe expanded steadily through much of the 20th century, peaking in the late 1990s and declining in the subsequent decades.

These dynamics have been a major influence in the index construction methodology, motivating adjustments to portfolio breakpoints across subperiods.

Classifying Stocks into Size Categories

The Ibbotson Equity Indices use two approaches to size segmentation, each reflecting the evolving structure in the US equity market. Before 1975, we rely on the preexisting CRSP decile portfolios for all indices except the Ibbotson 25, which is constructed directly from firm-level rankings to capture the 25 largest companies at each point through the entire century.

During the early decades of the sample, the equity market was rapidly evolving and the number of stocks listed increased quickly, including the addition of Nasdaq-listed securities in 1972. Using the CRSP decile definitions during this period provides a stable and consistent classification framework while the market structure matured.

After 1975, the Equity Indices are partitioned using fixed numerical market-cap rank thresholds. Using fixed rank thresholds offers key advantages. Most notably, it provides intuitive and transparent definitions, such as "top 500 firms," that are already commonly used among some of the largest commercial indices around the world.

The full equity index definitions are listed in **Exhibit 4.2**.

These definitions ensure that the indices remain economically comparable across time while accommodating structural changes in market breadth. Before 1975, CRSP deciles provide stable classification during a period of rapid change in the US public markets. After 1975, fixed rank thresholds offer intuitive and transparent segmentation.

Exhibit 4.2. Definitions of the Ibbotson Equity Indices

A. Base Indices		
Index Name	**1926–1975 Definition**	**1976–2025 Definition**
Ibbotson 25 (Mega Cap)	Ranks 1–25	Ranks 1–25
Ibbotson Large Cap	Deciles 1–2	Ranks 1–300
Ibbotson Mid Cap	Deciles 3–5	Ranks 300–1,000
Ibbotson Small Cap	Deciles 6–8	Ranks 1,000–2,000
Ibbotson Micro Cap	Deciles 9–10	Ranks 2,000+
B. Composite Indices		
Index Name	**1926–1975 Definition**	**1976–2025 Definition**
Ibbotson Large Composite	Deciles 1–5	Ranks 1–1,000
Ibbotson Small Composite	Deciles 6–10	Ranks 1,000+
Ibbotson SMID Composite	Deciles 3–10	Ranks 300+
Ibbotson All-Cap Composite	CRSP Market Portfolio	Entire universe

Capitalization Weighting

Within each size segment, securities are weighted by total market capitalization. Portfolio constituents are picked quarterly based on the previous definitions. Because all the portfolios are purely market-cap weighted, the individual weights need no rebalancing in response to ordinary price changes.[1] As a result, the portfolios remain aligned with market valuations and any major changes to portfolio weights occur only during the predetermined quarterly rebalancing dates.

When compared with many commercial indices, a major difference in the Ibbotson Equity Index portfolios is that they are constructed using full market-cap weighting instead of float-adjusted weighting. Float-adjusted weighting is very common among many modern commercial benchmarks and indices. In this weighting scheme, market value is calculated using only the shares available for public trading and excludes insider or otherwise restricted holdings. Float weighting can improve investability for index-tracking products by more closely matching tradable supply.

Consistent float data are not available for the full 1926–2025 period, however. Applying float adjustments only in recent decades would introduce a structural break in the methodology. Because the priority of the Equity Indices is long-run consistency, we have opted for full market-cap weighting over the entire period. This way, the indices also reflect the full economic footprint of publicly traded firms, rather than only the investable float-adjusted subset.

In practice, for many firms, the difference between total market capitalization and float-adjusted capitalization is modest, often in the single-digit percentage range. In extreme cases where insider ownership is substantial, the difference can be larger, in the 10%–20% range (large differences are more common for non-US securities). Over long horizons, however, these differences are generally small relative to overall market movements.

The choice to use full market-cap weighting can thus cause deviations from modern float-adjusted commercial benchmarks. A more appropriate set of benchmarks for the new Equity Index series can be found in other research indices, which typically do not use float adjustments. Over long horizons, differences between full-cap and float-adjusted weighting tend to be modest, with long-run mean returns and standard deviations nearly identical for the two methods.

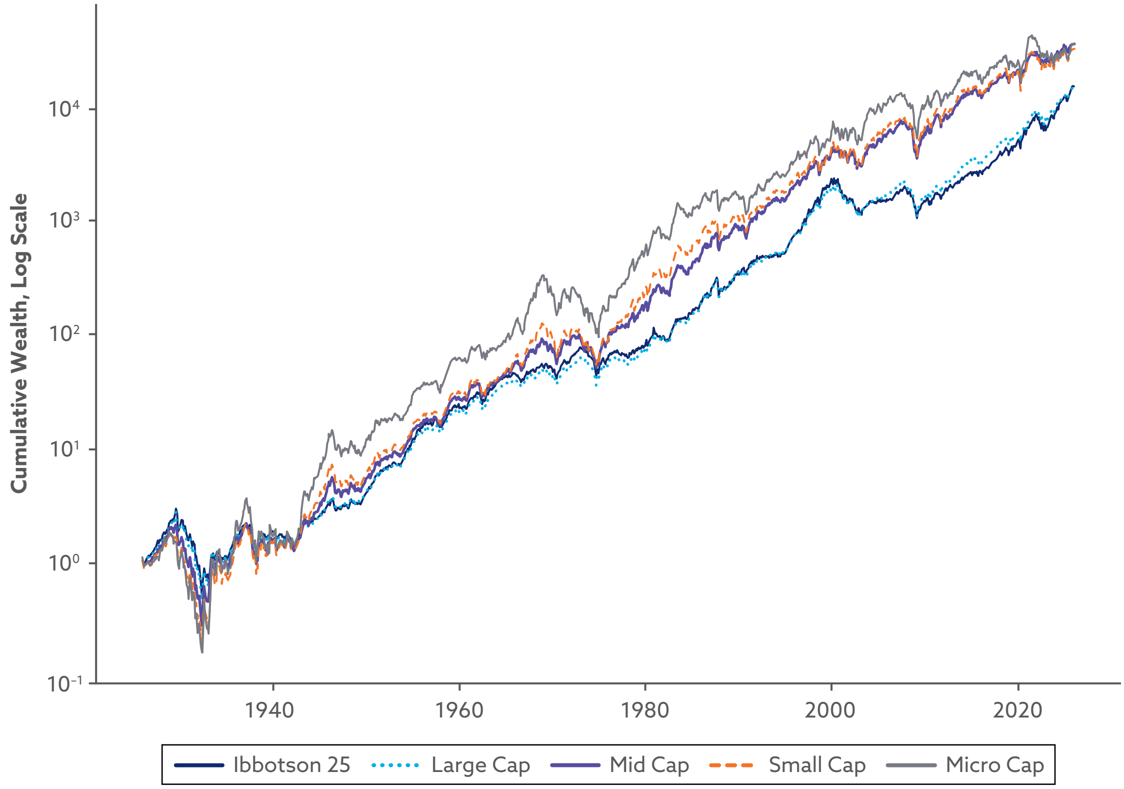
Results: A Century at a Glance

In this section, we take a wide-angle look at the past 100 years of US equity returns using the new Ibbotson Equity Indices. Our goal is to show the long-run level and variability of returns and provide a common frame of reference for investors and others whose primary focus is compounded portfolio growth and volatility. Thus, we focus on market-wide patterns and sustained trends, leaving in-depth statistical analysis for later.

We begin with the growth of $1 invested at the start of the sample period across our baseline indices of stocks sorted by market cap into the Ibbotson 25, Large Cap, Mid Cap, Small Cap, and Micro Cap categories. **Exhibit 4.3** plots each wealth index, using a logarithmic scale to highlight relative performance and periods of divergence and convergence between different size portfolios.

[1] Only such corporate actions as mergers, divestitures, and buybacks require changes in the weights between quarterly rebalancings.

Exhibit 4.3. Cumulative Wealth Indices of Size Categories of US Stocks, 1926–2025



Source: Ibbotson Equity Indices, underlying data from CRSP.

One of the useful features of the log scale is that in a graph of the growth of wealth over time, the slope indicates the compound rate of return identically no matter where you are in the time period studied (in other words, if a given slope means a 20% return in a year in the 1920s, it means the same thing in a year in the 2020s). An arithmetic scale, in contrast, gives the appearance of all the growth taking place at the end, although that is not in fact what happened.

The results over the past century vividly illustrate the power of compounding. Small, persistent return differences between size portfolios accumulate into large gaps over decades, made visible by the ending values of the cumulative wealth index of each portfolio. The upward log path of the wealth index is nearly linear, implying a roughly constant compound rate over long stretches of time, punctuated by a few dramatic events: the crash of 1929–1932 and the subsequent depression years of the 1930s, market declines in the recession of 1973–1974, the dot-com collapse of 2000–2002, and the global financial crisis of 2007–2009. The crash of 1987—the largest one-day drop in US stock market history—is a relatively tiny blip, as is the spring 2020 COVID-19 market meltdown. Exhibit 4.3 demonstrates that these sharp drawdowns were followed by multiyear recoveries, even though full recovery and a move to new highs sometimes arrived slowly, taking 16 years in the case of the 1929–1932 crash and the Great Depression.[2]

Summary Statistics

In **Exhibit 4.4**, we report summary statistics for the four base indices: Large Cap, Mid Cap, Small Cap, and Micro Cap. For each portfolio, we include the compounded (geometric) and arithmetic annual mean return, the annualized standard deviation of monthly returns, and, alongside, a histogram of the annual return distribution of each index. We display results for the full century, the first half (1926–1975), and the second half (1976–2025) separately. The data illustrate how the risk and return of the various portfolios have changed between different periods and how, over a sufficiently long horizon, US equities have delivered strong real returns across all size categories.

Across different portfolio sizes, smaller companies have on average outperformed their large-cap counterparts—a well-known fact about historical equity performance first documented by Rolf Banz (1981) and Marc Reinganum (1981) and later formalized by Fama and French (1993). What is perhaps surprising, however, is that the midcap portfolio matches or exceeds the small-cap portfolio on a compounded annual basis over all three sample periods. This result is largely a consequence of volatility drag: The higher standard deviations (higher risk) of the smaller portfolios erode their compound returns relative to their arithmetic means, with the gap widening substantially as we move down the size spectrum.

Another factor at play is the definition of small caps. Early treatments of the size premium typically used the small-cap definitions from such datasets as those of Ibbotson and Sinquefield (1976), who defined the small-cap portfolio as Deciles 9–10, corresponding to what we classify here as microcap. When this definitional shift is accounted for, the historical small-cap premium looks considerably more concentrated in the extreme tail of the size distribution, consistent with Banz's (1981) original findings that the effect was most pronounced among the very smallest firms. Notably, in the post-1976 period, the microcap portfolio achieved the lowest compound return of any base portfolio despite being the most volatile—a pattern that challenges the simple narrative of smaller stocks producing a higher long-run reward.

More broadly, both the return premium across size segments and the volatility of individual portfolios in the first and second halves of the sample look meaningfully different, suggesting that the structural features of the US equity market, rather than size alone, play an important role in shaping long-run outcomes. We examine these structural shifts in the sections that follow.

Exhibit 4.5 reports summary statistics for the composite indices, which aggregate the size-sorted segments into broader portfolio groupings. The composites largely confirm the patterns observed among the base indices, sitting between their component building blocks in both return and risk. The Small Cap Composite, which combines small-cap and microcap stocks, and the SMID Composite, which spans midcap, small-cap, and microcap stocks, show how blending size segments smooths out some of the extreme volatility associated with the smallest stocks individually, without meaningfully altering the return profile relative to the base indices. Across all composites, the arithmetic–geometric spread widens with volatility, showcasing the role of volatility drag discussed earlier.

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[2] In real total return terms, the 1937 high briefly surpassed the 1929 high, but the market then declined sharply again and did not fully recover until after World War II.

Exhibit 4.4. Summary Statistics and Distributions of Annualized Returns on Principal Asset Classes

	Geometric Mean (%)	Arithmetic Mean (%)	Std. Dev. (%)
A. Full Sample (1926–2025)			
Large Cap	10.07	11.85	19.04
Mid Cap	11.05	13.64	23.68
Small Cap	10.95	14.44	27.69
Micro Cap	11.06	16.52	37.28
Inflation	2.94	3.01	3.92
B. First Half (1926–1975)			
Large Cap	8.24	10.41	21.18
Mid Cap	9.29	13.01	28.83
Small Cap	9.31	14.48	34.09
Micro Cap	10.70	19.11	47.35
Inflation	2.29	2.40	4.79
C. Second Half (1976–2025)			
Large Cap	11.95	13.29	16.72
Mid Cap	12.84	14.28	17.34
Small Cap	12.61	14.40	19.66
Micro Cap	11.42	13.93	23.49
Inflation	3.59	3.63	2.70

Sources: Equity data from the Ibbotson Equity Indices, underlying data from CRSP; inflation data from the US Bureau of Labor Statistics.

Market Concentration and Diversification

One of the most practically relevant insights from a century of size-segmented return data is that “investing in the broad market” has meant something different at different points in history. Today, a passive investor holding a simple cap-weighted US equity index is, by construction, making a far more concentrated bet than their counterpart in 1980—not because they chose to but because the market itself has become much more concentrated.

Because the Ibbotson Equity Indices are capitalization weighted, changes in the relative market value of the largest firms translate directly into changes in index weights because security

Exhibit 4.5. Summary Statistics of Annualized Returns for Composite Indices, 1926–2025

	Geometric Mean (%)	Arithmetic Mean (%)	Std. Dev. (%)
Full Sample (1926–2025)			
All Cap Composite	10.27	12.16	19.59
Large Cap Composite	10.25	12.09	19.30
SMID Composite	10.96	13.84	24.91
Small Cap Composite	10.84	14.66	29.09

Source: Ibbotson Equity Indices, underlying data from CRSP.

weights evolve continuously with market prices without requiring discretionary rebalancing. Changes in index constituents (firms crossing size thresholds) occur only at predetermined quarterly rebalancing dates. Whenever a handful of companies grow to dominate a large share of total market capitalization, a passive investor's portfolio tilts toward them automatically and unavoidably.

Exhibit 4.6 shows how the market-capitalization shares of the five base index segments—Ibbotson 25 (Mega Cap), Large Cap (includes Ibbotson 25), Mid Cap, Small Cap, and Micro Cap—have evolved over 1926–2025. The share of the top 25 firms has fluctuated between roughly 20% and 50% of total US market capitalization over the past century. Concentration was elevated in the early part of the past century, declined steadily from the mid-1970s through the early 2000s as the number of listed firms broadened dramatically, and has risen sharply since then. Today, the top 25 firms account for approximately 50% of total market capitalization—a level not seen since the 1930s.

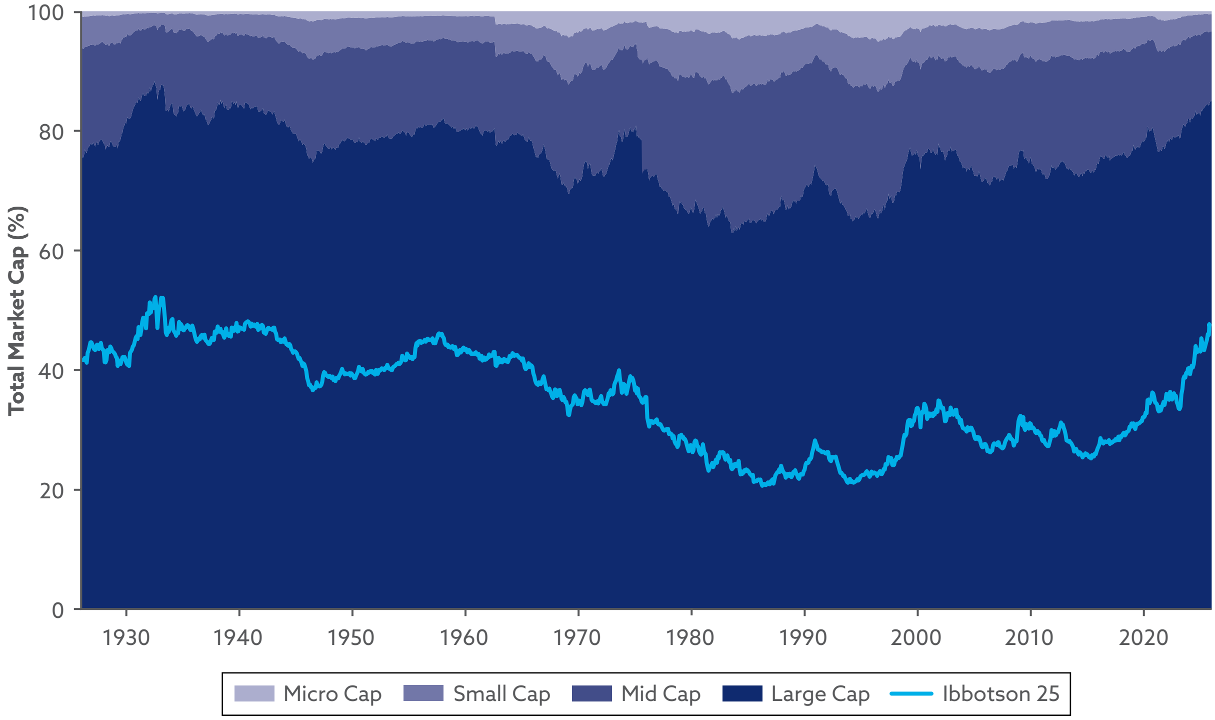
This recent concentration reflects the extraordinary rise of a small number of large technology firms. Such concentration is not without historical precedent: Railroads dominated US market capitalization in the early twentieth century much as software, semiconductors, and artificial intelligence do today. What distinguishes the current episode is that after controlling for the overall breadth of the listed universe, today's concentration is the highest it has been in the entire past century. **Exhibit 4.7** plots industry-level market-capitalization shares using the Fama–French 12-industry classification, showing that technology now accounts for nearly 40% of total market value—a level of industry concentration without parallel in the past century.

To further quantify this effect more rigorously, we use the Herfindahl–Hirschman Index (HHI), a measure of portfolio concentration defined as the sum of squared portfolio weights:

$$\mathrm{HHI} = \sum_{i=1}^{N} w_i^2,$$

where w_i is the market-capitalization share of firm i. Higher values indicate greater concentration. For reference, an equally weighted portfolio of N stocks has an HHI of $1/N$, while a

Exhibit 4.6. Evolution of the Market-Capitalization Share of Each Base Equity Index, 1926–2025



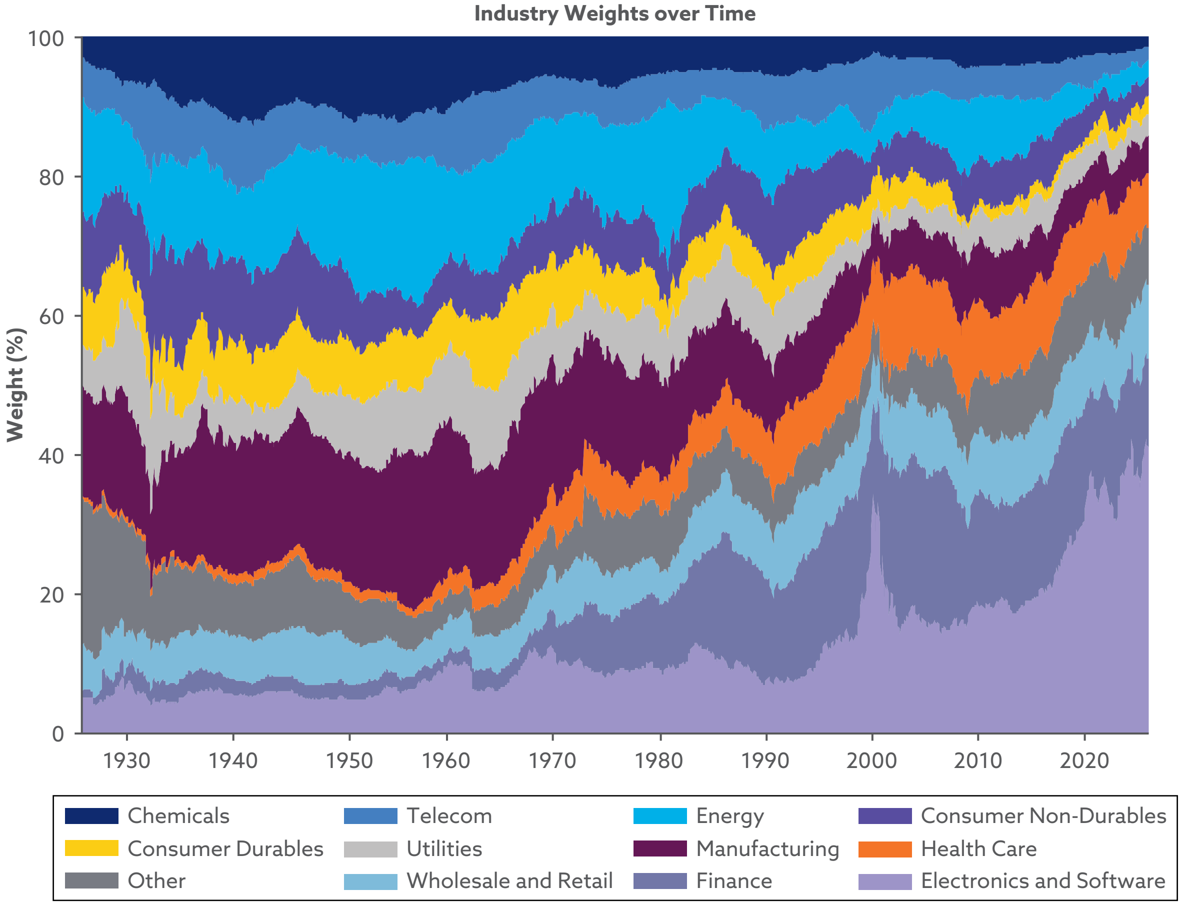
Source: Ibbotson Equity Indices, underlying data from CRSP. Calculations by the authors.

single-firm market achieves the maximum value of 1. We multiply all values by 10,000 for interpretability, so that typical US market values range from roughly 25 to 250 and the maximum attainable value becomes 10,000. In a portfolio context, 1/HHI has a natural interpretation as the effective number of independent positions—the number of equal-sized holdings that would produce the same level of concentration as the actual portfolio. This attribute makes the HHI a direct and intuitive measure of diversification.

Although the HHI is an intuitive and clear way to express concentration, comparing portfolios with different numbers of stocks in them can be difficult. A market with 500 firms will mechanically exhibit a higher raw HHI than one with 5,000, even if the largest companies hold identical relative weight. Thus, to be able to compare the early part of our sample, when the number of listed companies was well below 1,000, with the late 1990s, when publicly listed companies surpassed 7,000, we must apply an adjustment to the HHI. To isolate the actual changes in concentration from changes in market breadth, we scale the raw index by N/10,000. This normalization allows for meaningful comparison across decades with varying levels of market breadth.

Exhibit 4.8 plots both HHI series for the entire US market. The raw HHI mirrors the patterns in Exhibit 4.6, with the highest values at the beginning and end of the sample. The adjusted HHI, however, tells a more striking story. After we account for the number of listed firms, today's

Exhibit 4.7. Evolution of the Market-Capitalization Share of the 12 Fama–French Industries, 1926–2025

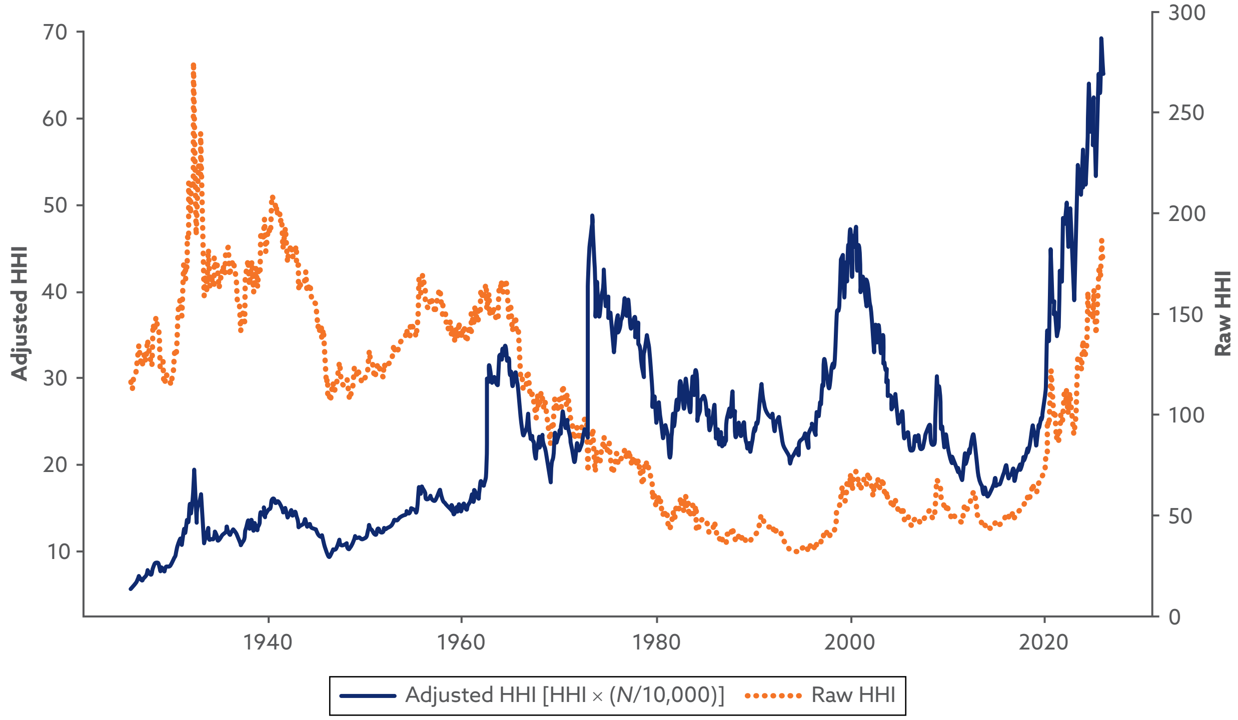


Source: CRSP. Industry labels follow the Fama–French SIC-based 12 Industry portfolio definitions from Kenneth French's Data Library.

concentration is the highest in the entire past century—exceeding even the elevated levels of the 1930s. This is not just a consequence of the decreasing number of firms in the universe from the peak of the late 1990s; instead, it reflects a genuine accumulation of market weight among a very small number of companies.

The practical implication for investors is direct. In the 1975–2000 period, when market weights were more evenly distributed across a rapidly expanding universe of listed firms, a broad cap-weighted index provided more diversification across industries and firm sizes than it does now. Today, that same index delivers a portfolio with a notable tilt toward technology—even more so to the few very large companies in the sector. Because of the strong past performance of this small market segment, holders of the US market portfolio have seen very good returns over the last few years while becoming even more sensitive to the future performance of these stocks. The effective number of independent positions, measured by 1/HHI (10,000/HHI in our case

Exhibit 4.8. Herfindahl–Hirschman Index of the Market Concentration, 1926–2025



Source: Ibbotson Equity Indices, underlying data from CRSP.

after the scaling), has declined sharply in recent years even as the headline number of index constituents remains large. Still, even at current concentration levels, a broad US equity index remains far more diversified than any individual sector or single-stock position.

The Shrinking Small-Cap Premium

The summary statistics presented earlier hinted at a well-documented phenomenon: the small-cap premium. Despite being present over the full century, the premium has diminished substantially in the second half of the sample. In the first half (1926–1975), the arithmetic mean return spread between large- and small-cap portfolios was approximately 3.5 percentage points annually. In the second half (1976–2025), the spread narrowed to around 1.1 percentage points, and for micro-cap stocks, the geometric return actually fell below that of the large caps.

The timing of the decline is worth noting. Banz published his documentation of the size effect in 1981, and there is evidence that the premium began shrinking shortly thereafter. McLean and Pontiff (2016) show systematically that anomaly returns decay after academic publication as capital flows toward documented mispricings and arbitrages them away. The size premium fits this description well: Institutional ownership of small-cap stocks increased substantially through the 1980s and 1990s, improving liquidity as dedicated small-cap investment vehicles became more common. These developments alleviated some of the illiquidity and information risk that had caused investors to previously require a premium as compensation for holding small-cap stocks, and as that underlying risk diminished, so too did the premium it commanded. Fama and French (1993) originally interpreted the size premium as compensation for systematic risk not captured by the CAPM, and under that interpretation, the decline in the premium is consistent with a true reduction in underlying risk rather than a simple correction of a mispricing.

The historical outperformance of small caps that does exist in the full-sample record is moreover heavily concentrated in a small number of exceptional episodes. The years immediately following the Great Depression and the period of high inflation during 1975–1983 account for a disproportionate share of the cumulative small-cap premium. Outside of these episodes, the performance advantage of small-cap stocks over the full century is more modest than the headline numbers suggest. This episodic nature of the premium means that realizing the small-cap premium in practice requires patience and conviction to remain invested through extended periods of underperformance, with no guarantee that the historical episodes of outperformance will repeat.

Despite the decline in the return premium, small-cap and microcap stocks retain diversification value within a broader portfolio. Their return patterns differ sufficiently from large-cap stocks that inclusion in a diversified portfolio can improve the overall risk–return profile even when the standalone expected return advantage of the small caps is modest. Investors should therefore evaluate the benefits of small caps in a portfolio context rather than solely on the basis of their expected excess return.

Decline in Aggregate Volatility

The summary statistics reveal a second structural shift that is easy to overlook: Aggregate equity volatility has declined substantially across all size segments between the first and second halves of the sample. Annualized volatility for large-cap stocks fell from roughly 21% in the 1926–1975 period to approximately 17% in the 1976–2025 period. The pattern holds across all size categories, although the absolute level of volatility remains considerably higher for smaller-cap portfolios throughout.

This long-run downward trend in aggregate volatility is well documented. Comin and Philippon (2005) document the decline in aggregate volatility in the postwar period, attributing it in part to improved macroeconomic stabilization and the reduced share of cyclical industries in the economy. An important nuance is that the decline in aggregate volatility has occurred alongside an increase in firm-level idiosyncratic volatility (Campbell, Lettau, Malkiel, and Xu 2001). This divergence reflects the growing importance of firm-specific information in driving individual stock returns, a development consistent with more informationally efficient markets. Simultaneously, the benefits of diversification have, if anything, increased over time.

The concentration dynamics documented in the previous market concentration discussion add a further layer of complexity to this picture. The declining aggregate volatility of the broad market index partly reflects the growing dominance of large, mature technology firms with relatively stable cash flows, whose increasing index weight mechanically dampens measured portfolio volatility. This compositional effect is distinct from any genuine reduction in the underlying riskiness of the economy, and investors should be cautious about extrapolating the lower volatility of the recent past as a reliable guide to future risk.

Despite the secular decline, the market has remained prone to sharp, systemic crises. The global financial crisis of 2007–2009, the COVID-19 shock of 2020, and the inflation-driven sell-off of 2022 each produced drawdowns that, although shorter lived than the Great Depression, were comparable in their immediate severity to many historical crises. Stock and Watson (2002) coined the term "Great Moderation" to describe the post-1980s reduction in macroeconomic volatility, and Blanchard and Simon (2001) documented the same phenomenon in output volatility more broadly. Although the reduction in volatility has been the trend, both sets of researchers were careful to note that reduced average volatility does not eliminate tail risk. For long-run investors, the practical implication is the same: Lower average volatility does not mean lower worst-case volatility, and scenario planning should not be anchored purely to the recent historical distribution.

Annual Returns on the Ibbotson Equity Indices

Although graphs show the big picture vividly, many readers are interested in the year-by-year returns on the indices, so we present them in **Exhibit 4.9**. The exhibit makes it easy to compare returns across size portfolios, and the many booms and busts that occurred over the past century can be studied numerically. The returns in the exhibit are nominal, and year-by-year inflation rates appear in the rightmost column for reference. (The real return, not explicitly shown in the exhibit, is approximately the nominal return minus the inflation rate.)

Exhibit 4.9. Annual Returns on the Ibbotson Equity Indices, 1926–2025

Year	Ibbotson 25 (%)	Large Cap (%)	Mid Cap (%)	Small Cap (%)	Micro Cap (%)	Inflation (%)
1926	16.02	12.51	1.48	–0.92	–6.72	–1.12
1927	34.81	32.72	34.68	27.80	29.04	–2.26
1928	38.71	38.77	39.85	33.22	44.03	–1.16
1929	–9.63	–10.03	–27.09	–38.09	–50.29	0.58
1930	–22.32	–27.02	–36.08	–39.66	–45.69	–6.40
1931	–41.21	–43.33	–46.82	–50.12	–49.65	–9.32
1932	–13.99	–8.79	–6.17	–2.51	8.24	–10.27
1933	46.48	49.93	103.76	115.75	203.47	0.76
1934	–0.58	1.43	10.91	19.80	31.60	1.52
1935	40.10	44.39	43.75	60.94	63.26	2.99
1936	31.14	30.77	36.16	53.18	75.84	1.45
1937	–30.49	–32.59	–41.96	–49.00	–52.34	2.86
1938	23.23	26.58	37.92	43.18	22.02	–2.78
1939	4.76	3.21	–1.47	4.57	0.05	0.00

(*continued*)

Exhibit 4.9. Annual Returns on the Ibbotson Equity Indices, 1926–2025 (*continued*)

Year	Ibbotson 25 (%)	Large Cap (%)	Mid Cap (%)	Small Cap (%)	Micro Cap (%)	Inflation (%)
1940	−6.07	−7.47	−5.11	−5.22	−12.96	0.71
1941	−11.34	−10.75	−8.16	−10.24	−14.19	9.93
1942	14.59	15.19	21.22	26.44	49.76	9.03
1943	22.38	25.04	37.95	58.15	101.72	2.96
1944	15.43	18.23	30.37	41.66	63.23	2.30
1945	26.46	33.02	56.50	64.74	83.17	2.25
1946	−7.15	−5.35	−8.51	−11.23	−13.36	18.13
1947	8.89	4.58	1.19	−2.90	−2.81	8.84
1948	4.46	2.82	0.12	−4.35	−6.59	2.99
1949	18.49	19.71	22.45	21.23	21.60	−2.07
1950	32.40	29.38	30.30	36.70	45.70	5.93
1951	24.23	21.82	18.39	15.30	9.57	6.00
1952	14.94	14.10	11.89	9.64	6.27	0.75
1953	2.63	1.29	−0.85	−2.94	−5.62	0.75
1954	51.98	48.59	56.12	57.48	63.73	−0.74
1955	32.89	26.89	18.62	20.81	22.40	0.37
1956	9.45	8.64	7.76	6.51	2.94	2.99
1957	−9.89	−9.14	−12.62	−17.77	−15.26	2.90
1958	40.42	42.15	56.23	61.87	70.53	1.76
1959	13.38	12.00	15.06	17.40	18.25	1.73
1960	−0.63	1.34	2.20	−3.30	−4.98	1.36
1961	28.71	26.46	28.81	29.53	31.21	0.67
1962	−6.39	−8.93	−13.13	−16.76	−16.52	1.33
1963	24.03	22.30	16.00	18.55	11.99	1.64
1964	16.82	15.70	18.07	16.53	18.56	0.97
1965	7.18	10.68	25.92	35.15	37.98	1.92
1966	−12.03	−9.47	−5.85	−7.15	−8.20	3.46
1967	23.45	21.75	39.94	63.88	103.43	3.04
1968	6.29	9.18	21.08	31.82	50.14	4.72
1969	−2.77	−7.26	−14.69	−22.16	−32.36	6.20
1970	4.55	2.23	−2.01	−9.87	−16.81	5.57
1971	15.34	14.54	21.23	20.32	17.67	3.27
1972	24.35	20.38	9.06	5.58	−1.38	3.41
1973	−15.05	−14.46	−25.94	−34.35	−40.80	8.71
1974	−29.65	−27.47	−25.13	−25.87	−26.72	12.34

(*continued*)

Exhibit 4.9. Annual Returns on the Ibbotson Equity Indices, 1926–2025 (*continued*)

Year	Ibbotson 25 (%)	Large Cap (%)	Mid Cap (%)	Small Cap (%)	Micro Cap (%)	Inflation (%)
1975	31.52	33.98	57.09	60.92	71.52	6.94
1976	20.77	22.06	38.26	46.84	48.19	4.86
1977	–7.87	–7.96	4.25	17.16	28.37	6.70
1978	8.25	5.65	10.59	18.21	26.21	9.02
1979	9.53	17.81	33.60	40.55	43.87	13.29
1980	35.39	32.85	32.87	36.81	39.17	12.52
1981	–11.54	–6.58	4.03	3.60	–2.69	8.92
1982	21.47	19.26	24.89	25.18	25.87	3.83
1983	19.80	20.33	24.65	30.05	33.05	3.79
1984	11.23	7.79	–0.22	–3.41	–11.75	3.95
1985	27.50	33.03	31.06	35.09	28.18	3.80
1986	13.52	18.07	16.33	6.87	3.89	1.10
1987	6.47	3.72	0.73	–6.79	–14.10	4.43
1988	12.91	16.15	21.17	24.88	19.74	4.42
1989	33.58	32.40	23.95	18.83	8.38	4.65
1990	5.03	–2.80	–10.77	–18.24	–27.77	6.11
1991	30.65	31.23	43.22	46.39	49.97	3.06
1992	–0.62	6.73	16.12	17.95	20.80	2.90
1993	2.98	8.06	16.74	18.24	18.67	2.75
1994	4.62	1.38	–3.31	–1.73	–4.19	2.67
1995	40.95	39.11	33.68	28.65	34.20	2.54
1996	27.68	23.36	18.03	15.36	18.13	3.32
1997	37.18	34.52	25.90	24.33	22.91	1.70
1998	41.48	33.43	8.95	0.44	–3.10	1.61
1999	27.33	22.90	29.87	35.14	33.95	2.68
2000	–23.67	–12.69	–4.36	–12.27	–14.30	3.39
2001	–11.85	–14.73	–4.04	7.73	17.95	1.55
2002	–23.36	–21.60	–19.13	–22.36	–16.81	2.38
2003	20.54	27.38	40.58	51.04	73.21	1.88
2004	4.80	9.70	17.58	21.03	15.77	3.26
2005	–0.09	4.76	12.16	6.63	2.17	3.42
2006	17.92	15.74	13.71	16.92	18.05	2.54
2007	8.44	6.85	6.00	–0.72	–8.34	4.08
2008	–32.72	–35.79	–40.18	–37.43	–42.45	0.09
2009	15.70	24.48	41.20	43.89	55.58	2.72

(*continued*)

Exhibit 4.9. Annual Returns on the Ibbotson Equity Indices, 1926–2025 (*continued*)

Year	Ibbotson 25 (%)	Large Cap (%)	Mid Cap (%)	Small Cap (%)	Micro Cap (%)	Inflation (%)
2010	9.99	14.09	28.32	29.27	26.20	1.50
2011	4.18	1.72	−0.22	−3.60	−13.23	2.96
2012	12.85	15.71	17.27	17.21	17.37	1.74
2013	23.74	33.18	39.07	42.39	48.24	1.50
2014	9.17	13.09	9.11	3.88	1.74	0.76
2015	3.44	0.93	−3.69	−6.71	−9.97	0.73
2016	12.48	12.39	15.92	21.51	22.35	2.07
2017	24.17	22.90	20.13	16.03	13.68	2.11
2018	−0.35	−3.62	−9.25	−11.52	−15.23	1.91
2019	34.29	31.19	28.75	23.64	19.87	2.29
2020	29.56	23.99	21.14	22.61	32.92	1.36
2021	29.96	26.45	16.57	12.78	10.77	7.04
2022	−27.14	−19.84	−18.43	−22.07	−26.60	6.45
2023	42.06	29.04	16.90	19.87	2.68	3.35
2024	41.09	27.77	14.57	9.86	10.80	2.89
2025	21.32	19.07	9.53	9.84	13.97	2.68

Source: Ibbotson Equity Indices, underlying data from CRSP and the US Bureau of Labor Statistics.

Why Long-Run Data?

Having documented the long-run behavior of US equities across size segments, we now turn to two more fundamental questions: How much statistical confidence should investors place in these historical estimates, and what does a century of data actually buy in terms of precision? At first glance, long-run data—especially data from nearly a century ago—may seem of limited value for decisions about the future. The US economy today is different from the economy of decades past. The drivers of economic growth, inflation, and market structure have all changed. Why, then, should distant history inform our beliefs about future risk and return?

First and foremost, history is a record of important events and their causes and consequences. History is particularly useful in evaluating rare, major economic events, precisely because they happen so infrequently. For example, in recent years, history has been an indispensable reference point for assessing the effects of a pandemic, inflation shocks, radical technological change, and disruptions in global trade. History may not directly predict what will happen, but it provides an analytical framework and guidance about the factors we should consider in modeling future consequences.

The virtue of continuous, long-term market data, as opposed to simply historical records of rare events, is the large-sample statistical properties of such data. There are important caveats to relying on even a large sample of data. Most importantly, the data exist for a reason. In the case of a century of US equity returns, the data exist because the US market survived (and thrived) for a century, unlike some other major markets that were interrupted or shut down by war, revolution, or other circumstances in the twentieth century. Accounting for this potential bias in the data is important.

Another thing to keep in mind is that the data we have today are bounded by history. The tails do not contain the limits of future extreme outcomes. The one-day crash in 1987 was roughly double the magnitude of the biggest one-day crash in 1929. An analyst in 1986 looking back at history might have thought such a crash impossible. Someday, there will almost certainly be another crash that sets a new record. Do not trust historical data as the only set of potential future outcomes.

With these caveats in mind, in this section, we explore how having lots of data can help assess the probabilities of future outcomes and provide higher levels of confidence. And we will show how "lots" can have different meanings for different measures.

Continuous, long-term historical data yield desirable statistical properties when estimating the key parameters investors care about: expected returns, volatility, and correlations. The central insight is that these three quantities respond to different dimensions of the data. As we will show, more calendar time helps pin down expected returns, whereas more frequent observations help pin down volatility and correlation. Understanding this distinction clarifies exactly what a long dataset buys—and what it does not.

Estimation of Expected Returns: Time Span Matters

The most important question in the practice of long-run investing is, How precisely can we estimate expected returns? One way to form an expectation of the future is to use historical data and estimate the mean return. This statistic and the accuracy of the estimate depend entirely on the length of the time period covered by the data, not on how frequently returns are measured within it.[3]

Intuitively, expected return is a slow-moving signal buried in noise. Adding more observations by increasing the frequency—for example, by switching from monthly to daily data over the same time window—does not help, because each additional observation carries proportionally less information.[4] What actually tightens the estimate is extending the sample window itself.

Formally, the standard error, SE, of the estimated mean return, $\hat{\mu}$, is

$$\mathrm{SE}(\hat{\mu}) \approx \frac{\hat{\sigma}}{\sqrt{T}}, \tag{4.1}$$

where $\hat{\sigma}$ is the estimated annual volatility and T is the number of years in the sample. To halve the standard error, one must quadruple the sample length. Thus, going from a 25-year sample

[3] The estimates presented assume that both $\hat{\mu}$ and $\hat{\sigma}$ are constant over the sample and not serially correlated.

[4] Each return observation contains a signal proportional to the length of the period and noise proportional to its square root. Shrinking the interval and moving to higher-frequency data make both the signal and the noise smaller, but the noise shrinks more slowly than the signal. These effects end up canceling out, so adding more observations by increasing the frequency never improves the precision for the estimate of the mean. Only extending the sample window allows the signal to grow relative to the noise.

to a 100-year sample cuts the uncertainty in half. This dynamic illustrates both the value of a century-long dataset and the practical difficulty of achieving high precision in expected return estimation.

The takeaway is that for expected returns, what matters is how long the sample runs, not how finely it is measured.

Estimation of Volatility and Correlation: Frequency Matters

In addition to expected return, investors also care about risk, especially volatility and correlation. The estimates of volatility and correlation behave differently from the mean. Here, the precision improves with the number of observations, n, not the time span. Thus, higher-frequency data, such as daily rather than monthly, can in fact help with risk measures, at least to the point at which microstructure noise (e.g., bid–ask bounce) begins to add noise to the signal.

The standard error of the estimated volatility, the standard deviation, shrinks as n increases:

$$\mathrm{SE}(\hat{\sigma}) \approx \hat{\sigma}\sqrt{\frac{1}{2n}}. \tag{4.2}$$

The same logic applies to correlation. Volatility is estimated by averaging squared returns, and correlation is estimated by averaging cross-products of returns. Each additional observation contributes a fresh squared or cross-product term, whereas for the mean, intermediate observations telescope away and add nothing. This is why finer sampling (to an extent) does reduce estimation error for risk parameters. Therefore, a practitioner using daily data has roughly $\sqrt{252} \approx 16$ times more precision regarding volatility than one using annual data over the same time window.

For this reason, a long dataset and a high-frequency dataset are complements, not substitutes, because they solve different problems. A century of annual data is invaluable for expected return estimation but nearly useless for improving volatility precision beyond what a decade of daily data already provides. Conversely, switching from annual to daily observations over the same 10-year window dramatically sharpens risk estimates but leaves the expected return estimate essentially unchanged.

To summarize, for volatility and correlation, precision depends primarily on the number of observations. Daily data can provide far more precision than annual data over the same window.

Summary

This chapter introduces the Ibbotson Equity Indices, a new family of capitalization-weighted US equity portfolios constructed using security-level data from CRSP spanning 1926–2025. The indices are designed to provide a transparent and economically meaningful representation of the US public equity markets and various size segments over a full century.

The construction methodology emphasizes stability over time. By relying on CRSP data and by using consistent size definitions—CRSP deciles before 1975 and fixed numeric rank market-cap thresholds thereafter—the Equity Indices allow for comparisons across decades that reflect economic change in the US markets. All the Equity Indices are constructed using full market-cap weighting, a decision that preserves continuity across the entire sample, while tying the index weights to the actual economic footprint of publicly traded firms.

Using the Equity Indices' coverage of the past century, we documented well-known facts about the US equity markets. First, long-run compounded average returns have been remarkably strong, approximately 10% per year on average, with meaningful differences across size segments. Second, although small-cap stocks have historically earned a premium over their large-cap peers, the magnitude of this premium has declined in the second half of the sample. Third, aggregate volatility has declined over time, despite the occurrence of several rare systemic crises during the past 50 years.

The evolution of market concentration provides additional perspective. Capitalization weighting naturally reflects changes in the distribution of firm size. Periods of elevated concentration in the megacap segment—for example, in the 1930s or currently—reduce the effective breadth of diversification in broad market indices, although they remain well diversified when compared to smaller portfolios.

Finally, we demonstrated why long-run data remain valuable for investment analysis. In particular, the precision of estimation of the sample mean depends on the total span of the sample, improving at a rate proportional to $1/\sqrt{T}$, while volatility and correlation estimates improve with the number of observations. A long, high-quality dataset can therefore enhance statistical confidence while allowing investors to focus on subperiods they believe are most relevant to current market conditions.

Taken together, the Ibbotson Equity Indices provide a consistent empirical foundation for understanding US equity market behavior through different market conditions and size segments. Thus, they are intended to serve as a durable benchmark for research and supplement long-term investment decision making.

Key Takeaways

- The Ibbotson Equity Indices are built from CRSP security-level data using stable size definitions and full market-cap weighting, ensuring as much methodological consistency as can practically be achieved, over the 1926–2025 period.
- The broad US equity market generated approximately 10% annual geometric returns over the past century, with persistent but time-varying differences across size segments.
- Equity market volatility has declined across all size portfolios over the past century.
- The capitalization of the top 25 firms as a share of the entire market has fluctuated between roughly 20% and 50%. When this share is high, the effective diversification of cap-weighted indices is reduced, even though these indices remain broadly diversified overall.
- Long-run data provide greater precision when estimating the sample mean, and the precision improves at the rate $1/\sqrt{T}$. The longer the sample, the better the estimate.

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CHAPTER 5. STATISTICAL ANALYSIS OF EQUITY RETURNS

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Introduction

In this chapter, we examine the long-run behavior of US equity returns through several complementary lenses. We begin by assessing how performance has evolved over decades and across investment horizons.

Over the past century, US markets have not grown in a smooth or uniform fashion. Different decades have delivered sharply different outcomes. Long stretches of strong performance have sometimes been followed by lost decades, and the experience of an investor in one era can look very different from that of an investor in another period. To capture this variation, we begin by looking at both rolling returns and decade-by-decade returns to highlight the dispersion of realized outcomes and the importance of horizon length.

The deeper story of this chapter, however, concerns what the shape of return distributions reveals about risk. Mean returns and standard deviations—the first two moments of a distribution, discussed in the previous chapter—make up the standard toolkit, but they conceal features that matter enormously to investors. These characteristics are asymmetry, heavy tails, and the frequency of extreme events. Equity returns are not Gaussian (normally or lognormally distributed), and the departure from normality is the driving force behind why crashes happen more often than tidy models predict, why a handful of stocks generate most of the market's long-run wealth, and why diversification is more consequential than it appears when viewed through a variance lens alone. By examining skewness and kurtosis alongside the historical record of drawdowns and rolling returns, we gain a more complete and honest picture of what equity investing has actually looked like.

The time-series perspective on stock returns in this chapter complements the sector and industry analysis in Chapter 4, which goes beyond observing what the market has returned to ask when, how, and from which parts of the economy those returns have come.

Past Performance

Over the past century, US equities have delivered extraordinary compounded growth, but that long-run success tends to mask a highly volatile and uneven path. The equity premium has rewarded investors who are willing to tolerate risk, yet the journey has been marked by deep drawdowns, regime shifts, and extended recoveries. As a result, most US equity investors did not earn the long-run average return, for various reasons (the most important being the subperiods over which they were invested). To understand market volatility and its implications for the past century's returns, we will first inspect return paths within each decade, followed by long-horizon rolling returns. Both perspectives reveal how realized outcomes can differ across decades and other holding periods, which full-sample statistics and wealth indices tend to wash away.

Returns by Calendar Decade

Examining cumulative returns within each calendar decade highlights the booms, busts, and recoveries that have defined the investor experience. **Exhibit 5.1** plots the 10-year return paths for each decade of the past century for the Ibbotson All Cap Stock Index™. Each line represents the growth of $1 invested at the beginning of each decade.

What stands out is that despite numerous major drawdowns, markets have usually recovered fairly quickly. Exceptions are the Great Depression and the early years of World War II, which constituted the largest and longest drawdown; the 1970s stagflation; and the more recent "lost decade" that included the 2000–2002 dot-com collapse and the global financial crisis of 2007–2009. Note that the decade-by-decade plots can understate risk because crises rarely align with calendar decades and severe declines are often split between two panels in the exhibit. Still, this decade analysis gives a useful picture of market volatility, including booms, crashes, and recoveries. All of them are defining features of equity investing.

The volatility observed in these 10-year periods naturally translates to drawdowns—that is, periods when the market falls from a peak and has yet to surpass the old high. **Exhibit 5.2** summarizes the duration and magnitude of the major market-wide US equity drawdowns from 1926 to 2025 using the nominal Ibbotson All Cap stock total return index. Excluding single-month declines, the average drawdown lasted roughly 11 months; including single-month declines reduces the average to roughly 7 months. Fourteen drawdowns exceeded one year in duration. Outside of the 1929 crash, the effects of which persisted for more than a decade, recoveries from major downturns, such as in 1973, 2000, and 2007, occurred within three to six years.

For investors, the duration of a drawdown can matter just as much as the magnitude. A short-lived, sharp decline may be tolerable for an investor who is decades from retirement, but even a mild drawdown may be consequential for someone already retired with a majority of assets held in equities. Thus, a thorough understanding of past drawdowns and their duration is needed when thinking about long-term investing, especially if the investments face some sort of liability side, as is the case with pension funds. For these types of investors, the relevant risk is not only the likelihood of a drawdown but also the time to recovery relative to the investment horizon.

Exhibit 5.1. All Cap Total Returns by Decade with Drawdowns Highlighted, 1926–2025

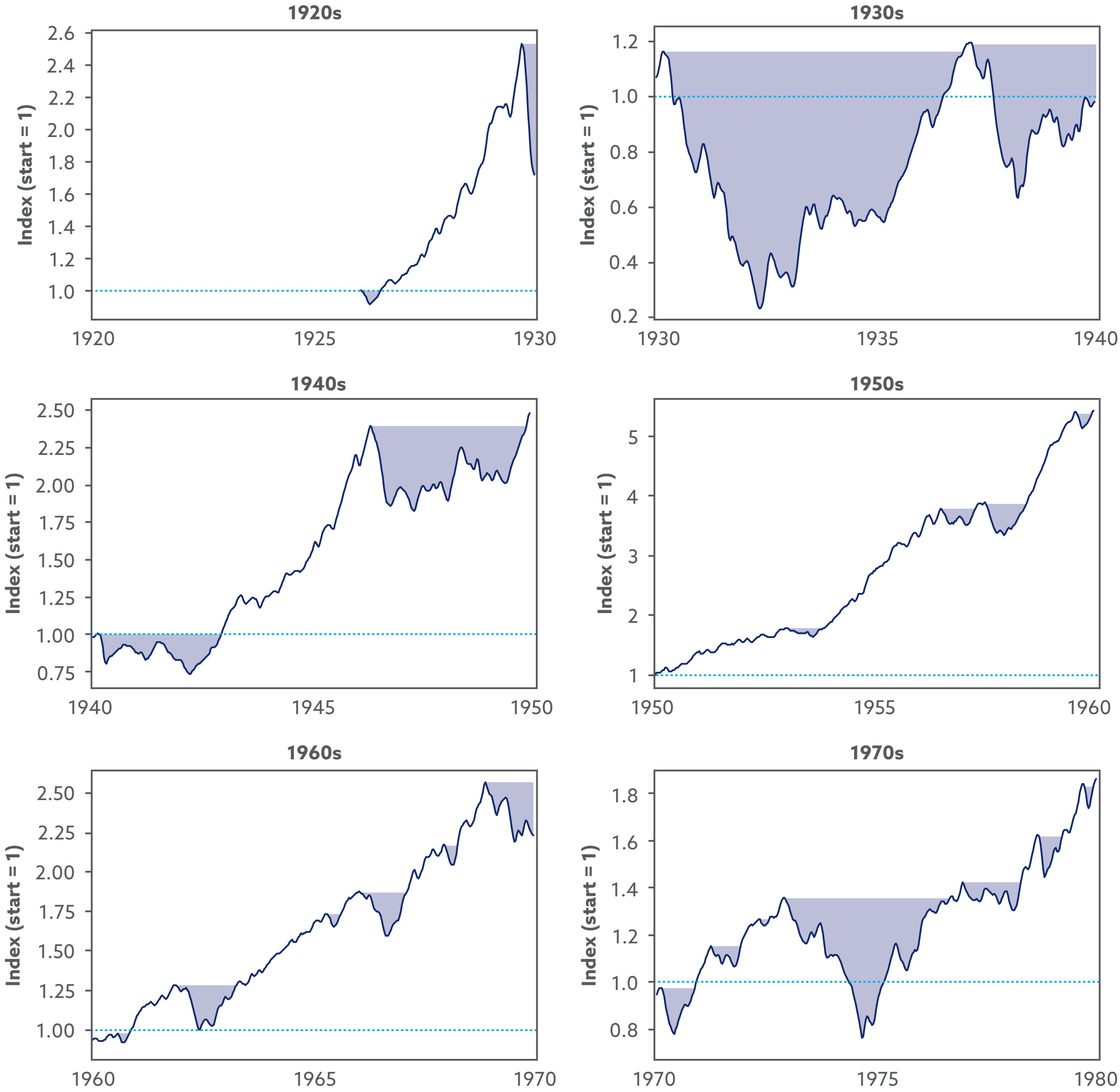
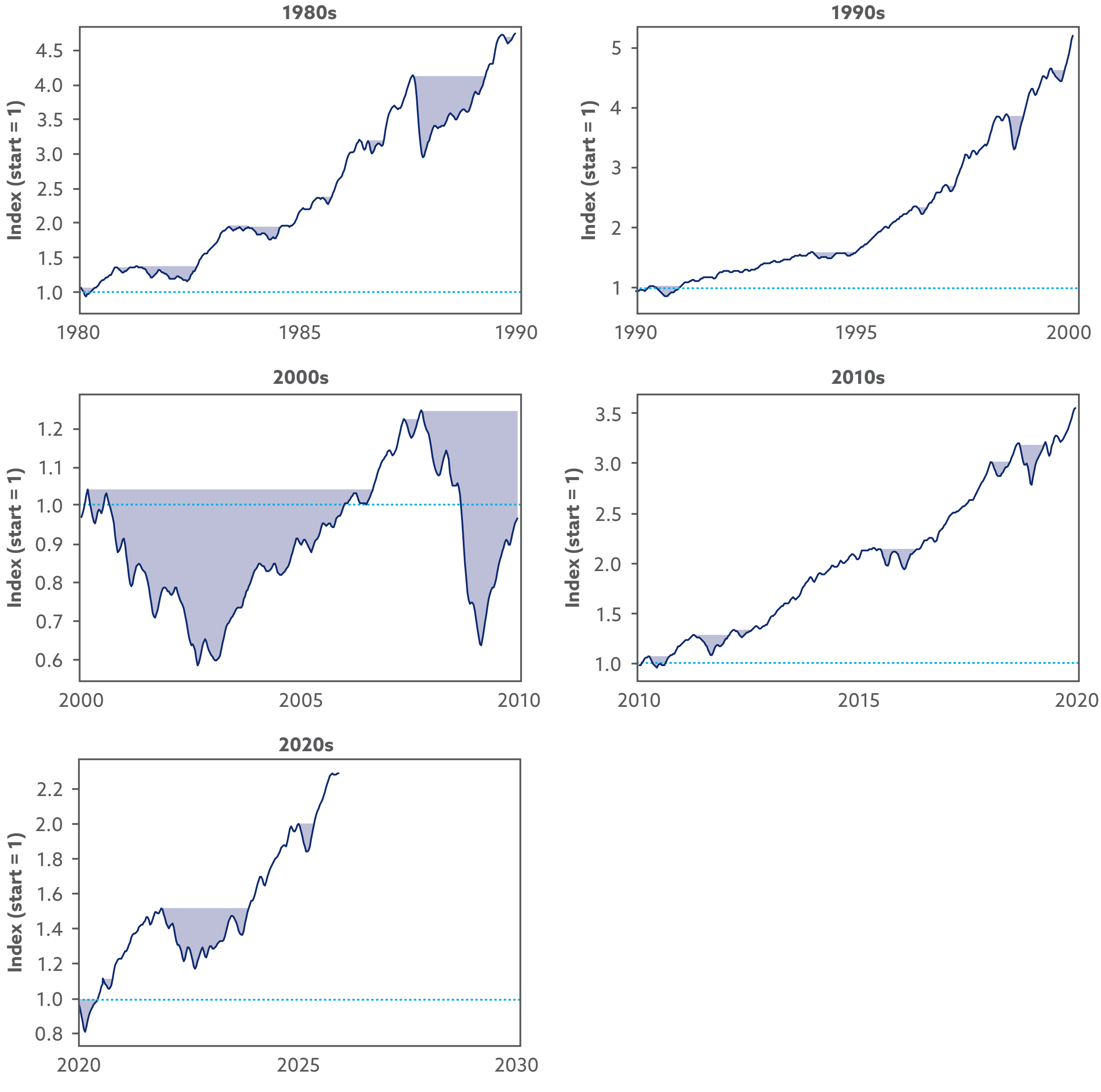
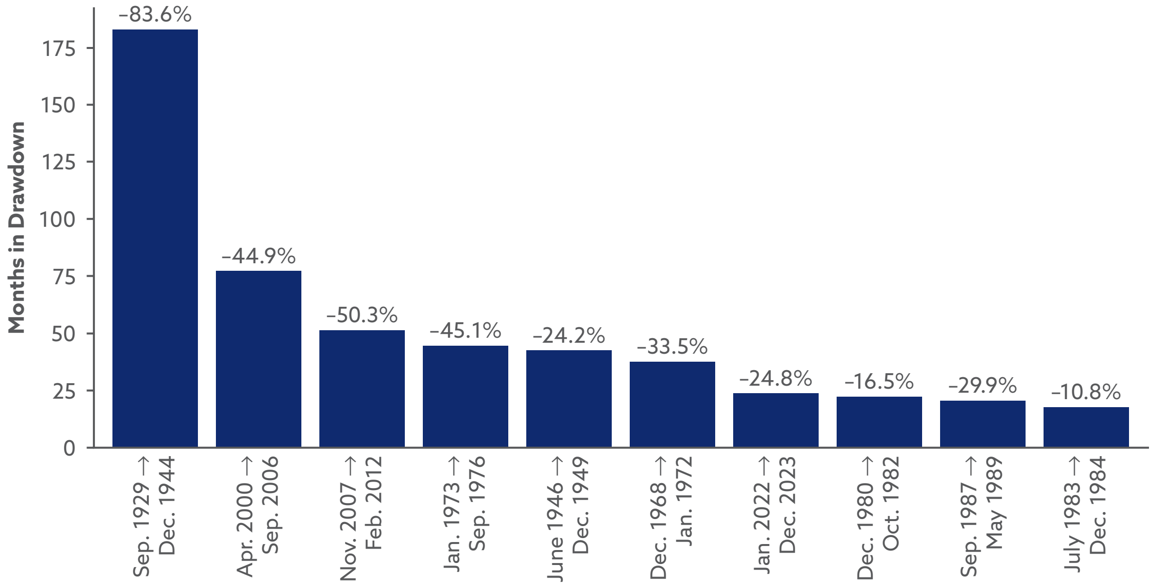


Exhibit 5.1. All Cap Total Returns by Decade with Drawdowns Highlighted, 1926–2025 (*continued*)



Source: Roger G. Ibbotson. Data from the Ibbotson All Cap stock index.

Exhibit 5.2. Histogram of US Market Drawdown Lengths (months), with Maximum Drawdown (%)



Source: Roger G. Ibbotson. Data from the nominal Ibbotson All Cap stocks total return index.

Rolling-Period Returns

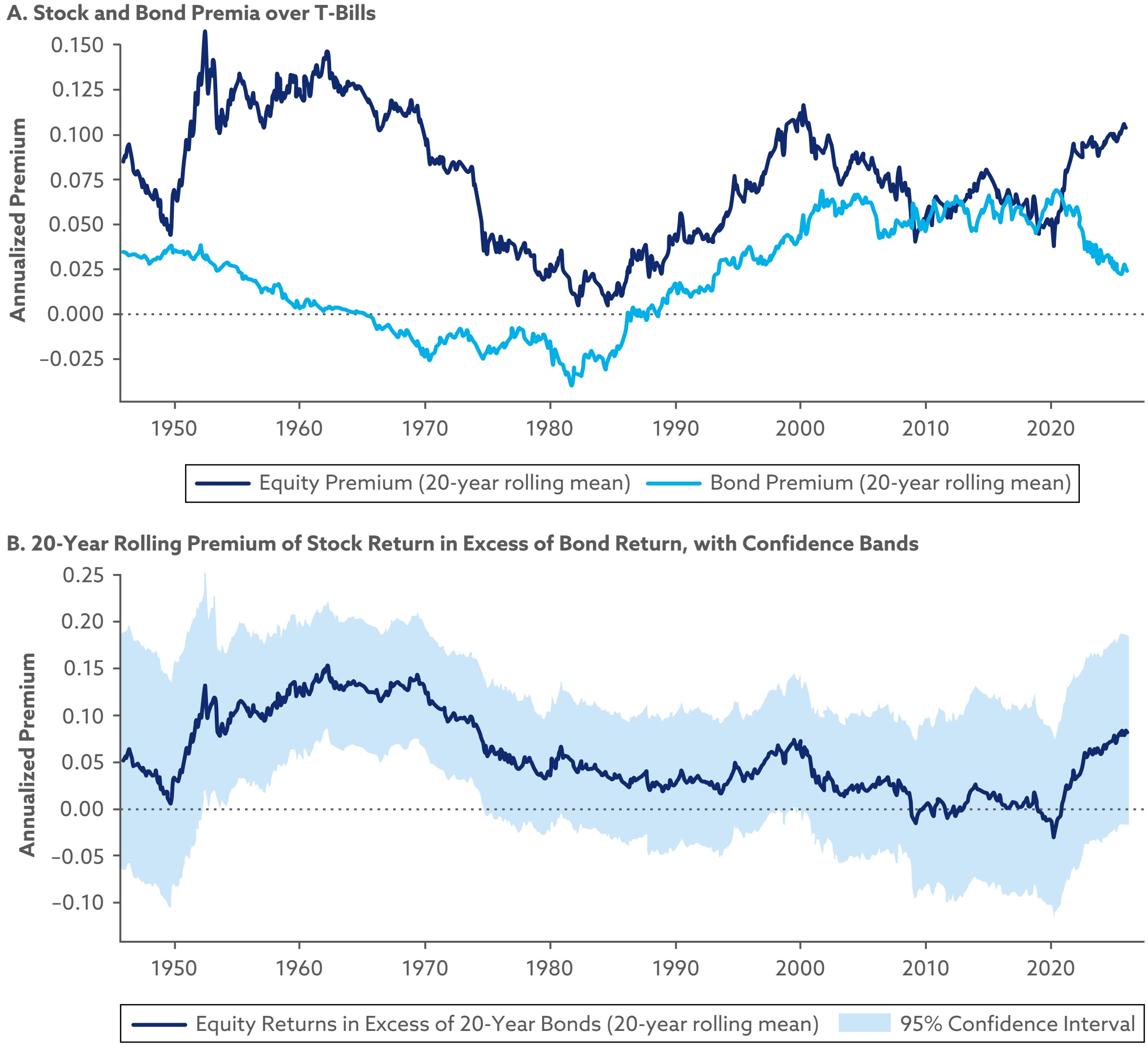
To move from decade-by-decade views to a longer-run perspective, **Exhibit 5.3** plots 20-year compound annualized real returns for both US equities and 20-year Treasury bonds. These overlapping windows show how the realized equity premium and the term premium of long-term bonds over bills have fluctuated through time.

Despite these wild fluctuations, equities have generally outperformed long-term Treasury bonds over the post-1926 period. On average, large-cap US equities have delivered an arithmetic mean real return 6 percentage points higher than that of 20-year bonds,[1] with the two asset classes having Sharpe ratios of 0.45 and 0.18, respectively.

This gap has fueled the "stocks for the long run" narrative (Siegel 2022) because of the size and persistence of the realized equity premium. McQuarrie (2023) questioned the universality of this finding by introducing a new dataset for the pre-1926 period. He showed that prior to 1926, the advantage of equities over bonds varied substantially, with bonds beating stocks for long stretches of time. Our focus here remains on the modern (post-1926) era, where a century of rolling 20-year returns demonstrates both the persistence and the variability of the US equity premium when measured against long-term government bonds.

[1] This is the difference between the arithmetic, not geometric, means.

Exhibit 5.3. 20-Year Rolling Premia of Large-Cap Equities and 20-Year Treasury Bonds over T-Bills, 1946–2025



Source: Roger G. Ibbotson. Data from Ibbotson Indices.

Note: Confidence bands are based on Heteroskedasticity and Autocorrelation Consistent Newey–West standard errors.

These patterns underscore a recurring theme: The realized history of equity returns is punctuated by events whose frequency and magnitude are difficult to square with simple distributional models. The decade-by-decade and rolling return views document what happened. To understand why such events occur—and how often investors should expect them to recur—we need to look more carefully at the full shape of the return distribution, not just its center.

Distributions of Stock Returns

Every numerical variable, from human height to exam scores, follows some distribution, a pattern that describes how often different values occur. Many natural phenomena tend to cluster around an average with fewer observations far from the center. Empirical distributions can be calculated from data. Theoretical distributions are derived from mathematical models of the data-generating process. The most familiar of these is the bell-shaped, Gaussian normal distribution, which is symmetric around the mean and has approximately two-thirds of the occurrences within one standard deviation of the mean.

Are Stock Returns Best Modeled as Normal, Lognormal, or Something Else?

The starting point is the distribution of returns over a single period—say, a month or a day. Neither the normal nor the lognormal distribution is a perfect fit, but the lognormal is a better approximation. The primary reason is limited liability: A long-only equity position cannot lose more than 100%, which rules out the symmetric unbounded losses implied by the normal distribution. Even so, empirical single-period returns exhibit fat tails and skewness that the lognormal does not fully capture, a phenomenon on which we focus in this chapter.

A related but distinct question concerns the behavior of compounded wealth over long horizons. Because compounded wealth is the product of successive gross returns, taking logarithms converts it into a sum of log returns. This sum then tends toward normality as the number of periods grows because of the central limit theorem, implying that long-horizon wealth tends toward lognormality even when individual-period returns are not themselves lognormal. Chapters 19 and 20 explore the forecasting implications of this result.

This distinct property of periodic return distributions is important and has a long history of research in financial economics. For example, in a seminal option pricing formula, Louis Bachelier (1900) assumed a normal distribution for bond returns, which implied the possibility of negative prices. Maurice Kendall (1953) made a similar assumption in an early test of the random walk hypothesis. M. F. M. Osborne (1959) was the first to recognize that this assumption violated the lower bound of –100% return and to propose that stock returns are lognormally distributed.

Benoit Mandelbrot (1963) raised an important challenge to the lognormal assumption for asset returns. He observed empirically that they had "fat tails"—in other words, that extreme high and low log returns were more common than predicted by the model. He hypothesized that a stable distribution with undefined variance was a better fit.[2] Because the foundation of modern portfolio theory is the tradeoff between measurable risk and return, the stable distribution with undefined variance invalidates most of its key implications.[3] Eugene Fama (1963, 1965) was the first to test the stable model against the lognormal with stock market data and firmly rejected lognormality. Since then, the fat-tail feature of asset return distributions has remained both a theoretical challenge and a very practical concern in financial economics. It is popularly known as the "black swan" problem—the notion, popularized and more formally studied by

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[2] A simple example of a stable distribution with undefined variance is a variable with tail probability PX > x = x – α for $x \geq 1$ and $1 < \alpha \leq 2$.

[3] See, by way of comparison, Kaplan (2012).

Nassim Taleb (2010, 2020), that extreme events happen more frequently than any probabilistic model, even the stable distribution, can predict.

On the theoretical side, a number of resolutions to the issue of fat tails have been proposed since Mandelbrot (1963). Stanley Kon (1984), for example, showed that a mixture of normal distributions can also generate fat-tailed distributions—a solution that fits nicely with a pattern of economic regime changes in which some periods have high risk and low return. Other solutions model the stock-return-generating process with jumps as well as continuous variation. Robert Merton (1976) introduced this approach to calculate the price of options when a continuous hedge to the underlying asset is not possible. Robert Engle (1982) introduced a time-varying, conditional volatility model of stock returns (generalized autoregressive conditional heteroskedasticity, or GARCH) and showed that this process could also generate fat-tailed distributions. Further advances have been made in modeling and empirically estimating the variation in the volatility of tail risk itself.[4] Thus, for most practical financial applications, as long as a variable such as a stock return has a finite bound, there are useful modeling tools to evaluate risk. One approach to modeling that does not depend on regime changes, jumps, or innovations in volatility is to adjust the normal distribution for return asymmetry and allow for fatter tails. In Chapter 19, Paul Kaplan shows how to use the more general Johnson distribution in estimating the probability of investor ruin over long investment horizons.

Why Investors Should Care About the Distribution of Returns

Why does all this matter for investors? It matters because the return-generating process and the resulting shape of the distribution of realized returns tells us not only about the typical fluctuations but also the rare events that have an outsized influence on performance and risk. Knowing whether the return distribution of an asset is symmetric or skewed, thin or fat tailed, can set our expectations about the likelihood of likely extreme gains or losses and how the presence of the asset in a portfolio could impact the degree to which the portfolio is effectively diversified.

The good news for long-term investors is that log returns are a very good first approximation for forecasting the cumulative wealth distribution. As shown in Chapter 3, compound growth is the product of a sequence of single-period growth rates, defined as 1 plus the return. Taking the natural logarithm of these growth rates turns this calculation into a summation of random variables. The central limit theorem shows that the mean of a series of independently and identically distributed random variables drawn from any distribution with a defined variance—not just the normal or lognormal—converges to a normal distribution. This convergence result has been extended to nonindependent and nonidentical distributions.

Advances in modeling the return-generating process have been particularly relevant to shorter-horizon investors as well. For example, in option pricing, the value of derivative contracts depends crucially on understanding the distribution of future prices in the period up to and including expiration of the option. The classic Black–Scholes option pricing model assumes a lognormal distribution of the return to the underlying security. Researchers have consistently shown that this assumption can lead to the mispricing of out-of-the-money options. For example, out-of-the-money put options on the S&P 500, which pay off on big market declines, regularly appear overpriced, either because the perceived probability of a

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[4] See, for example, Gabaix (2012); Santa-Clara and Yan (2010); Wachter (2013); Bollerslev and Todorov (2011); Bollerslev, Todorov, and Xu (2015); Andersen, Fusari, and Todorov (2020); Calvet and Fisher (1999).

Exhibit 5.4. Probability of Experiencing at Least One Single-Day Crash in the Dow Jones Industrial Average of More Than 10% Within Your Remaining Lifetime

Investment Horizon	Lognormal, i.i.d. Return Distribution	GARCH (1,1) Time-Varying Mean and Volatility Clustering Model	Johnson Distribution[a]	Historical Frequency Model
60	0%	31%	72%	79%
50	0%	27%	65%	73%
40	0%	22%	57%	65%
30	0%	17%	47%	54%
20	0%	12%	35%	41%
10	0%	6%	19%	23%

[a]with estimated mean, standard deviation, skewness, and kurtosis parameters.

stock market crash is higher than the return-generating model implies or because the market demands a higher than theorized compensation for insuring against that risk. Hence, properly modeling tail risk is essential for option trading and hedging.

Planning for Crashes

Another use of the higher moments of distributions is in planning for crashes. The single-day crash of more than 20% in the S&P 500 on 24 October 1987 was an event that had a virtually zero chance of happening if stock returns actually followed a lognormal distribution.[5] In fact, none of the 10 worst single-day crashes in the 140-year history of the Dow Jones Industrial Average of daily stock prices would have had a reasonable chance of occurring—and yet "black swan" events happen. Most readers will recall 16 March 2020, when the Dow dropped by more than 12%—another event that the lognormal model would say is impossible.

To show how the return distribution is relevant in planning for market crashes, we will ask, What are the chances you will experience a single-day loss in a diversified equity portfolio of more than 10% within your remaining lifetime? **Exhibit 5.4** shows probability estimates for this event for various remaining lifespans. The lognormal model says such a crash will not happen. The empirical frequency column on the far right, however, says that it can happen because it did. This column simply counts the number of these events that happened in the history of the Dow, divides by the number of years in that history, and then multiplies by the remaining lifespan. An important caveat is that the historical frequency depends on the fact that the Dow Jones Industrial Average—and the US stock market itself—survived over the past 140 years.

[5]The 19 October 1987 crash had a 1 in 10^{128} chance of occurring under the lognormal assumption. For comparison, the estimated number of stars in the universe is 10^{24}.

Historical frequencies do not take into account the possibility of events that could have happened but did not happen in the observed sample. As such, they are a bounded—and thus likely to be a conservative—estimate of future extreme events. The benefit of using a theoretical model is that it extends the bounds of the empirical distribution, alerts investors to the possibility of extreme events, and provides a probability of them occurring that is not bounded by the limitations of the historical data.

Among the most widely used tools to model time-varying returns is the GARCH model. It is a sophisticated econometric approach that starts with the observations that volatility itself is volatile—that is, some periods are more volatile than others—and that high-volatility periods tend to cluster together. GARCH accounts for these attributes by allowing today's volatility estimate to depend on recent returns and recent volatility. As a result, it produces more realistic probability estimates for extreme events than the simple lognormal model, as shown in Exhibit 5.4. GARCH still underestimates the historical frequency of crashes, however, because its strength lies in short-horizon volatility clustering rather than in capturing the extreme tail behavior that drives the single-day declines.

Unlike the GARCH model, the Johnson model—an econometric model that uses the first four moments of the return distribution, presented in detail in Chapter 19—assumes that stock returns are independently and identically distributed (i.i.d.). Despite this assumption, which is not supported empirically, the model nevertheless captures the effect of variation over time in the mean and variance of the return distribution. It accomplishes this seemingly impossible task by taking into account kurtosis (discussed later), a moment of the distribution that takes on a higher value if volatility has changed over time. The Johnson probability estimates for a 10% one-day decline are reported in the middle column of Exhibit 5.4. This model assigns a higher probability of a crash than does the empirical distribution, suggesting that investors could expect an even higher chance of a single-day crash than history thus far indicates. That result is consistent with our earlier observation that the historical estimate is conservative.

The takeaway from this exercise is that most investors should be prepared to experience another day when the market drops by 10%. For those with a 50- or 60-year investment horizon, such a crash has a 70%–80% probability of occurring. For those with a 10-year horizon, the probability of a 10% drop is roughly 20%–25%. No theoretical model of asset return distribution is perfect, but neither is reliance solely on the realized history of returns. Nevertheless, econometric methods that allow for fatter tails and skewness produce probability estimates that are more likely to be accurate.

Distributions of Returns: Summary

In short, the distribution of asset returns tells the deeper story of risk. Empirical distributions describe what did happen; theoretical distributions describe what could happen and assign probabilities to these outcomes. Both are useful. Theoretical distributions have "tails"—that is, they assign probabilities to extreme events even if such events did not occur historically. However, they are mathematical constructs that are tractable approximations to the underlying processes generating data. They do not and cannot fully capture the economic processes, shocks, transitions, and market evolution that will inevitably characterize the future. Although researchers have long recognized the limitations of the lognormal model of stock returns and have worked to improve on it, particularly for the purposes of asset pricing and risk modeling, the model remains an effective first approximation to estimating long-run investment performance.

Theoretical distributions are useful tools, but empirical distributions based on historical data are the fundamental basis for understanding the return-generating processes underlying asset returns. To describe these distributions with more rigor, statisticians summarize their basic contours using higher-order moments—parameters beyond mean and standard deviation that measure the key dimensions of the shape of the distribution and further help us understand extreme outcomes. We explore these in detail next.

Moments of Distributions

Moments are quantitative measures that describe the shape of a distribution. The first two moments are the mean and the variance, which capture the average return and its volatility. In Chapter 4, we examined the differences in these two properties for different size indices and saw how their estimation can benefit from the length of the sample for the mean and the number of observations for the variance and standard deviation. But distributions can differ in other ways even when they share the same mean and variance. To capture these differences, we turn to the third and fourth moments, known as skewness and kurtosis.

The third and fourth moments reveal information about how returns behave in the tails, describing the extreme positive or negative outcomes that investors care most about. Throughout this subsection, all statistics are based on monthly returns because at this horizon, distributions remain meaningfully nonnormal and returns of this frequency are widely used by investors of all levels.

Skewness: A Measure of Asymmetry in Returns

Skewness measures how tilted a distribution is to one side or the other. For a normal distribution, which is perfectly symmetric, skewness equals zero. If skewness is negative, then the left tail is longer and the bulk of the distribution is concentrated on the right side of the mean. A negatively skewed distribution can also be called left tailed or left skewed. In contrast, a positive skew indicates a longer right tail with the mass concentrated on the left. In a positively skewed distribution, the mean is lower than that of a negatively skewed distribution but there are more extreme positive events because of the long right tail.

Mathematically, skewness is the third moment:

$$\frac{\mathrm{E}[(X-\mu)^3]}{\sigma^3}. \tag{5.1}$$

But the intuition is simpler: Skewness tells us on which side of the distribution the extremes or "surprises" tend to occur.

In financial markets, skewness has recognizable patterns. Individual stocks often exhibit positive skewness: Most monthly returns are small, but occasionally a firm's stock surges dramatically following good news, innovations, or other shocks. Index-level returns are more likely to be closer to symmetric because aggregation diversifies away many of these firm-specific extremes. Both very large losses and very large gains become much rarer for broad portfolios than for individual stocks. In broad market indices, skewness is often slightly negative or close to zero, reflecting the fact that large systematic declines and crashes occasionally pull the left tail outward. Smaller-stock indices can, however, retain more of the positive asymmetry from their constituents.

Skewness is particularly important for portfolio choice. Hendrik Bessembinder (2018) and Bessembinder, Chen, Choi, and Wei (2023) show that a small fraction of companies with very high returns generate the majority of the equity risk premium. This observation has important implications for portfolio diversification. Missing out on a handful of highly successful companies can dramatically lower long-term equity portfolio performance. Attempting to pick these big winners *ex ante* is difficult, however, and a strategy of selecting stocks based on skewness has not proven profitable. Research has shown that individual investors tend to hold and have a preference for small, concentrated stock positions and prefer lottery-like, positively skewed stocks.[6] Given the evidence that it is difficult to pick which stocks will generate outsized future returns, this undiversified strategy is a recipe for missing out on the benefits of skewness that accrue to holding a broad index.

Kurtosis: The Weight of the Tails

The fourth moment, kurtosis, measures how thick or heavy the tails of a distribution are. Formally, it is

$$\frac{E[(X-\mu)^4]}{\sigma^4}. \tag{5.2}$$

For a normal distribution, kurtosis equals 3, so we often use the term *excess kurtosis*, defined as kurtosis minus 3. A high (positive) excess kurtosis means that extreme outcomes, both positive and negative, occur more frequently than under a normal distribution, the distribution has a higher central peak, and—if it is roughly symmetric—there is both greater tail risk and a higher chance of repeated large positive returns.

Both individual stocks and indices show more extreme monthly returns than are consistent with a normal distribution. The degree varies, however: Small-cap stocks tend to have far higher kurtosis than large-cap indices, reflecting their tendency toward large jumps and speculative bursts. For example, Fama and French's market factor shows an excess kurtosis of roughly 7, whereas the small minus big (SMB) and high minus low (HML) factors both have excess kurtosis of around 18.

Comparing Stocks and Indices

Because we already covered the mean and variance of returns in Chapter 4, we now compare the higher moments between different indices and individual-stock-level returns. The contrast between the two types of returns is substantial—at the constituent level, returns are highly nonnormal with high skewness and substantial excess kurtosis. At the index level, aggregation smooths much of this idiosyncratic noise. Firm-specific jumps, crashes, and reversals are muted when many stocks get combined into a single portfolio, leading to much lower index-level skewness. Aggregation, however, does not make index returns normal. Rare systemic shocks

[6] See, for example, Goetzmann and Kumar (2008) and Kumar (2009).

Exhibit 5.5. Skewness and Excess Kurtosis of Monthly Index- and Stock-Level Returns, 1926–2025

	Ibbotson 25	Large Cap	Mid Cap	Small Cap
Skewness (Index)	−0.08	0.08	0.78	1.30
Excess kurtosis (Index)	5.23	7.02	11.77	14.51
Skewness* (Stock)	0.80	1.17	1.64	2.30
Excess kurtosis* (Stock)	7.61	10.96	14.83	23.99

*Stock-level distributions are Winsorized at the 0.01% level for the excess kurtosis results.

Note: The indices are the Ibbotson Indices, and stock-level distributions are from CRSP, using the same definitions as the corresponding Ibbotson Indices.

still affect many stocks at once, so they survive aggregation and continue to generate fat tails at the index level.

Exhibit 5.5 summarizes these relationships using monthly data for US equities from 1926 through 2025. Index-level skewness is close to zero for the portfolios that consist of the largest stocks, with skewness of −0.08 for the Ibbotson 25 and 0.08 for the Large Cap index, but it rises to 0.78 for Mid Cap and 1.30 for Small Cap. At the constituent level, the increase is much sharper, with the stock-level skewness of 0.86 for the Ibbotson 25 stocks, 1.28 for Large Cap stocks, 14.85 for Mid Cap stocks, and 20.50 for Small Cap stocks. The size pattern is very clear in both index and constituent returns, but individual stocks display much more extreme positive asymmetry as expected. Similar patterns persists in the kurtosis while remaining significantly nonnormal across both index and stock returns.

In practical terms, skewness and kurtosis help quantify why markets sometimes move more violently than predicted by the normal distribution. They remind us that diversification reduces but does not fully eliminate tail risk and that real-world investment returns can defy the tidy bell curve we see in many other areas of life. Over the past century, such events as those in October 1929, October 1987, March 2000, and March 2020 have underscored the reality of fat tails and large common shocks in aggregate markets. Conversely, the large gains of a few high-growth firms in each decade are a vivid example of positive skew in individual stock returns.

In summary, mean and variance tell only a part of the story. Skewness reveals the direction of asymmetry in returns, telling us whether it is the extreme gains or losses that dominate. Kurtosis reveals the magnitude of those extremes and how common those extreme events are. Together, they offer a more complete view of return distributions and help us interpret both the calm and the chaos of the past century in markets. Yet it is important to keep in mind that we observe empirical distributions only after the fact, and large events continue to surprise investors. A century-long sample of the US market is enough to demonstrate that standard theoretical models and even relatively sophisticated econometric models do not fully capture the empirical frequency of experiencing rare but large losses and gains. Skewness and kurtosis are essential measures for recalibrating these probabilities using actual data.

Key Takeaways

- US equities have generated large gains in real wealth over the long run, despite occasional long drawdowns.
- Lognormal returns provide a good first-order model for long-run wealth accumulation, but more sophisticated models can account for deviations from lognormality. These are useful for other financial applications, such as option pricing.
- The distribution of individual stock returns and stock index returns is fat tailed compared to the lognormal distribution. This means extreme returns are more likely than the lognormal predicts.
- The distribution of individual stock returns is strongly positively skewed, with a few extreme winners accounting for much of the equity risk premium.
- Broad diversification captures these rare winners without requiring stock selection skill, while concentrated portfolios increase the risk of missing the stocks that matter most.
- Most long-horizon investors will experience at least one major single-day market crash, but these events have not prevented stocks from being a successful long-term investment.
- Understanding tail risk helps investors endure drawdowns and stay invested. It helps investors plan for rare but important shocks.

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CHAPTER 6. BUBBLES, BOOMS, AND CRASHES, 1792–2024

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Introduction

Bubbles are of great interest to investors because they are periods in which stock prices rise dramatically and drop quickly, generating large speculative profits for some and large losses for others. They have spawned many theories, ranging from market constraints to irrational behavior to the fact that bubbles are only identifiable *ex post*: An extreme temporary rise will not be called a bubble unless it is followed by a crash.

A theoretical definition of an asset bubble is a large, positive, temporary deviation from fundamental value. Testing for a bubble under this definition requires a valuation model. Such models must incorporate not only such fundamentals as expected future cash flows but also the complex interaction of differing investor beliefs and behavior.

In this chapter, we settle on a simple, empirical definition that most would agree on. A bubble is a large boom in stock prices followed by a crash. If, for example, a market doubles in value over three years, it would qualify in most people's minds as a stock market boom. If prices then halved in the following years, this would certainly qualify as a crash. Putting these two together defines an empirical bubble. One could choose different thresholds or compounding intervals, but the principle of defining a bubble in terms of price dynamics provides an intuitive framework for enumerating their historical frequencies.

A practical issue for investors is whether a rapid increase in prices predicts a rapid future price drop. The historical rarity of bubbles, at least in the US capital market, makes this question difficult to test empirically. One approach is to expand the sample to the full population of global equity markets using all available time periods, the approach taken in Goetzmann (2015).[1] Another approach is to follow Greenwood, Shleifer, and You (2019) and test whether industry-level price booms are more likely to be followed by crashes. This method is clearly relevant to investors concerned with a boom in a single industry.

[1] See also Goetzmann and Kim (2018), who use a global sample to study negative bubbles.

We begin by using the available history of aggregate US stock market returns to document the historical frequency of booms, crashes, and bubbles. We then use industry portfolios to test for bubble dynamics. We extend the Greenwood et al. (2019) analysis through 2024 and perform an out-of-sample analysis using industry returns from an earlier era in US capital market history, 1871–1938. Finally, we compare the conditional distribution of returns following 12-month industry booms with the entire distribution of returns.

We find that bubbles are extremely rare in both the aggregate index and industry indexes. Negative bubbles, in which a large decline is followed by a large gain, occur slightly more frequently than positive bubbles. Our replication of Greenwood et al. (2019), using earlier data and a sample from 1926 through 2024, closely matches their original findings. Booms do not predict crashes, but crashes are more frequent following booms. Comparing conditional and unconditional distributions shows us why. Booming markets are more likely to be volatile markets in the subsequent period, with a higher likelihood of both large gains and losses.

Booms and Busts in the US Stock Market Since 1792

In this section, we examine the frequency of booms, crashes, and bubbles over the whole course of US stock market history, from 1792 to the present. We use a monthly price index of 100 large-cap stocks, compiled by Finaeon, a data provider specializing in historical financial data. For simplicity, we ignore the substantial return provided by dividends and their re-investment; we are interested primarily in counting big price rises followed by declines.

We define a bubble as a boom followed by a crash that reverses all the market's prior gains. For various boom thresholds—ranging from a 50% gain over three years to a doubling—we count the number of episodes in our overlapping monthly sample and then count how many of those episodes were followed, within one, three, or five years, by either (a) a further boom of the same magnitude or (b) a full reversal that gave back all the earlier gain. We present these counts graphically rather than as tables of conditional probabilities because the raw counts make two facts immediately visible: (1) the rarity of extreme events and (2) the very small number of observations on which any inference about extreme outcomes must rest.

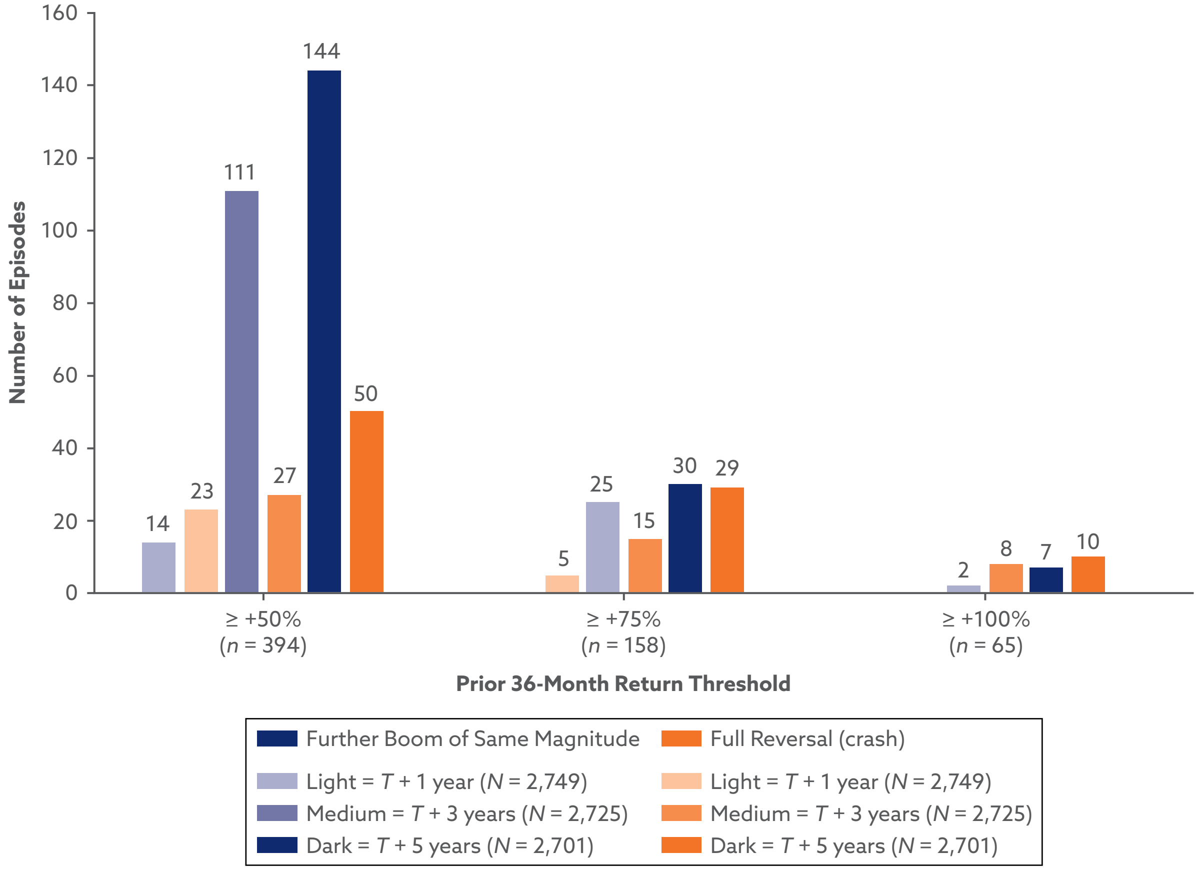
36-Month Booms

Exhibit 6.1 plots episode counts for booms measured over trailing 36-month windows. Orange bars in the figure count the number of bubbles according to the simple definition of a price drop that fully reverses a large prior gain. Consider the 50% threshold: Of the 394 overlapping episodes in which the market rose by at least 50% over three years (an annualized price increase of roughly 14.5%), 144 were followed by another gain of at least 50% within five years (dark blue bar), and only 50 were followed by a full reversal (dark orange bar).

At the three-year horizon, the contrast is even starker: 111 further booms (medium blue bar) versus 27 reversals (medium orange bar). Even within one year, the number of further booms (light blue bar), 14, is comparable to the number of crashes (light orange bar), 23. The visual pattern is clear: Blue bars dominate orange bars at most horizons. For big price runups—75% and 100% over three years—the number of bubbles is a tiny fraction of the sample size, *n*.

At higher thresholds, the same qualitative pattern holds, but the counts become very small. Among the 158 episodes of a 75% three-year gain, 30 were followed by a further 75% gain

Exhibit 6.1. Conditional Outcomes After 36-Month Booms: US Stock Market, 1792–2024



Source: Data from Finaeon, Inc.

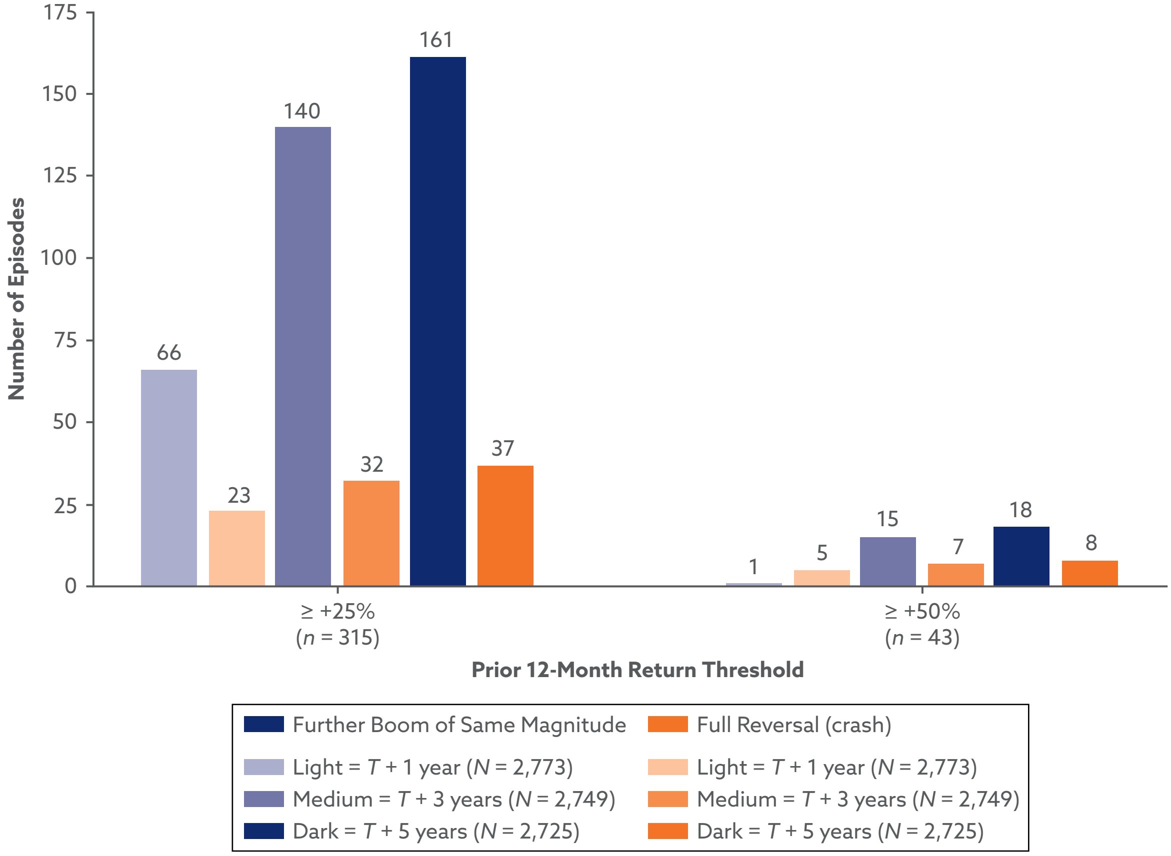
Note: The exhibit shows raw counts of episodes in which a subsequent gain (further boom) or loss (full reversal) of equal magnitude occurred, at forward horizons of one, three, and five years (overlapping monthly observations).

within five years and 29 preceded a full reversal—nearly a coin flip but one based on overlapping observations of a handful of historical events. At the 100% threshold, only 65 episodes occurred in 232 years. Within five years, 7 experienced a further doubling and 10 saw a full reversal. These low counts caution against computing precise odds ratios; the exhibit makes apparent the sparseness of the data.

12-Month Booms

Exhibit 6.2 repeats the exercise for booms measured over 12-month windows. Rapid price increases of this magnitude are rarer still. A gain of 25% or more in a single year occurred 315 times in the sample; 161 of those were followed by another 25% gain within five years, versus 37 full reversals. A gain of 50% or more in 12 months occurred only 43 times. Of those, 18 subsequently gained another 50% within five years, while 8 fully reversed. At higher thresholds, the data are

Exhibit 6.2. Counts of Booms and Crashes After a 12-Month Price Boom: The US Stock Market, 1792–2024



Source: Data from Finaeon, Inc.

Notes: The exhibit shows raw counts, with boom thresholds measured over the preceding 12 months (overlapping monthly observations). The ≥ +75% (*N* = 3) and ≤ +100% (*N* = 0) thresholds are omitted.

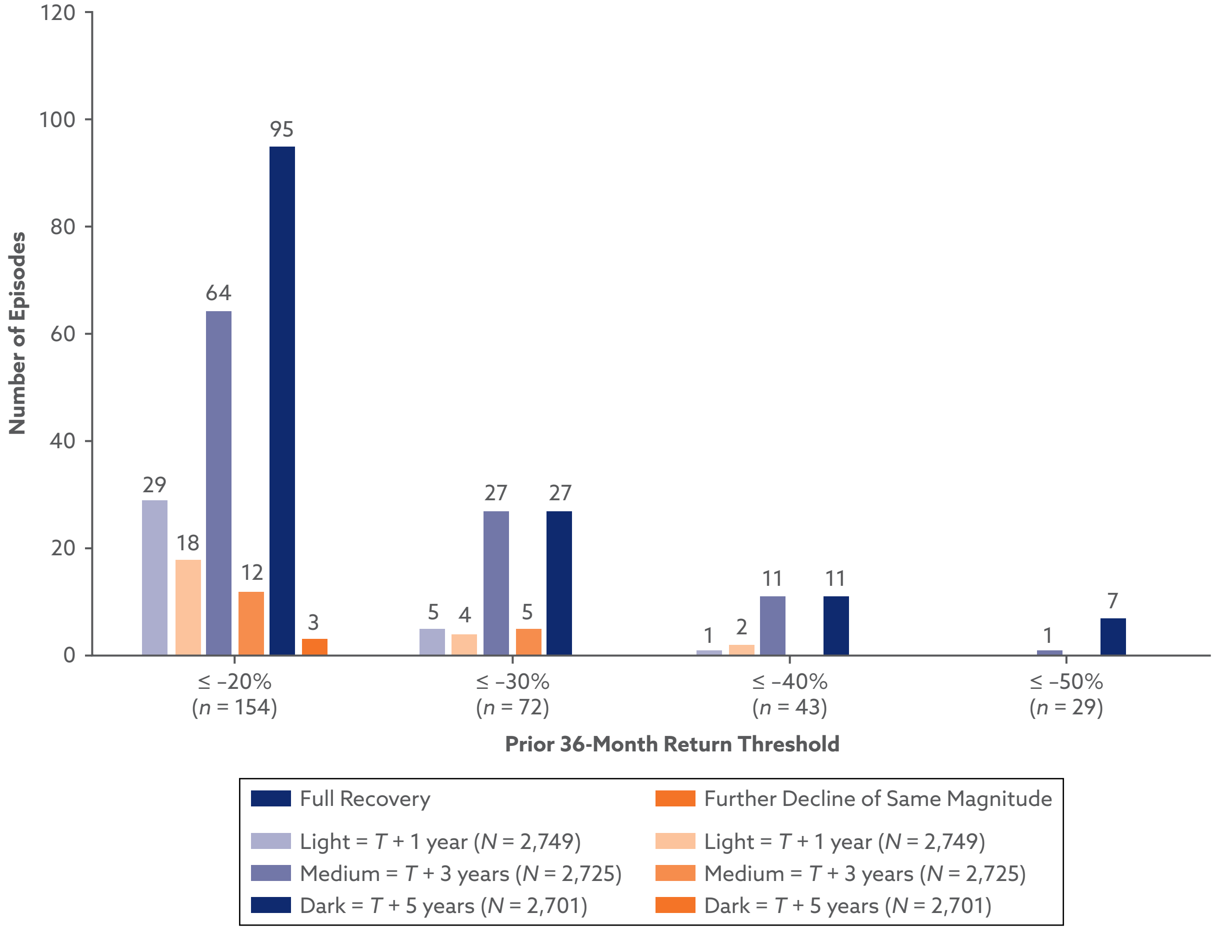
too sparse to report: A 75% 12-month gain occurred just three times, and a doubling in 12 months never occurred. We omit these thresholds from the exhibit. Taken together, Exhibits 6.1 and 6.2 show that booms are more often followed by further booms than by full reversals.

36-Month Crashes

Crashes tell a different story. **Exhibit 6.3** plots episode counts for 36-month declines. Here, the blue bars represent full recoveries—cases in which the market regained all of its prior losses—while the orange bars represent further declines of the same magnitude. The visual asymmetry as the horizon extends is striking: The blue recovery bars grow while the orange further-decline bars shrink toward zero.

After a decline of 20% or more over three years (154 episodes), a full recovery followed within five years 95 times, while only 3 such declines saw a further 20% loss. After a 30% decline

Exhibit 6.3. Counts of Booms and Crashes After a 36-Month Crash: US Stock Market, 1792–2024



Source: Data from Finaeon, Inc.

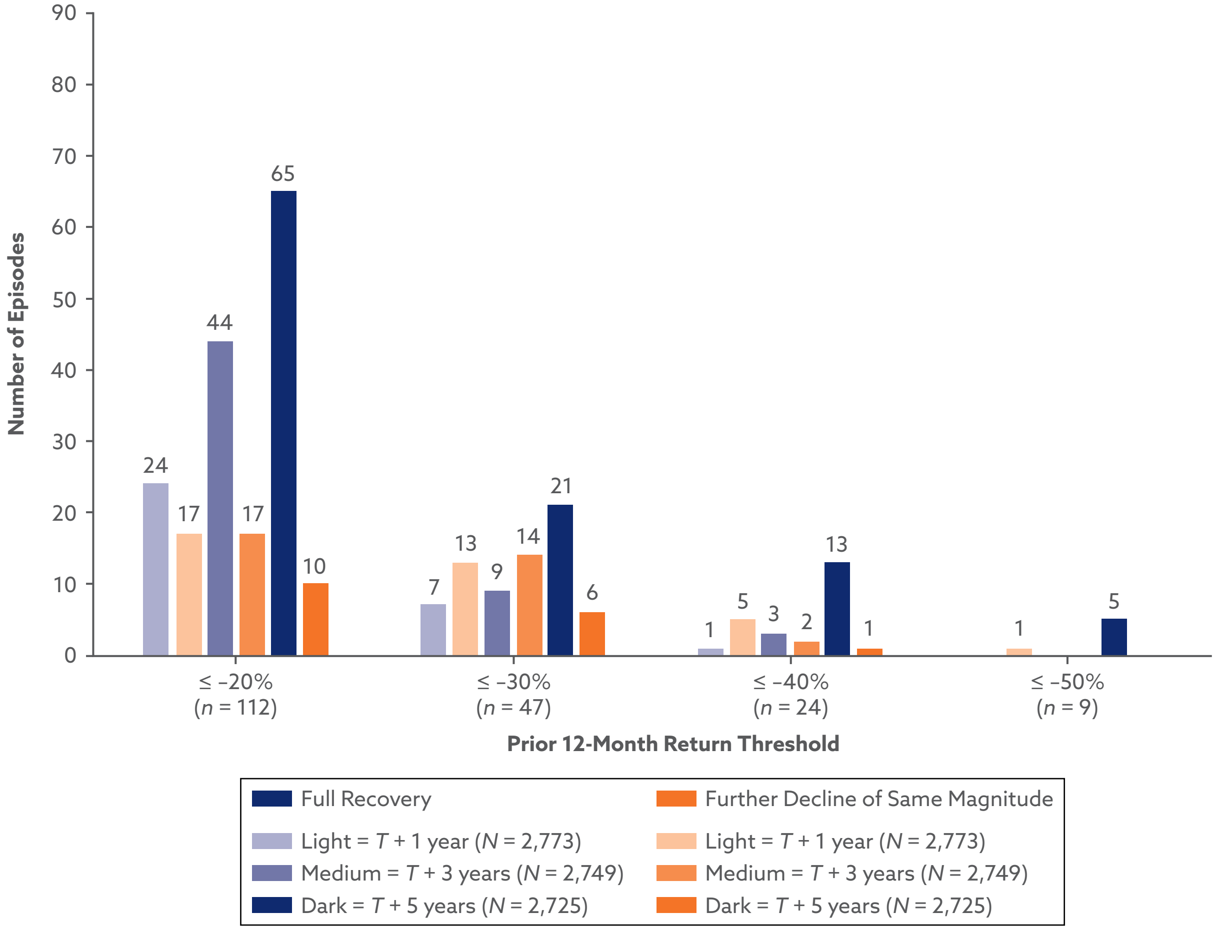
Note: The exhibit shows raw counts of episodes in which a subsequent recovery (reversing the prior decline) or further decline of equal magnitude occurred, at forward horizons of one, three, and five years (overlapping monthly observations).

(72 episodes), 27 recoveries occurred within five years and no further 30% declines occurred. At the 40% and 50% thresholds, the pattern is the same: Recoveries occur and further declines of equal magnitude do not. Not a single episode of a 50% three-year decline was followed by an additional 50% decline at any horizon.

12-Month Crashes

Exhibit 6.4 examines rapid, 12-month crashes—the events most frightening to investors. There were only nine episodes in which the market fell by 50% or more in a single year, less than one-third of 1% of the sample. None of these episodes was followed by a further 50% decline at any horizon, but five of the nine saw full recovery within five years.

Exhibit 6.4. Counts of Booms and Crashes After a 12-Month Crash: US Stock Market, 1792–2024



Source: Data from Finaeon, Inc.

Note: The exhibit shows raw counts, with crash thresholds measured over the preceding 12 months (overlapping monthly observations).

At the 30% threshold (47 episodes), the near-term picture is more sobering: Within one year, 13 episodes saw a further 30% decline versus only 7 recoveries. But within five years, the pattern reverses: 21 full recoveries versus 6 further declines. This finding suggests that rapid crashes carry genuine short-horizon risk of further loss but over longer periods, the dominant outcome is recovery.

Discussion

Several features of these exhibits warrant attention. First, booms are more likely to be followed by further booms than by full reversals. This is true at every threshold and nearly every horizon for the 36-month measurement window and at the 25% and 50% thresholds for the 12-month window. The popular intuition that a large runup in stock prices is a reliable signal of an impending crash is not supported by 232 years of US data.

Second, crashes are even more likely to be followed by recoveries than booms are to be followed by further booms. At the five-year horizon, recoveries dominate further declines at every crash threshold. An investor experiencing an extended decline in the market and considering whether to sell would find little historical support for doing so.

Third, the unconditional probability of a bubble—defined as a boom followed by a full reversal—is very small. At the 50% three-year threshold, there were 50 reversals out of roughly 2,700 overlapping observations, an unconditional frequency below 2%. At the 100% threshold, 10 reversals occurred out of 2,700 observations, roughly one-third of 1%. Reverse bubbles—crashes followed by full recoveries—are somewhat more common, consistent with the general tendency of markets to rise over long horizons.

Fourth, the counts at extreme thresholds are very small, and all are based on overlapping monthly observations. A single historical event such as October 1929 appears in every 36-month window that overlaps with it. The 7 further doublings and 10 reversals at the 100% threshold are not independent observations; they may reflect one or two episodes. We present counts rather than conditional probabilities precisely to make this limitation transparent. Any precise odds ratio computed from a handful of overlapping observations of extreme events should be treated as anecdote, not evidence.

The caveats discussed earlier apply similarly. We have only one historical time series to study, and the fact that it is the US market should make us cautious. Since 1792, the US capital market rose from obscurity to prominence, partly through survival in its early years as an emerging market, recovery after a massive civil war in the nineteenth century, success in two major wars in the twentieth century, and successful management of the global financial crisis of the twenty-first century. Inferences drawn about market recovery from disasters would likely differ if we were using data from pre-revolutionary Russia, Eastern European markets prior to World War II, or markets that survived large shocks but faded in importance with secular changes in the world economic order.

Documenting extreme events in financial history is important for forecasting the distribution of future investment returns. The few large-scale booms and crashes experienced by the US stock market over its history help assess the probability of future tail events but are likely to be conservative estimates of their potential magnitude, if only because they are a very small sample. Bubbles are even more rare than extreme booms and crashes because they require two rare events to occur in succession—although if one causes the other, that changes the probabilities. As we will show next, when we examine industry bubbles, both booms and busts could be correlated because of higher volatility and thus are more likely to occur concurrently.

Industry Bubbles

Thus far we have examined booms, crashes, and bubbles in the historical record of the US market as a whole. Investors are equally interested in the possibility that a single industry is in a bubble. In this section, we extend our boom, crash, and bubble analysis to industry portfolios that make up the US index. Historical data provide a rich cross section of industries extending back to 1871. We use the Cowles (1938) data to test the findings of Greenwood et al. (2019) out of sample, and we use Fama–French industry portfolio data to extend their analysis to the current time. We did not chain the two periods together, because definitions of industries slightly differ. The Cowles data include more industries with presumably finer gradations among them.

As we did earlier with the aggregate market index analysis, we define a boom as a large return over a given time period, either 12 months or 36 months. Because there are many industry indexes, we can construct a large sample of extreme booms and extreme crashes. We thus define a boom as a 100% price increase over a 12-month window, a crash as a 50% price decline, and a bubble as a boom followed by a crash in the subsequent 12 months. To avoid double-counting, if a month is tagged as a boom, the following 12 months cannot initiate a new boom episode. This methodology combines the approaches of Greenwood et al. (2019) and Goetzmann (2015) and provides a simple, transparent way to identify extreme events.

We conducted our analysis using the 49 Fama–French (FF49) total return industry portfolios spanning the period 1926 to 2024 and the 68 Cowles Commission monthly total return industry portfolios, which span the period 1871–1938.[2] The benefit of using these two samples is that by analyzing subsectors of the broad index, we can control for overall market movements, defining a boom as an increase over the market trend as opposed to an absolute return. Greenwood et al. (2019) showed that this control is potentially important because it avoids the results being driven by a handful of market-wide boom and crash periods. Finally, the industry-level analysis addresses an important question for investors: What happens when one industry suddenly booms? Is it likely that a boom in the subsector of the market continues, reverses, or reverts to average industry behavior?

Following Greenwood et al. (2019) with slight modification, a boom is identified when an industry earns both (1) a raw and market-adjusted return of 100% or more over the past two years and (2) a raw return of at least 50% over the past five years. **Exhibit 6.5** reports two event studies conditional on this boom definition.

The booms in both samples had an average growth of 300% over two years. Conditional on this huge gain, however, their average subsequent price path was flat. Panel A of Exhibit 6.5 shows the analysis for the Cowles industries, and Panel B shows the post-1926 period. The graphs look nearly identical. They support the basic finding by Greenwood et al. (2019) that on average, booms are not followed by crashes. The number of booms in each sample was about the same: 52 for the Cowles data, 48 for the Fama–French data.

Positive and Negative Bubbles

For another view, we examine both positive and negative bubble episodes. **Exhibit 6.6** plots average paths for booms (12-month doublings) and "negative booms" (12-month halvings) using raw and market-adjusted returns for the Cowles and Fama–French industries. We also use the less stringent boom definition, used in Goetzmann (2015), of an industry doubling or more in 12 months and a crash definition of a decline by half or more. Normalizing the return paths to 1 at the end of their booms or crashes allows us to better see the post-trend cumulative returns. Panels A and C of Exhibit 6.6 show the conditional average path of raw returns

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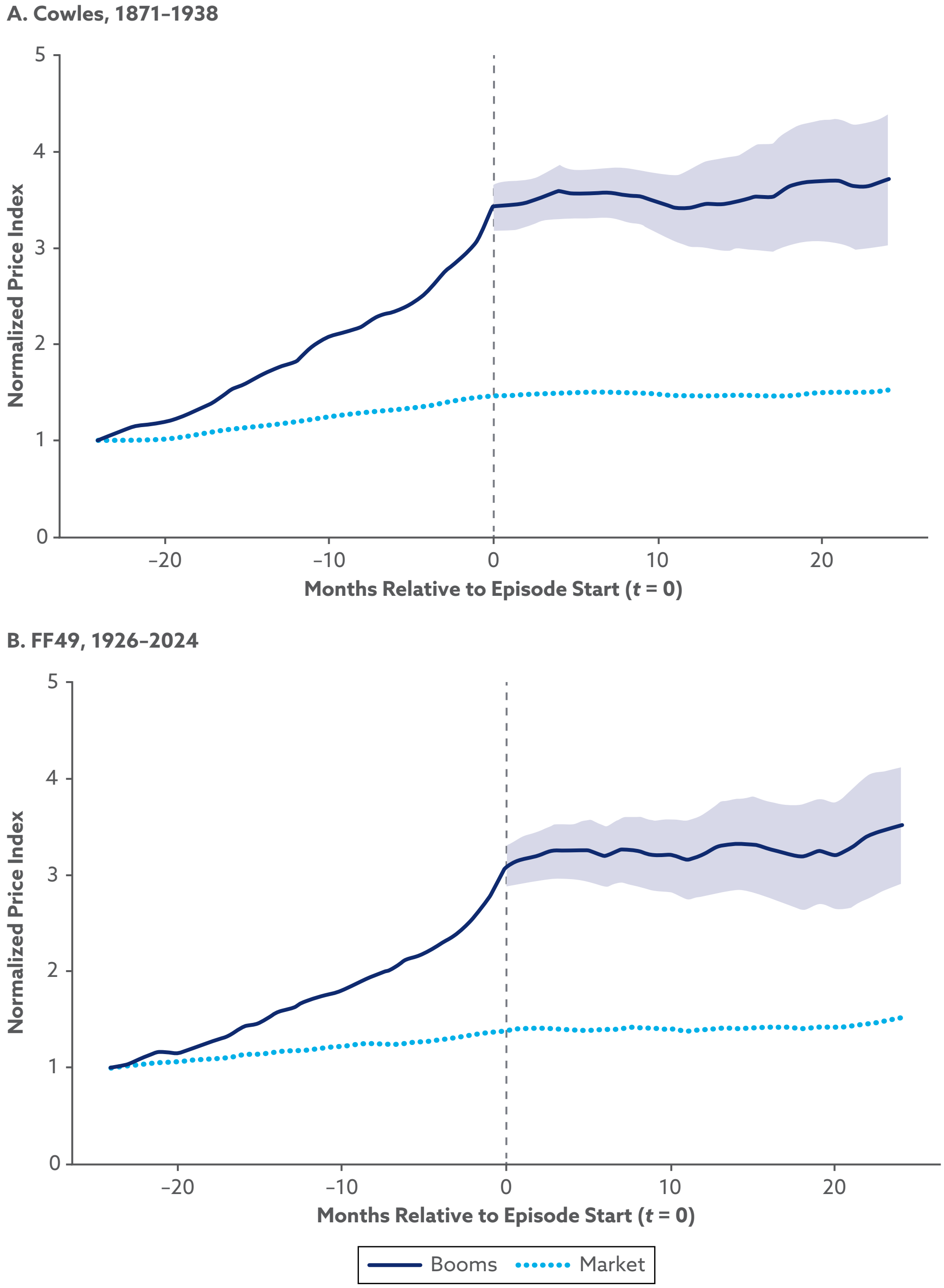
[2] Cowles Commission indices use monthly average prices rather than the typical end-of-month prices.

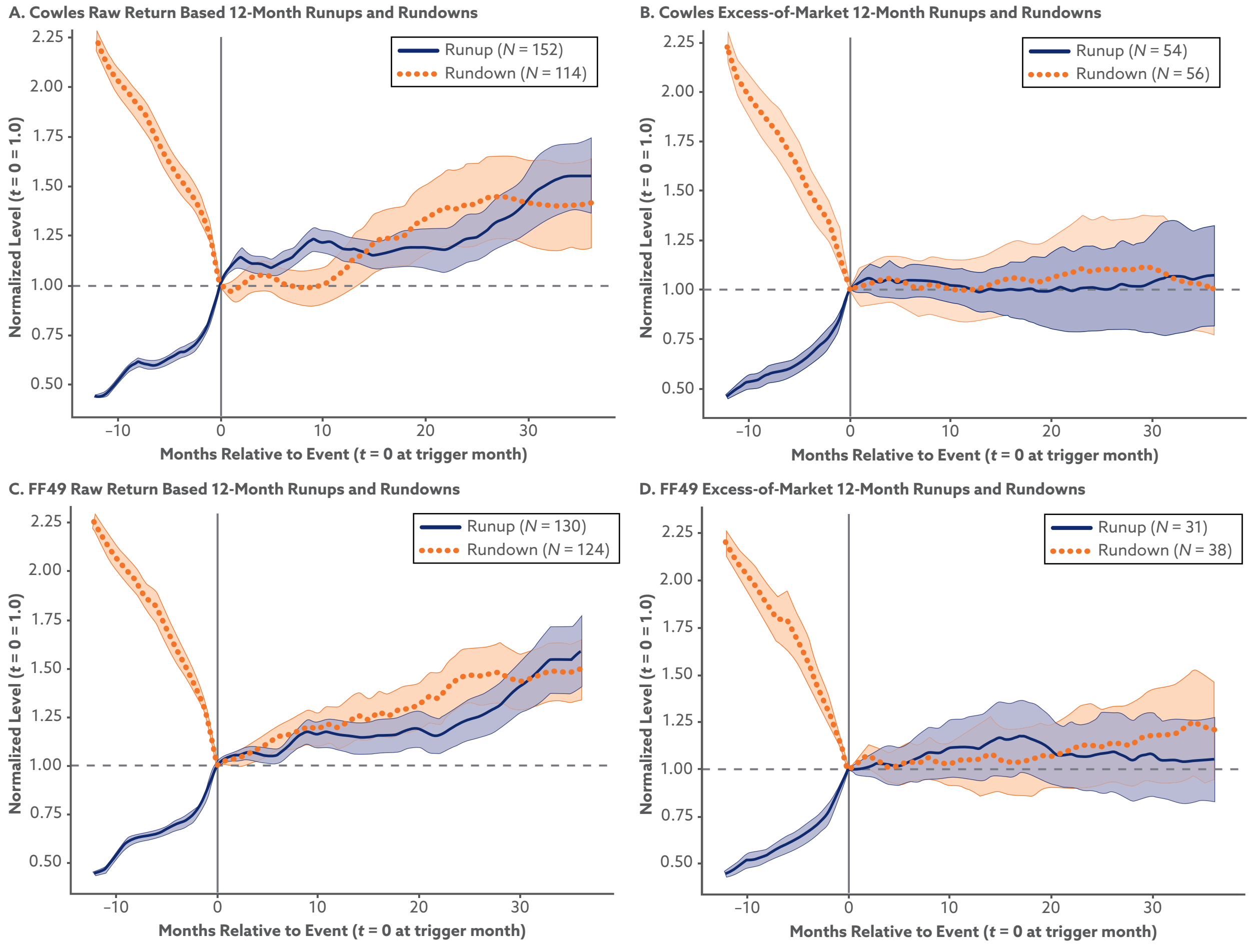
Exhibit 6.5. Post-Boom Outcomes for Cowles and Fama–French 49 Industries, Average Return for Each Boom Episode from *t* – 12 to *t* + 24



Sources: Cowles (1938); Kenneth R. French's Data Library (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_49_ind_port.html).

Note: The shaded band reports a 95% confidence interval for the cross-episode mean normalized price path.

Exhibit 6.6. Post-Boom and Post-Bust Outcomes Based on Raw and Excess-of-Market Returns, Cowles (1871–1938) and FF49 (1926–2024)



Sources: Cowles (1938); Kenneth R. French's Data Library (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_49_ind_port.html).

with confidence bands. Both paths drift up over the subsequent 36 months following their rise or decline, consistent with positive average equity returns for the US market over the sample periods. Confidence bands indicate that for most horizons, the null of post-event equality of boom paths and crash paths cannot be rejected, except for the first few months following the event date.

Panels B and D of Exhibit 6.6 define booms and crashes as, respectively, a doubling or halving in excess returns over the market. This definition significantly reduces the sample size; however, it removes the market trend from the conditional return paths. For both the early sample and the more recent sample, the average paths following booms and crashes are indistinguishable from the market. Notice a subtle difference between the raw and excess figures: In the Cowles sample (Panels A and B), the raw return paths exhibit a lot of time-series variation even though the sample size is larger than the excess return sample. This variation is likely caused by a handful of major market events that made a number of industries boom or crash at the same time. Defining booms and crashes in terms of excess returns over the market mitigates some of this sample selection bias.

A possible survivor bias is introduced by dropping industries when they disappear from the sample, resulting in averaging only across surviving industries in event time. To address this issue, we made the conservative assumption that capital in a discontinued industry was moved to the market portfolio at the end of its last monthly industry observation. The results are little changed by this assumption.

The terminal date of 1938 also censors industries from the event study. To test the effect of this, we analyzed a subset of booms and crashes prior to 1936, allowing us a full three-year potential history. The results do not differ significantly from those reported. To further investigate the source of the slightly positive paths in the excess return figures, we plotted the median of the cumulative excess return indices in each period. Doing so resulted in a terminal median value close to zero.

The results are strikingly similar across the two datasets: On average, prices rise into the boom and then on average level off, with mean paths roughly in line with the market thereafter. In the Cowles data, prices typically go flat after a sharp increase. In the more modern Fama–French data, the price evolution is closer to a smooth transition from the initial runup.

Conditional Distributions

In the analysis so far, we have studied boom-conditional and crash-conditional return distributions. In this section, we explicitly test whether crashes are more likely if there is a preceding boom. We do this by comparing conditional distributions with unconditional distributions—that is, with the entire set of historical industry return paths, not only those that condition on a previous boom or crash. We test the null hypothesis that post-boom return paths are not unusual when compared with the large, unconditional sample.

Greenwood et al. (2019) noted that even though booms do not on average predict crashes, they are associated with a higher subsequent probability of a crash. This apparent contradiction results from the fact that by picking industries that had dramatic runups and declines, we are conditioning on high volatility. In this section, we investigate the shape of the conditional distributions compared to the unconditional distribution of industry returns and test for conditional volatility and skewness using the unconditional distribution as a benchmark.

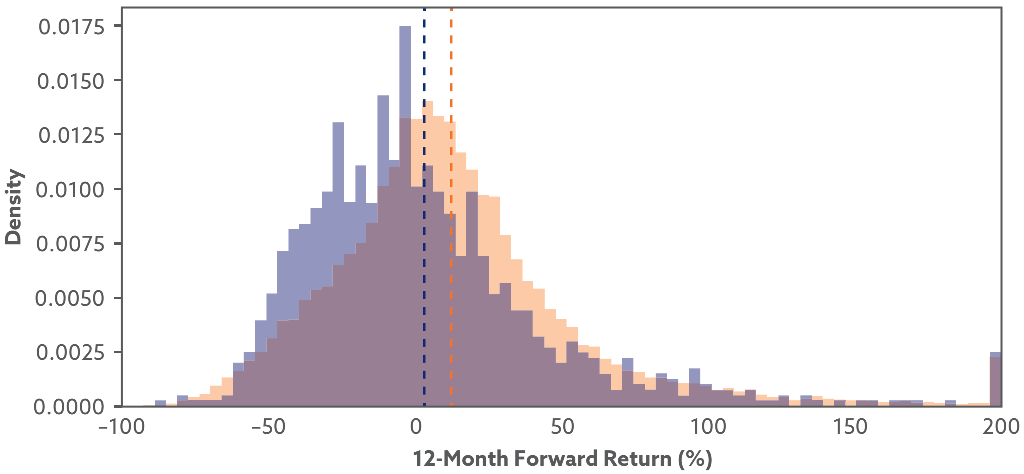
Exhibit 6.7 plots the distribution of industry returns conditional on a prior 12-month boom in blue and the entire distribution of unconditional 12-month returns in orange. As previously noted, the sample of unconditional returns includes multiple overlapping periods; conditional 12-month returns do not overlap.

Panels A and B of Exhibit 6.7 use the Cowles sample, which contains 68 industries, and Panels C and D use the Fama–French sample of 49 industries. Panels A and C show results for raw returns; Panels B and D show results for excess returns. The dashed vertical lines mark the means of each distribution.

Notice that the distribution of conditional raw returns for the 1926–2024 period (Panel C) is wider and shifted to the left compared with the unconditional distribution. The difference in means is large and significant, and the difference in modes in Panel C is also dramatic.

Exhibit 6.7. Post-Boom Outcomes Based on Raw and Excess-of-Market Returns, Clipped to (–100%, +200%): Cowles (1871–1938) and Fama–French 49 (1926–2024)

A. Cowles Raw Returns



B. Cowles Excess-of-Market Returns

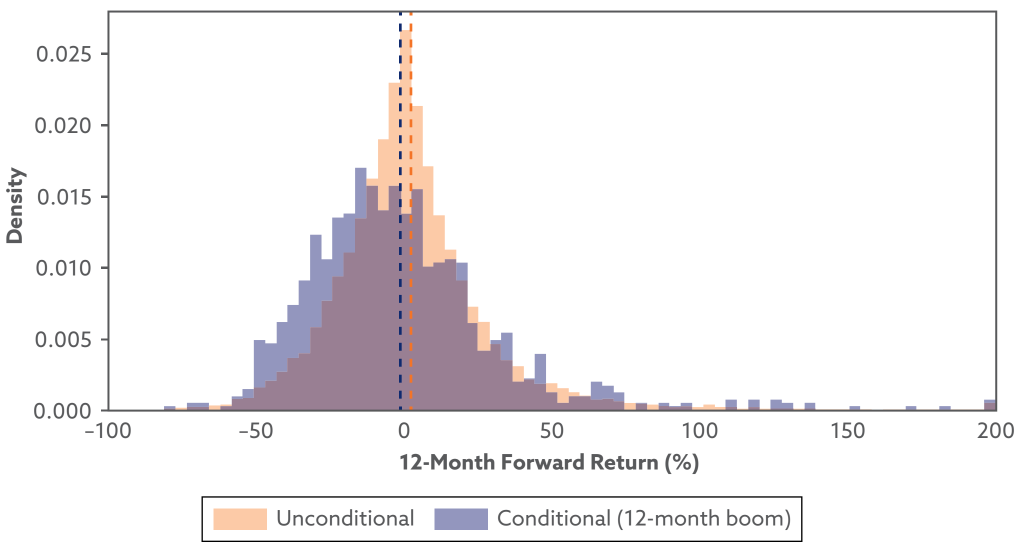
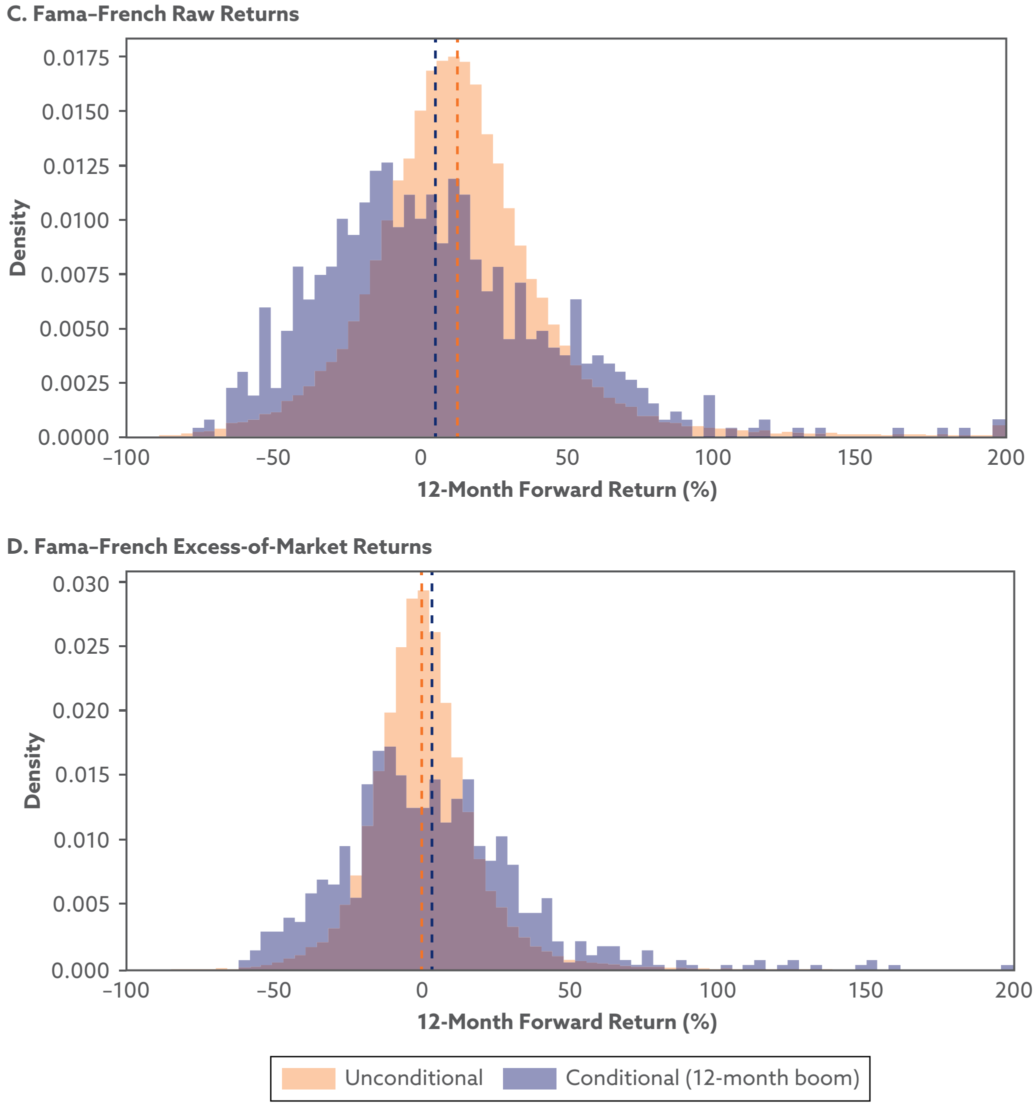


Exhibit 6.7. Post-Boom Outcomes Based on Raw and Excess-of-Market Returns, Clipped to (–100%, +200%): Cowles (1871–1938) and Fama–French 49 (1926–2024) (*continued*)



Sources: Cowles (1938); Kenneth R. French's Data Library (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_49_ind_port.html).

Panel C suggests that at the industry level, 12-month booms are a strong predictor of low excess returns in the following 12 months. The distribution of subsequent excess returns shown in Panel D, however, suggests this is not necessarily the case. The mean of the subsequent excess returns is slightly higher than the unconditional mean. The wide spread remains:

The probability of a crash after an industry boom is much higher than the unconditional probability, but so is the probability of another boom.

Conditioning on a dramatic boom selects for either high-volatility industries or industries that are in a transitory but persistent phase of high volatility (see **Exhibit 6.8**).

Exhibit 6.8. Post-Bust Outcomes Based on Raw and Excess-of-Market Returns, Clipped to (–100%, +200%): Cowles (1871–1938) and Fama–French 49 Industries (1926–2024)

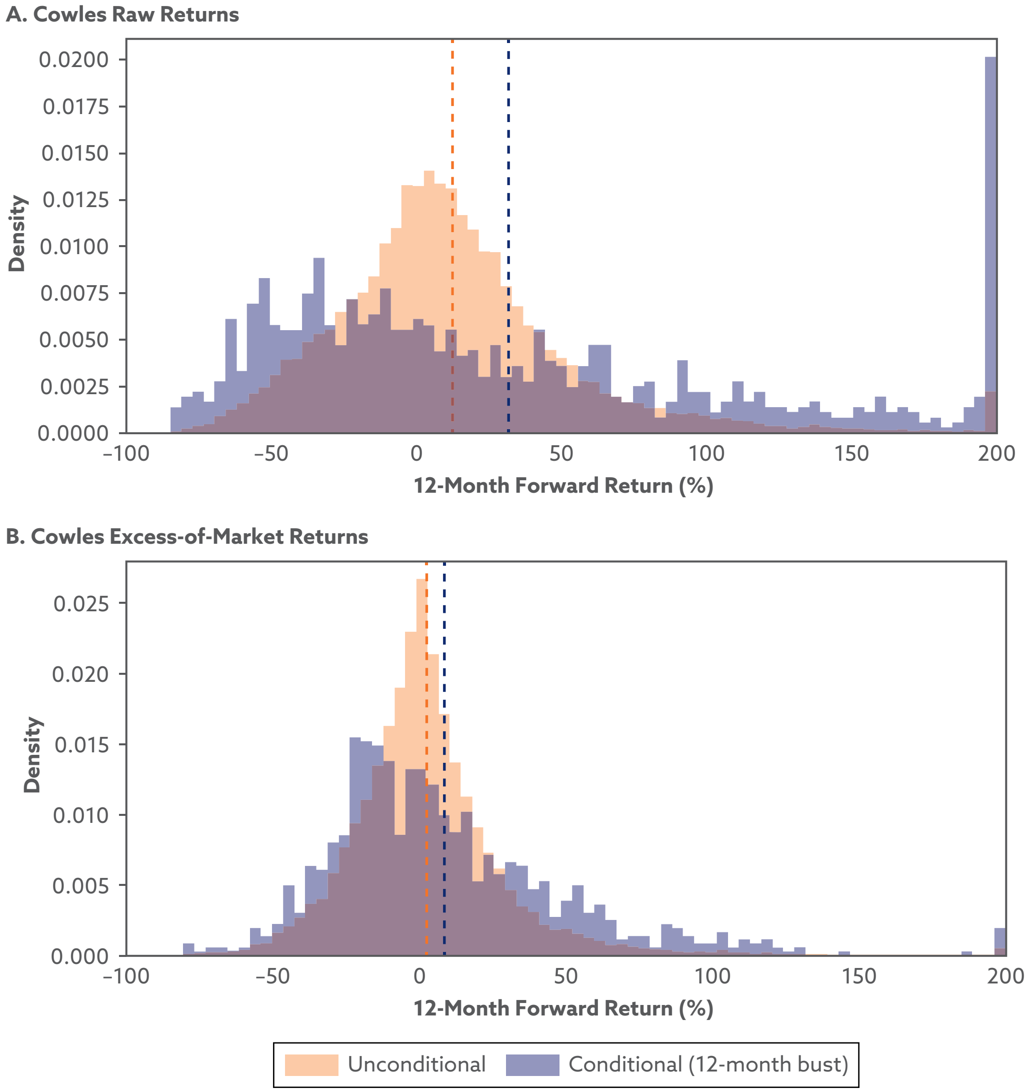
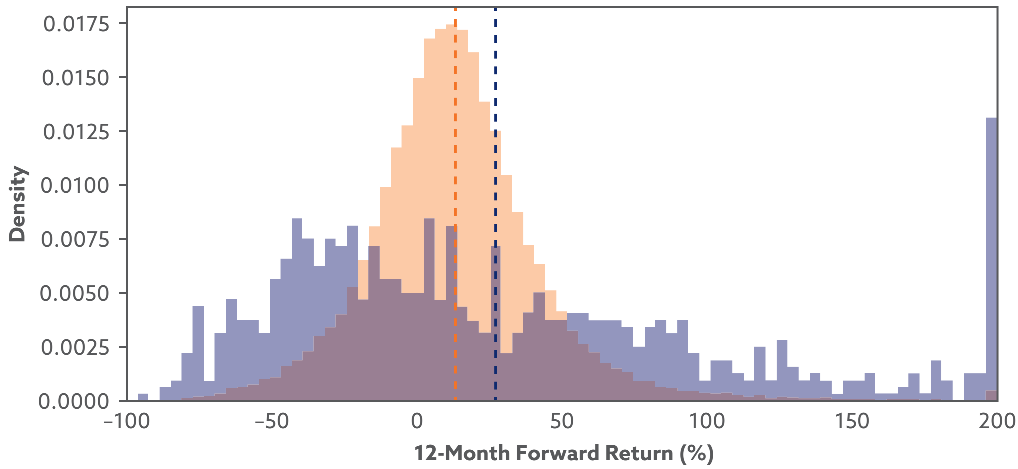
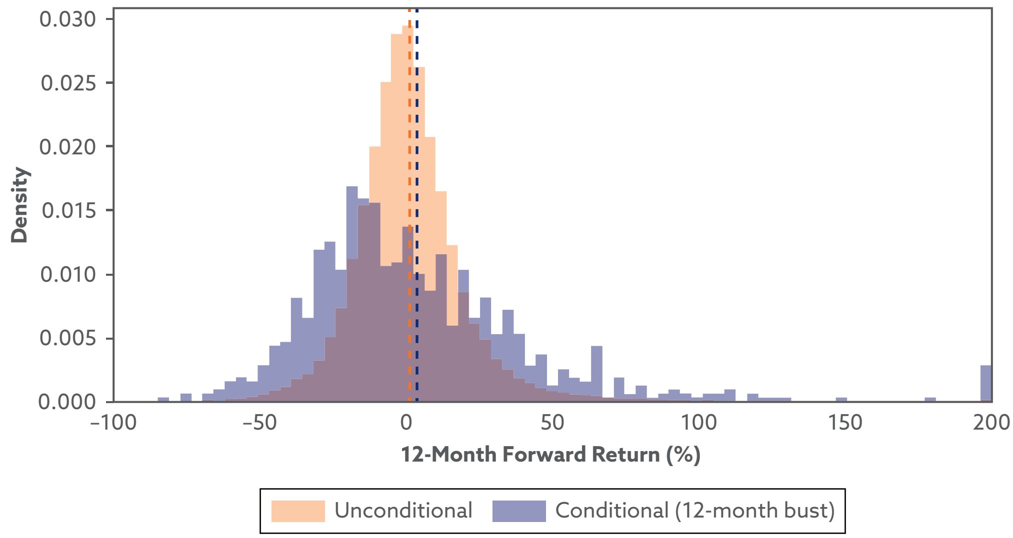


Exhibit 6.8. Post-Bust Outcomes Based on Raw and Excess-of-Market Returns, Clipped to (–100%, +200%): Cowles (1871–1938) and Fama–French 49 Industries (1926–2024) (*continued*)

C. Fama–French Raw Returns



D. Fama–French Excess-of-Market Returns



Sources: Cowles (1938); Kenneth R. French's Data Library (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_49_ind_port.html).

Conclusion

This chapter uses an empirical approach to define stock market booms, crashes, and bubbles. Large-scale booms and crashes have been relatively rare in US market history. Bubbles, defined as a boom followed by a crash, are by definition even rarer—one rare event must occur right after another rare event. The probability of this happening is heightened in periods of higher volatility, but so is the opposite sequence—a negative bubble in which a crash is followed by a boom. Most important for investors is that the bubbles and crashes the US market experienced over more than two centuries of data have not been fatal to either the existence of the market or the fortunes of long-term investors.

There are many potential explanations for this continuity. Our analysis of the aggregate US index studies one market that grew to global dominance by the end of the twentieth century. Indeed, it is the first market for which high-quality, long-term equity return data were collected and studied by financial economists (e.g., Cowles 1938). Scholars studying the cross-sectional history of global equity markets (e.g., Jorion and Goetzmann 1999; Dimson, Marsh, and Staunton 2002; Siegel 1994) have had to deal with breaks caused by war, political disruption, and rejection of the market economy. Ultimately, analysis of international equity data showed that the United States was an unusually good performer but that the equity premium is widespread and robust, even taking into account the major shocks and disruptions experienced over the past two centuries.

The problem with analyzing a single market is the rarity of extreme events, which makes it difficult to test predictive models. In practical terms, the conclusion we can draw about booms and crashes based on a single, albeit multicentury return series is that they are infrequent and hard to predict with prior price trends.

The industry-level analysis in this chapter provides a richer test bed for boom and crash prediction and the study of bubbles. The rise and fall of industrial sectors are a fundamental prediction of Schumpeter (1942). For much of its history, the US stock market has channeled investment into innovative technologies that rise, succeed, and decline over time, replaced by successive waves of competition. Pástor and Veronesi (2009) model this Schumpeterian process and find that technologies characterized by high uncertainty and fast adoption are prone to bubbles.

The industry-level analysis shows that booming (and crashing) industries are associated with subsequent high volatility, making both crashes and repeat booms more likely. Once one controls for market trends, however, post-boom performance does not differ significantly from unconditional returns. For crashing industries, rebounds are slightly more likely than further declines. This information is potentially useful for investors considering tactical industry allocations in real time.

Key Takeaways

- True bubbles are rare. A bubble, defined as a large boom fully reversed by a crash, requires two rare events in sequence. In more than two centuries of US data, such full boom-and-bust episodes represent a tiny fraction of all return observations.
- Even very large multiyear or one-year runups in the US equity market have historically been more likely to be followed by further gains than by full reversals.

- Crashes (whether or not preceded by big booms) are rare, and deep crashes are usually followed by recovery rather than further collapse.
- At the industry level, dramatic runups are followed by a much wider distribution of subsequent returns: Both crashes and repeat booms become more likely. Thus, industry booms signal higher volatility (up or down), not necessarily an impending crash.
- The US market is exceptional in that it has survived wars, crises, and regime changes. The fact of its survival means that crash and recovery statistics from this single successful market could understate the range of outcomes in less fortunate markets. It is difficult to infer precise probabilities from only one run of history in the most successful market in the world.

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CHAPTER 7. US TREASURY YIELDS AND RETURNS

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US Treasury Yields: What They Are and Why We Care

US Treasury bond yields are the foundation of finance—the “riskless” (no risk of default) yields across all time horizons from one week to 30 years. The Treasury market makes up the largest category of bonds in the United States: 61% of the $48.9 trillion fixed-income market in 2025. All other such markets (corporate bonds, municipal bonds, asset-backed securities, home mortgage rates) are priced *relative* to Treasury yields.

The yield-to-maturity for a bond is the discount rate or internal rate of return that balances the price we pay today (the present value) against future coupon cash flows and the return of principal at maturity. Yields allow us to compare bonds with different prices and future coupons. In a real sense, the yield-to-maturity measures the “price” of a bond, with a higher yield representing a lower price today—a lower dollar price relative to higher future coupons.

When the Treasury issues new bonds, it sets the coupon so that the price of the bond is at or close to $100; the coupon is set higher or lower so that investors are just willing to pay $100 in return for those future coupons. A bond with a price of $100 is called a *par bond* because it is trading at par—$100 per $100 of principal to be returned at maturity. In a period of high market yields (as in the early 1980s in the United States), the Treasury will need to promise a high coupon, and in a period of low yields (as in the 2010s), the coupons will be low. Par bonds and the yield or coupon on such par bonds are the fundamental measure of the Treasury market, the reference yield from which all other securities are priced.

Par bonds and thus par bond yields often are not available directly from the market for all maturities on all dates. As bonds age and market yields go up or down, the price of a bond (originally at or near $100) will go down (as yields go up) or up (as yields go down). For any particular day, a variety of bonds issued in the past will have prices quite different from $100. In other words, although investors always want to know the par bond yield, there are almost never exact par bonds for the maturities we want.

The goal of our Treasury yield curve project is to estimate synthetic par bond yields from the prices and yields of traded bonds for each month—to estimate a full yield or forward curve from which we can then calculate par bond yields for any desired maturity. The Center for Research in Security Prices (CRSP), originally founded at the University of Chicago and now part of Morningstar, has collected prices on all outstanding Treasury bonds for each month from December 1925 to the present. We use these traded bond prices to estimate a full yield or forward curve, as outlined in the next section. From the estimated forward curve, we can calculate par bond yields.

Price, Yield, and Par Bonds

Investors buy and sell bonds based on their price; that is a truism. But we cannot use raw prices to compare one bond with another because bonds generally involve different-size cash flows that occur at different times. For example, is it better to pay \$101.93 today for a 7% bond (\$7 in the next year plus \$100 at the end of the year) or a lower upfront price of \$100 for a 5% bond with lower future cash flows? We need to evaluate the two bonds using a common unit of measurement, determining whether the higher upfront price of the 7% bond is justified by the larger future cash flows.

It turns out that these two bonds provide (for all intents and purposes) the same value, but we cannot answer the question without the *yield-to-maturity* (or yield). This calculation provides the common unit of measurement for balancing upfront price against the size and timing of future cash flows. We can think of the yield as the "promised or expected earnings per dollar invested"—in other words, what you will earn if you hold the investment until maturity.

For bonds that pay coupons twice a year (such as Treasury bonds and notes),[1] the formula is

$$\text{Price} = \frac{c/2}{1+y/2} + \frac{c/2}{(1+y/2)^2} + \cdots + \frac{c/2}{(1+y/2)^{2n}} + \frac{100}{(1+y/2)^{2n}}.$$

In our example, both investments (wherein you pay \$101.93 for the 7% bond or \$100 for the 5% bond) yield 5%. They are in an important sense the same "price" because they yield the same return. Note that because the yield, y, appears in the denominator, *as yields go up, prices go down*.

For displaying our estimated yield curves, we want to graph the yield on the hypothetical or synthetic bond versus its maturity. The most convenient method of ascertaining that yield is to calculate the yield on a coupon bond that trades at \$100, where the coupon is adjusted until it and the yield are the same. These calculations, called *par bond yields*, are the basic building block we use in most of the exhibits in this chapter.

[1] Treasuries pay coupons semiannually, and the market convention is to calculate semiannually compounded yields for bonds with one or more coupon periods. For bills and bonds with six months or less until maturity, markets use the simple yield annualized at a rate of actual days divided by 360. In this study, for consistency across the curve, we calculate all our yields on a semiannually compounded basis.

Estimation of Bond Yields and Returns

Our goals for US Treasury markets are straightforward: Estimate returns for selected one-bond "portfolios" with maturities of, say, three months, 2 years, 10 years, and 20 years.[2] The challenges are manifold. We wish to buy a bond today (say, the bond with two years to maturity) and sell it in one month (when it has one year and 11 months to maturity). This procedure requires an estimated forward-rate or yield curve to create synthetic exact-maturity bonds with at-market coupons and then to revalue those bonds one month later. Estimating such a forward curve for each month over the past 100 years involves the challenge of choosing a flexible forward curve methodology that works for both the many bonds of the modern era (more than 400 now) and the small number of bonds in the 1920s. We choose a piecewise twisted forward curve, discussed in more detail in Chapter 8.

For our forward curve methodology, we build on and extend the methodology used in Coleman, Fisher, and Ibbotson (1989, 1992, 1993). In those studies, we assumed forward rates were constant (flat forwards) over preset maturity periods. In this chapter, we allow forward rates to twist and we more flexibly determine the maturity or knot points.

Government bonds today are simple: Bills pay $100 upon maturity (and are issued with maturities of one year or less), and notes and bonds pay coupons semiannually plus $100 on the stated maturity date. Historically, the bond market has had many quirks, which we now discuss.

Tax Regimes and Tax Status Changes from the 1920s to the 1940s

In the first part of the twentieth century the Treasury issued bonds with varying tax treatment: partially tax-exempt bonds in the 1920s, fully tax-exempt bonds in the 1930s, and taxable bonds starting in the 1940s. Out of necessity, we estimate three different curves over different periods: partially exempt from 1926 to 1931, fully exempt from 1932 to mid-1941, and taxable from mid-1941 to present. In Chapter 8, we detail how we stitch together the disparate regimes to provide the most consistent set of returns and curves available.

Callable Bonds and Noncallable Yields Through the Early 1990s

Through 1984 the Treasury issued mostly callable long-dated bonds—callable at the option of the Treasury, at $100. For example, the 11.75% coupon bonds maturing on 15 November 2014 were callable starting in November 2009; a five-year call period was common, but the period could be longer or shorter. Callable bonds were outstanding through the early 2000s. Traditionally, an ad hoc "yield-to-worst-call" rule was used for calculating an ad hoc (but incorrect) yield for the bond. This rule treats the next call date as if it were the maturity date if the bond is trading at a premium today. If the bond is trading at a discount, the rule treats the final maturity date as the maturity date.

[2] Our detailed exhibits include a wider range of maturities: one, three, and six months; 1, 2, 3, 5, 7, 10, and 20 years; and the longest bond.

Instead of "yield-to-worst," we estimate the value of a European call to the first (or next) call date, a far better approximation for the callable nature of such bonds. This approximation allows us to strip out the value of the call feature and estimate the pure discount forward curve. Thus, our forward and par yield curves are estimates of discount rates for fixed cash flows after removing the call option value.

Flower Bonds Through the 1970s

Most long-dated bonds issued before 1973 could be redeemed at par for payment of estate taxes, giving them the name "flower bonds." Starting in 1973, the Treasury issued longer-dated non-flower bonds. Prior to mid-1973, we estimate a curve including flower bonds, giving a "flower-bond long end" for this period. In mid-1973, we switch to non-flower bonds and exclude flower bonds. In Chapter 8, we detail how we stitch together the curves to produce the most consistent curve possible.

Returns with Our Estimated Forward Curves

We construct par bond yield curves, which we display in the next section. We can also, of course, calculate prices of bonds. This approach enables us to calculate prices and returns for the following:

- This month, buy a new par bond for $100.
- Next month, sell the bond, which is one month shorter.

The trick here is that by using our estimated forward curves to calculate our bonds, we can start with a bond this month that is exactly $100 with, say, a maturity of exactly one year. Next month, the bond's maturity will be only 11 months, but we can use next month's curve to estimate what the price of that old bond would be. We can decompose the *total* return into an *income return* component equal to the promised yield (par bond yield) and the *return in excess of promised yield*. The following sidebar gives more detail.

Calculating Returns

We wish to calculate returns for a variety of bonds (a three-month bond, a one-year bond, and so on), and we wish to decompose the *total return* into an *income return* and a *return in excess of yield*. Because no coupons are paid in the one-month holding period for which we calculate the month-to-month returns, the total return is simply the change in the price of the bond: For a two-year bond from January to February, we need to buy a two-year par bond (trading at $100) at the end of January and sell the same bond at the end of February. The result is now a one-year and 11-month bond. We price the original bond (calculate the coupon or par bond yield, Y^{pb}_{Jan}) from our January curve, and then we price the one-year and 11-month bond (calculate the new price, P_{Feb}, for the January bond we started with) from our February curve.

The Coleman Fisher Ibbotson (henceforth CFI) total return (TR) is simple:

$$\text{TR}_{CFI} = \frac{P_{Feb}}{100} - 1.$$

The income return (Inc) is the par bond yield from January, Y_{Jan}^{pb}, converted to a monthly return:

$$\text{Inc}_{CFI} = (1 + Y_{Jan}^{pb}/200)^{AD/182.625} - 1,$$

where *AD* is the actual number of days from end-January to end-February. The return in excess of yield, RxY_{CFI}, is the total return minus the income return—the "minus" meaning "geometric subtraction" of dividing 1 plus total return by 1 plus income return and then subtracting 1:

$$RxY_{CFI} = \frac{1 + \text{TR}}{1 + \text{Inc}} - 1.$$

US Treasury Bond Yields and Returns, 1926–2025

In addition to presenting our analysis for the full century-long period of 1926–2025, we divide it into two roughly equal subperiods (1925–1980 and 1981–2025) because the subperiods differed radically in the economic environment for bonds and bills.

The Full Period, 1926–2025

From our estimated forward curves, we derive a variety of yields and rates:

- CFI US Treasury bill, note, and bond yields: par bond yields, the yield on a bond that is trading at $100 (with yield = coupon)
- CFI US Treasury bill, note, and bond total returns: the return from buying a bill or bond at Month 0 and then selling the same bond one month later
- CFI income return: the yield-to-maturity or promised yield of the par bond
- CFI return in excess of yield: the total return minus the yield-to-maturity (promised yield) of the bond when purchased (with "minus" meaning the geometric subtraction as detailed previously)

Exhibit 7.1 shows the annualized average of monthly values (and, where appropriate, the annualized standard deviation) over the full century from 1926 to 2025 for these series across the yield curve. The entry for "Long" is the yield for the longest bond for each month, which varied from a low of 14.5 years (in 1980) to 40 years (in 1955).

Exhibit 7.1. Par Bond Yields and Returns, 1926–2025

	1 M	3 M	6 M	1 Yr	2 Yr	3 Yr	5 Yr	7 Yr	10 Yr	20 Yr	Long
Par bond yield (average)	3.25	3.41	3.54	3.72	3.95	4.12	4.35	4.51	4.64	4.86	4.86
Compound Annual Return											
Total return	3.26	3.52	3.76	4.03	4.37	4.56	4.84	4.89	4.97	4.88	4.78
Income return	3.26	3.41	3.54	3.73	3.96	4.14	4.37	4.54	4.67	4.90	4.90
Return in excess of yield	0.00	0.10	0.21	0.29	0.39	0.41	0.45	0.34	0.29	−0.01	−0.12
Arithmetic Mean Annual Return											
Total return	3.30	3.57	3.81	4.09	4.44	4.66	5.00	5.10	5.27	5.40	5.51
Annualized Standard Deviation											
Total return	0.87	1.00	1.14	1.53	2.41	3.24	4.53	5.52	6.68	9.12	10.32
Income return	0.87	0.93	0.93	0.92	0.90	0.88	0.85	0.84	0.82	0.79	0.78
Return in excess of yield	0.00	0.26	0.60	1.19	2.19	3.07	4.38	5.39	6.56	9.00	10.21

Source: Author calculations from CFI forward rates database. Forward rates estimated from CRSP Treasury bond prices using CFI methodology, as discussed in Chapter 8.

Note that for the *average* total return, most of the return is generated by the *yield* return, with the return in excess of yield being not far from zero (because yields at the end of the century were similar to those at the beginning). For volatility, the situation is reversed, with almost all the volatility resulting from variation in the return in excess of yield. One can think of this in terms of Aesop's parable of the hare and the tortoise: Returns in excess of yield may sprint ahead in any given month, but the tortoise of steady accumulation of income returns pays off in the long run.

It is important to understand the relation between changes in yields and returns. As yields go up, prices go down. One can understand this dynamic either intuitively—by recognizing (as pointed out earlier) that a high yield corresponds to a low price, so a rising yield means a falling price—or by the present value (PV) formula discussed earlier. It is also crucial to understand that when yields go up and prices down, prices for longer bonds go down by more: Longer bonds are more sensitive to yields than shorter bonds. This interest rate elasticity (technically a semi-elasticity, also called the *modified duration*) provides the numerical link between changes in a bond's yield and price. We will discuss this relationship in more detail later. The important fact is that

$$\%\Delta \text{ in Price} \approx \text{ModDur} \times (-\Delta\text{Yield}). \tag{7.1}$$

With a modified duration of 4.9 (roughly the value for a five-year zero-coupon bond at a 5% yield, 4.9 ≈ 5/1.025), a change in yield from 5% to 5.10% (an increase of 0.10 percentage points) would mean the bond price falls by roughly 0.49%:

$$-0.49\% = 4.9 \times (-0.10). \tag{7.2}$$

The modified duration for a one-year bond is slightly less than 1.0, so the same rise in yield would lead to a roughly 0.1% price decrease for a one-year bond.

We can (conceptually) decompose the total return for a bond that we buy in January and sell in February into two parts: the income or accrual from holding the bond for a month (the *income return* discussed earlier) and the price change resulting from changing markets or yields (the *return in excess of yield*). The income return is approximately the yield divided by 12 (the exact formula was given previously), and the excess return is approximately −ModDur × ΔYield,[3] which gives

$$\text{Total return} \approx \frac{\text{Yield}}{12} + \text{ModDur} \times (-\Delta\text{Yield}). \tag{7.3}$$

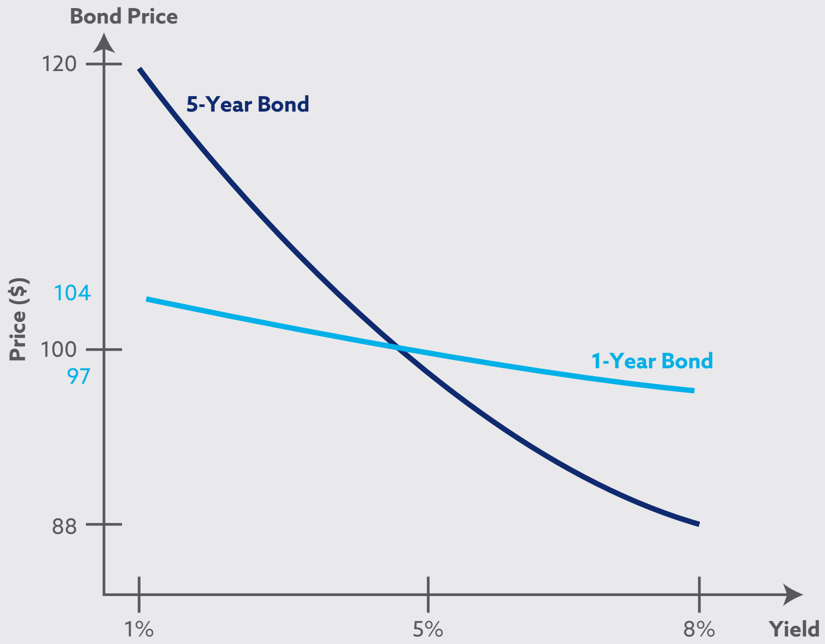
Because longer bonds have a higher modified duration and par yields generally move together (which we will show later), longer-maturity bonds will have more volatile returns than shorter-maturity bonds. Exhibit 7.1 showed that the volatility of returns (the standard deviation of total returns) increases with maturity.

Interest Rate Sensitivity and Modified Duration

Bond prices go down when yields go up, and the prices of longer bonds go down more than those of shorter bonds. **Exhibit 7.2** shows what happens for one-year and five-year bonds when yields change; in this case, both bonds have a 5% coupon. The five-year bond changes more with yields than does the one-year bond, and the slope of the curve measures the degree of sensitivity.

[3] This expression is only an approximation for a number of reasons. First, the percentage change in price is only approximately Modified duration × Change in par yield. Second, the change from one month to the next involves not only the change in yields but also rolling down the curve. A two-year bond this month becomes a shorter one-year and 11-month bond next month. The modified duration we need is some average of the modified duration for a two-year bond and a shorter one-year and 11-month bond, and we must account for "rolling down the curve"—that is, experiencing the return due to the change in yield going from a two-year to one-year and 11-month par yield.

Exhibit 7.2. Price vs. Yield for One- and Five-Year Bonds



Source: Author calculations.

As Exhibit 7.2 shows, longer-maturity bonds are more interest rate sensitive than shorter-maturity ones, but we need a numerical measure for the slope. The interest rate semi-elasticity is the standard measure: the percentage change in price for a unit change in yield, which is negative because the slope is negative (prices go down when yields go up). The elasticity is the slope (in percentage terms) in Exhibit 7.2. The semi-elasticity, also commonly called modified duration (for reasons that will become apparent), is defined as

$$\text{Semi-elasticity (a.k.a. modified duration)} = -\frac{100}{PV(y)} \cdot \frac{dPV(y)}{dy} = \frac{\%\Delta PV}{\Delta y}.$$

Longer-maturity bonds are more sensitive, but by how much? For bonds with a single cash flow, the answer is simple: the bond maturity "modified" by dividing it by 1 + y/2:[4]

$$\text{Elasticity} = \frac{\text{Maturity}}{1 + y/2}.$$

[4] For single-cash-flow bonds, we use the PV formula, $PV = \frac{CF}{(1+y/2)^{2n}}$, and obtain $\frac{1}{PV(y)} \cdot \frac{dPV(y)}{dy} = \frac{n}{1+y/2}$.
If we measured sensitivity to *continuously compounded* rates (rather than semiannually compounded rates), then the "modification" would disappear and we could simply use the maturity.

For bonds with intermediate coupon cash flows, such as Treasuries, it is still true that longer bonds have greater sensitivity, but the final maturity is, of course, not the right measure of "length" or duration. So, we need to find the appropriate measure. In the early twentieth century, Frederick Macaulay (1938, Chapter 2, pp. 48–49) defined a bond's "duration" as the weighted average amount of time to receiving cash flows, using the present value of payments as weights. He did not realize at the time that this definition turns out to be the correct measure of the bond's length of life to use in calculating the bond's interest rate sensitivity:[5]

$$\text{Semi-elasticity (a.k.a. modified duration)} = \frac{\text{Macaulay duration}}{1 + y/2}.$$

For a single-cash-flow bond, we use the maturity; for other bonds, we use the Macaulay duration.[6] Longer-maturity bonds have a longer Macaulay duration and thus higher sensitivity. Two-, 10-, and 20-year par bonds (in a 5% rate environment and with 5% coupons) have Macaulay durations of 1.9, 8.0, and 12.9 years, respectively.

It is crucial to understand that despite sharing the word "duration," Macaulay duration and modified duration are distinct concepts. Modified duration is an interest rate sensitivity measure, which may apply to a wide range of fixed-income instruments (e.g., options as well as bonds). Macaulay duration measures time (duration in the true sense of the word) and technically applies only to fixed-cash-flow bonds.

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[5] Bierwag and Fooladi (2006, p. 149) asserted that Macaulay (1938) mentioned, in a footnote, that his duration could be related to the derivative of the bond price, but we have not found that footnote. Macaulay used his duration in discussing the relation between volatility of short-term and long-term *yields* but did not apply his duration to the problem of yields versus prices. To the best of our knowledge, Fisher (1966, p. 113) was the first to provide an explicit derivation of the modified duration relationship for continuously compounded rates. Fisher and Weil (1971) made explicit the use of modified duration for immunization of bond portfolios.

[6] For the technically inclined, the Macaulay duration for a fixed-cash-flow instrument is

$$\text{Macaulay duration} = \sum_{i=1}^{n} t_i \cdot \frac{PV_i}{PV_{tot}},$$

where t_i = Time (maturity in years) of cash payment *i*, PV_i = Present value of cash payment *i*, and PV_{tot} = Total (sum) of cash flow PVs.

Subsets of the Full Period

Exhibit 7.3 and **Exhibit 7.4** break up the full-period data in Exhibit 7.1 by showing summary statistics for the first half (through the period of rising inflation to 1980) and second half (moderating inflation from 1981 to 2025) of the past 100 years. Income returns were higher during the latter period (because of the higher par bond yields), which pushed up total returns.[7] Furthermore, at the long end, returns in excess of yield (effectively capital gains) were also higher.

Exhibit 7.3. Par Bond Yields and Returns, 1925–1980

	1 M	3 M	6 M	1 Yr	2 Yr	3 Yr	5 Yr	7 Yr	10 Yr	20 Yr	Long
Par bond yield (average)	2.81	2.91	3.05	3.22	3.44	3.60	3.75	3.85	3.91	3.98	4.01
Compound Annual Return											
Total return	2.80	2.94	3.17	3.37	3.58	3.50	3.42	3.26	2.90	2.69	2.59
Income return	2.80	2.88	3.03	3.21	3.44	3.60	3.76	3.86	3.92	3.99	4.02
Return in excess of yield	0.00	0.05	0.13	0.15	0.13	−0.09	−0.32	−0.57	−0.98	−1.25	−1.38
Arithmetic Mean Annual Return											
Total return	2.83	2.98	3.21	3.40	3.61	3.55	3.49	3.34	3.01	2.86	2.80
Annualized Standard Deviation											
Total return	0.79	0.93	1.07	1.47	2.32	3.05	3.90	4.37	5.13	6.26	6.51
Income return	0.79	0.85	0.85	0.82	0.76	0.73	0.70	0.68	0.66	0.63	0.63
Return in excess of yield	0.00	0.30	0.65	1.26	2.20	2.96	3.84	4.33	5.10	6.24	6.49

Source: Author calculations from CFI forward rates database. Forward rates estimated from CRSP Treasury bond prices using CFI methodology, as discussed in Chapter 8.

[7] Average par bond yields and income returns are not exactly the same, because of compounding: Par bond yields are semi-annually compounded yields, while the annualized income returns are uncompounded—the simple monthly income return times 12.

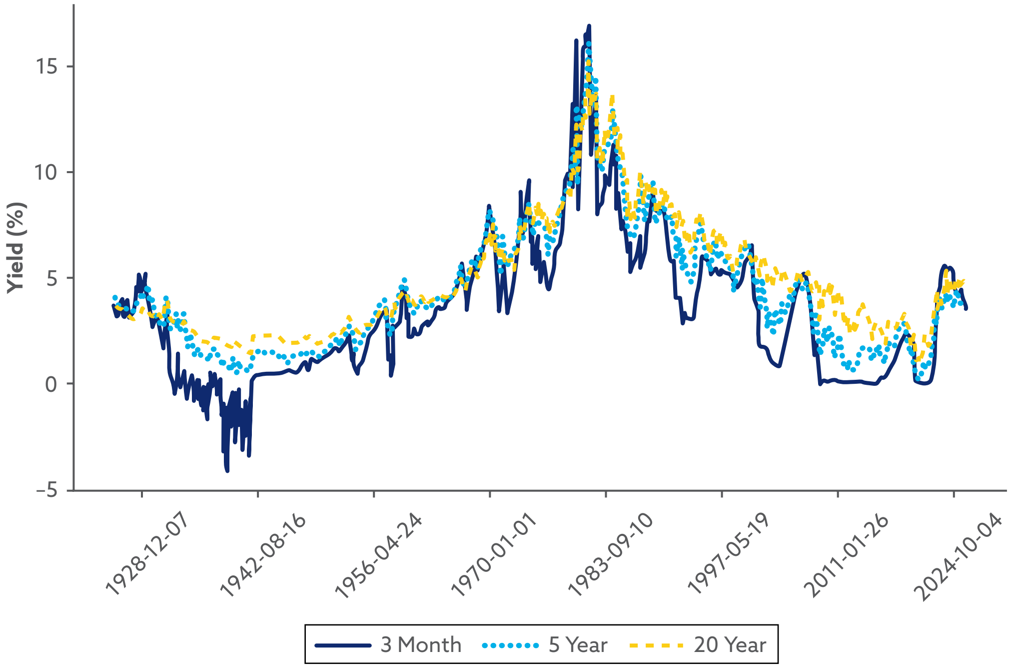
Exhibit 7.4. Par Bond Yields and Returns, 1981–2025

	1 M	3 M	6 M	1 Yr	2 Yr	3 Yr	5 Yr	7 Yr	10 Yr	20 Yr	Long
Par bond yield (average)	3.79	4.03	4.14	4.33	4.56	4.75	5.07	5.32	5.53	5.93	5.91
Compound Annual Return											
Total return	3.82	4.22	4.49	4.84	5.34	5.87	6.60	6.92	7.56	7.62	7.53
Income return	3.82	4.06	4.17	4.36	4.60	4.79	5.12	5.38	5.60	6.01	5.99
Return in excess of yield	0.00	0.16	0.30	0.46	0.70	1.02	1.40	1.46	1.86	1.52	1.45
Arithmetic Mean Annual Return											
Total return	3.87	4.29	4.56	4.92	5.46	6.02	6.84	7.26	8.04	8.50	8.82
Annualized Standard Deviation											
Total return	0.94	1.06	1.20	1.57	2.49	3.44	5.15	6.61	8.13	11.65	13.55
Income return	0.94	0.99	0.99	1.00	1.01	0.99	0.97	0.94	0.91	0.85	0.84
Return in excess of yield	0.00	0.21	0.53	1.09	2.17	3.19	4.96	6.44	7.97	11.49	13.40

Source: Author calculations from CFI forward rates database. Forward rates estimated from CRSP Treasury bond prices using CFI methodology, as discussed in Chapter 8.

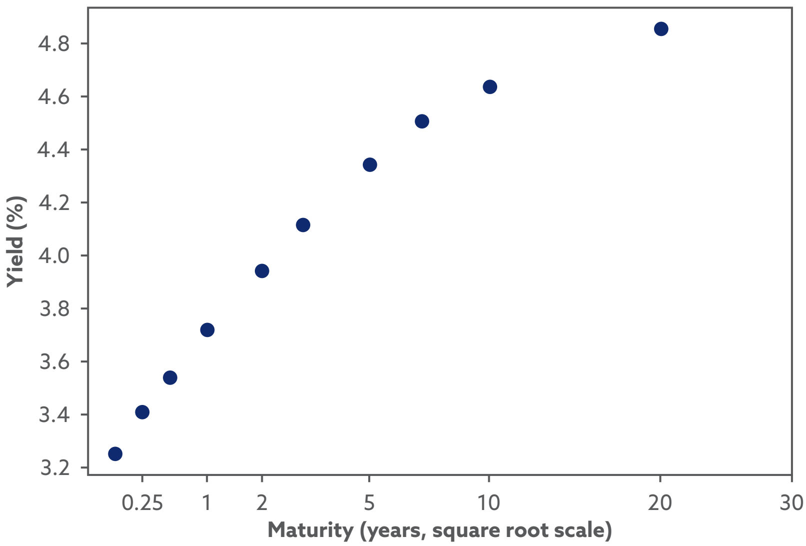
Exhibit 7.5 shows the time series for 2-, 10-, and 20-year yields—a "yield pyramid" of rising yields peaking in 1981 and falling thereafter. **Exhibit 7.6** shows the average par bond curve over the whole period, a graphical representation of the first row of Exhibit 7.1. We use as the horizontal axis the square root of the maturity, simply to expand somewhat the scale at the short end and compress the scale at the long end.

Exhibit 7.5. Par Bond Yields, 1926–2025



Source: Author calculations. CFI par bond yields calculated from CFI forward rates database. Forward rates estimated from CRSP Treasury bond prices using CFI methodology, as discussed in Chapter 8.

Exhibit 7.6. Average Par Bond Curve, 1926–2025

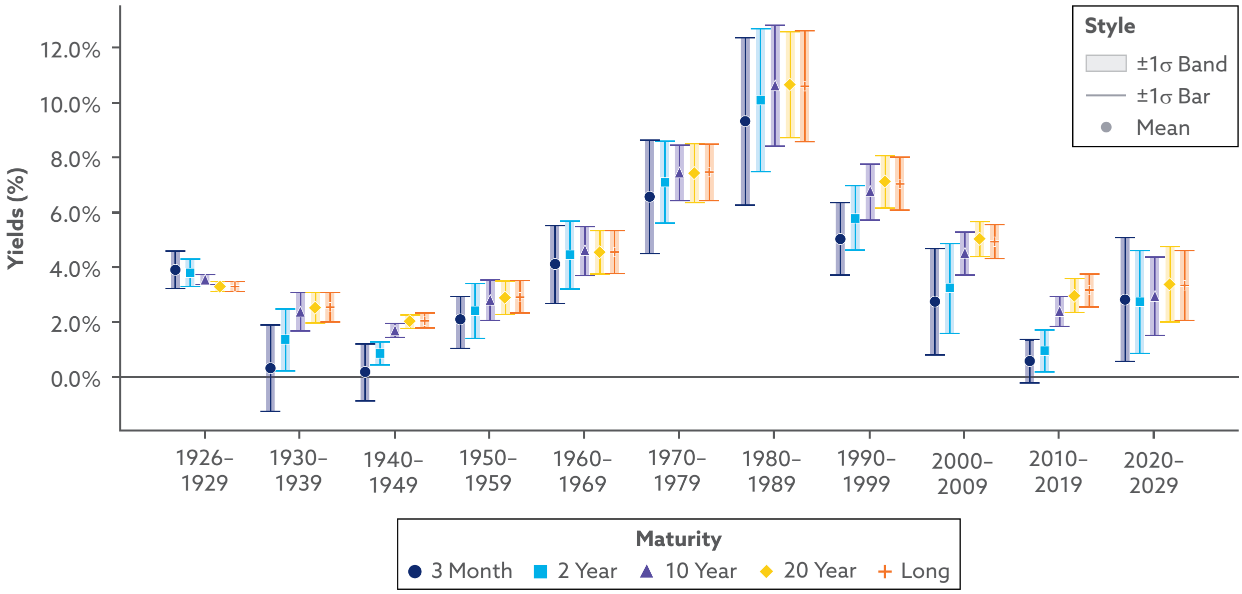


Source: Author calculations. CFI par bond yields calculated from CFI forward rates database. Forward rates estimated from CRSP Treasury bond prices using CFI methodology, as discussed in the Chapter 8.

Decade-by-Decade Par Bond Yields and Returns

The par bond yield is the yield on a par bond—a bond trading at $100 with coupon equal to yield. **Exhibit 7.7** shows the decade averages for three-month and 2-, 10-, 20-year and longest-maturity par bond yields, together with bars showing the spread around the average. **Exhibit 7.8** is a montage of decade-by-decade average par bond yield curves. Except for the 1926–1929 period and the 2020–25 period (at the short end), the average curves are consistently upward sloping.

Exhibit 7.7. Par Bond Yield Curves by Decade Showing One-σ Bands



Source: Author calculations. CFI par bond yields calculated from CFI forward rates database. Forward rates estimated from CRSP Treasury bond prices using CFI methodology, as discussed in Chapter 8.

Exhibit 7.8. Average Par Bond Yield Curves, 1926–2025

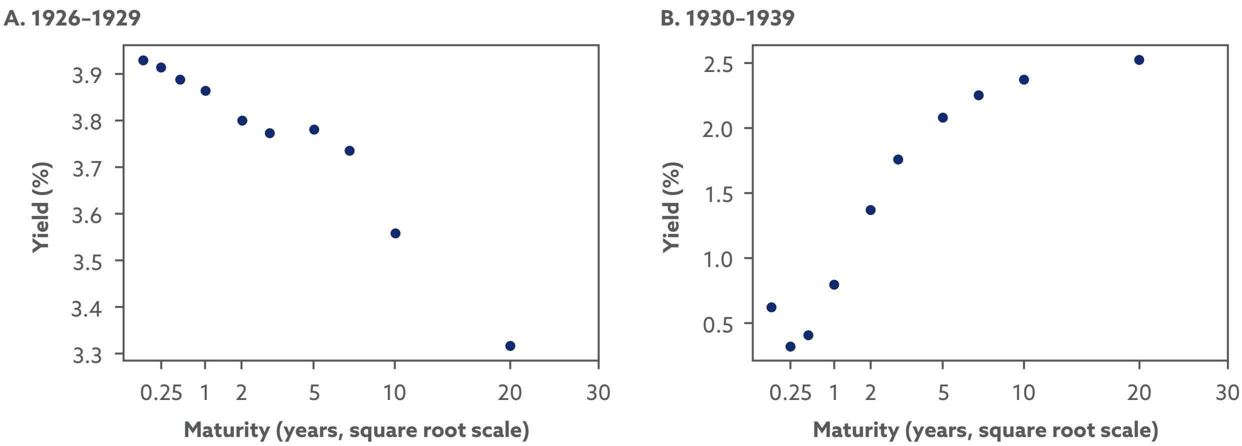


Exhibit 7.8. Average Par Bond Yield Curves, 1926–2025 (*continued*)

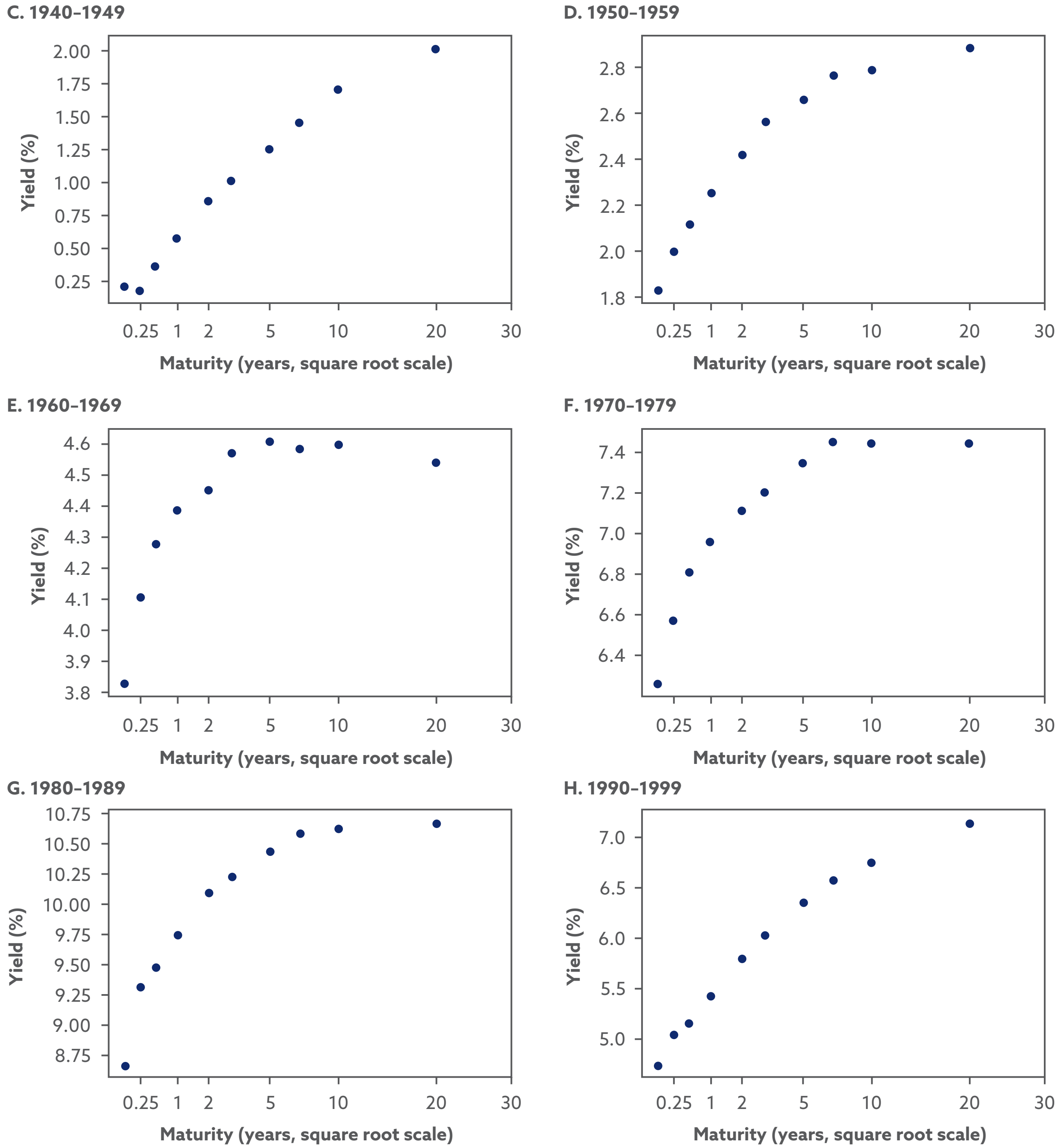
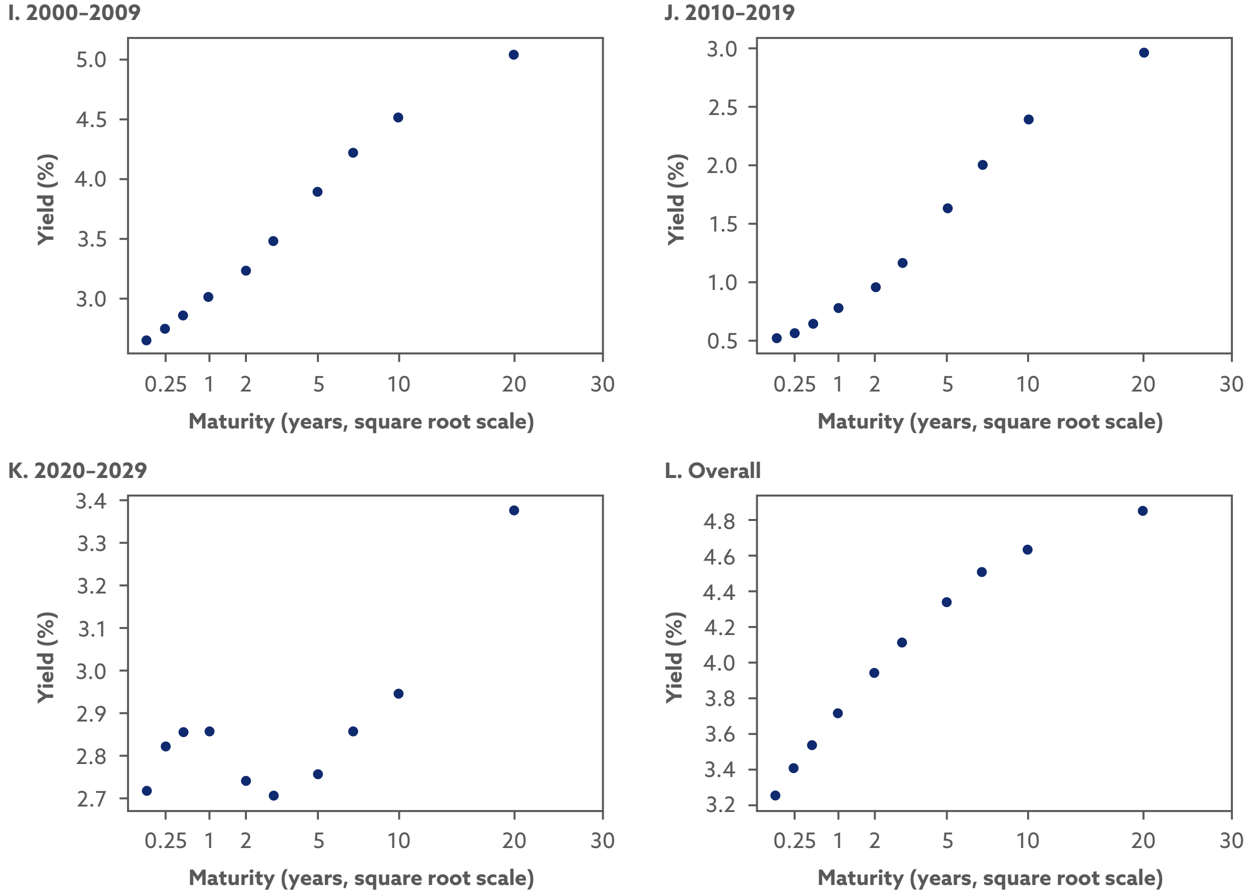


Exhibit 7.8. Average Par Bond Yield Curves, 1926–2025 (*continued*)



Source: Author calculations. CFI par bond yields calculated from CFI forward rates database. Forward rates estimated from CRSP Treasury bond prices using CFI methodology, as discussed in Chapter 8.

Year-By-Year Par Bond Yields and Returns

Our CFI datasets consist of estimated forward rates covering the full US Treasury bond yield curves for each month-end over the full 100-year period from 1926–2025. From these estimated forward rates, we can construct yield curves of any type, such as par bonds, zero coupon or discount bonds, and annuities. We have chosen to construct par bonds because most US Treasury bonds are issued at $100 with semi-annual coupons. From our CFI estimated forward rates, we can construct the monthly and annualized yields, returns in excess of yields, and total returns for synthetic bonds of any maturity or duration.

Exhibit 7.9 shows par bond annualized yields (last trading day of the year) and par bond total returns (during the year for buying the designated maturity at the beginning of each month and then selling at the end of the month) annually for a few selected maturities, over the period 1926–2025 (starting from 1925 year-end). The exhibit shows the 1-month, 1-year, 10-year, and 20-year maturities.

Exhibit 7.9. Par Bond Yields (end of year, %) and Returns (during the year, %)

	1 Month		1 Year		10 Year		20 Year		Long	
	Yield	Total Return	Yield	Total Return	Yield	Total Return	Yield	Total Return	Yield	Total Return
1926	3.26	3.52	3.26	4.22	3.55	5.23	3.40	6.82	3.40	7.03
1927	3.33	3.43	3.29	3.19	3.25	5.68	3.02	9.06	3.02	9.25
1928	4.73	4.18	4.54	2.52	3.62	−0.19	3.26	−0.63	3.27	−0.74
1929	3.57	4.75	3.51	5.52	3.42	4.72	3.24	3.60	3.23	3.81
1930	2.84	3.24	2.81	3.88	3.09	5.89	3.14	4.85	3.13	4.35
1931	4.13	2.53	4.07	1.56	4.11	−5.12	3.88	−7.32	3.87	−9.34
1932	0.18	0.87	0.34	6.02	2.82	10.46	2.91	14.32	2.94	16.98
1933	0.47	0.28	1.91	0.49	3.07	0.72	2.96	2.10	2.93	2.99
1934	−0.16	0.24	0.15	3.20	2.31	9.91	2.49	10.66	2.53	11.06
1935	1.02	0.19	0.04	0.49	1.83	7.07	2.02	10.49	2.06	12.07
1936	−0.41	−0.27	0.29	0.19	1.68	3.58	1.91	4.04	1.96	4.20
1937	0.01	0.37	0.13	1.45	1.88	0.39	2.12	−1.18	2.15	−1.71
1938	−0.91	−0.57	−0.93	2.06	1.54	5.68	1.85	7.02	1.88	7.32
1939	−0.28	−0.36	−1.16	1.07	1.45	2.93	1.83	2.39	1.85	2.28
1940	−0.18	−0.08	−1.03	0.49	1.26	3.89	1.55	7.07	1.55	7.27
1941	0.05	−1.67	0.26	−0.45	1.35	0.93	1.59	0.93	1.59	0.92
1942	0.35	0.25	0.86	1.01	1.90	2.80	2.25	2.93	2.34	3.02
1943	0.28	0.33	0.79	1.09	1.96	2.08	2.28	2.12	2.35	2.14
1944	0.20	0.30	0.84	0.92	1.94	2.74	2.26	2.80	2.32	2.83
1945	0.12	0.26	0.85	1.14	1.48	6.90	1.83	10.09	1.89	11.23
1946	0.24	0.22	0.87	1.00	1.64	0.70	1.93	0.47	1.96	0.37
1947	0.90	0.42	1.06	0.94	1.99	−0.95	2.26	−3.15	2.28	−3.56
1948	1.14	0.91	1.22	1.01	1.95	2.78	2.17	3.85	2.18	3.97
1949	1.06	1.08	1.09	1.34	1.70	4.61	1.89	7.06	1.88	7.13
1950	1.36	1.19	1.46	0.94	1.94	−0.15	2.08	−0.98	2.06	−0.92
1951	1.72	1.45	1.87	1.28	2.40	−1.69	2.53	−4.78	2.51	−4.31
1952	1.97	1.61	2.02	1.94	2.45	2.18	2.66	0.52	2.62	1.04
1953	1.33	1.77	1.54	2.77	2.34	3.66	2.70	2.60	2.81	4.61
1954	1.04	0.89	1.10	1.56	2.40	1.71	2.45	7.04	2.46	9.52

(*continued*)

Exhibit 7.9. Par Bond Yields (end of year, %) and Returns (during the year, %) (*continued*)

	1 Month		1 Year		10 Year		20 Year		Long	
	Yield	Total Return	Yield	Total Return	Yield	Total Return	Yield	Total Return	Yield	Total Return
1955	2.46	1.55	2.68	0.83	2.80	−1.25	2.81	−2.62	2.98	−3.95
1956	3.13	2.40	3.44	2.66	3.53	−3.60	3.46	−6.25	3.41	−6.19
1957	2.78	3.02	2.79	4.12	2.85	9.41	3.11	8.87	3.20	8.05
1958	2.37	1.37	3.04	2.17	3.87	−5.09	3.65	−4.49	3.89	−11.37
1959	4.16	2.83	4.87	2.56	4.85	−3.90	4.43	−6.35	4.41	−7.20
1960	2.02	2.51	2.62	5.99	3.68	13.90	3.74	14.12	3.87	16.14
1961	2.53	2.04	3.15	2.78	4.14	−0.10	4.06	−0.47	4.13	−1.12
1962	3.02	2.66	3.04	3.43	3.80	6.90	3.87	6.71	3.93	8.16
1963	3.59	3.08	3.79	2.69	4.12	1.23	4.16	−0.08	4.16	−0.29
1964	3.61	3.53	3.88	3.92	4.02	3.39	4.08	5.13	4.17	4.00
1965	4.54	3.92	4.90	3.22	4.65	−0.83	4.27	1.64	4.50	−1.58
1966	4.76	4.71	4.96	5.15	4.51	5.64	4.45	2.25	4.44	4.71
1967	4.54	4.12	5.73	4.25	5.57	−3.39	5.48	−8.09	5.48	−11.45
1968	6.39	5.28	6.29	5.20	5.98	2.09	5.89	0.36	5.89	−1.51
1969	7.30	6.59	8.18	5.40	7.62	−5.39	6.97	−5.80	7.14	−6.71
1970	4.67	6.39	4.96	10.43	6.48	16.00	6.44	12.94	6.45	14.36
1971	3.43	4.28	4.35	6.07	5.85	11.41	5.86	13.12	6.03	10.78
1972	5.10	3.84	5.59	4.39	6.38	2.52	5.76	6.03	6.01	4.82
1973	7.67	7.07	7.26	5.37	6.84	3.68	7.26	−4.69	7.23	−1.73
1974	6.73	8.13	7.15	8.05	7.06	5.97	7.84	2.06	7.68	3.02
1975	5.20	5.72	6.16	8.47	7.66	3.39	7.92	7.65	7.83	6.56
1976	4.36	5.05	4.88	7.92	6.81	14.57	7.14	17.30	7.05	16.61
1977	5.92	5.15	6.96	4.55	7.77	0.57	7.91	−0.28	7.85	−0.22
1978	9.04	7.25	10.53	5.26	9.15	−0.87	8.89	−1.25	8.98	−1.62
1979	10.74	10.48	11.70	9.02	10.28	1.77	10.00	−0.93	10.09	0.27
1980	13.27	11.51	13.50	10.18	12.39	−1.62	11.90	−4.30	12.05	−3.22
1981	9.98	15.14	13.55	14.73	13.97	4.54	13.65	0.22	13.65	0.36
1982	8.57	10.71	8.83	18.22	10.72	35.69	10.57	41.85	10.57	41.79
1983	9.04	8.84	10.07	9.21	11.80	4.54	11.79	1.22	11.79	1.22
1984	8.15	9.78	9.23	12.88	11.54	14.19	11.62	14.10	11.62	14.12

(*continued*)

Exhibit 7.9. Par Bond Yields (end of year, %) and Returns (during the year, %) (*continued*)

	1 Month		1 Year		10 Year		20 Year		Long	
	Yield	Total Return	Yield	Total Return	Yield	Total Return	Yield	Total Return	Yield	Total Return
1985	6.31	7.57	7.69	10.88	9.09	29.03	9.54	32.02	9.41	34.95
1986	5.07	5.98	6.04	8.60	7.33	22.06	8.06	23.64	7.68	29.76
1987	3.65	5.17	7.29	6.58	8.89	−1.95	9.08	−1.48	8.98	−5.73
1988	6.60	6.16	9.10	6.63	9.16	7.42	9.09	8.89	9.03	8.51
1989	6.50	8.21	7.91	10.11	8.00	17.37	8.09	19.14	8.02	20.83
1990	5.91	7.61	6.96	9.32	8.12	8.15	8.39	5.66	8.26	5.92
1991	3.93	5.42	4.22	9.48	6.84	18.70	7.45	19.22	7.47	18.24
1992	2.91	3.41	3.64	5.34	6.80	8.65	7.44	8.22	7.45	7.99
1993	2.94	2.88	3.65	4.03	5.89	14.72	6.56	17.95	6.50	20.43
1994	4.36	3.81	7.26	2.58	7.89	−6.56	8.01	−7.69	7.89	−9.61
1995	4.68	5.46	5.20	8.31	5.70	25.49	6.06	32.11	6.00	35.33
1996	5.09	5.12	5.58	5.68	6.49	0.93	6.75	−1.08	6.69	−2.90
1997	5.04	5.07	5.57	6.19	5.83	12.21	6.02	16.01	5.96	17.23
1998	4.45	4.73	4.61	6.29	4.82	14.42	5.48	12.79	5.24	16.71
1999	5.10	4.57	6.07	4.41	6.57	−6.68	6.85	−9.54	6.61	−12.34
2000	5.92	5.81	5.51	7.09	5.23	17.49	5.61	22.12	5.49	22.99
2001	1.66	3.75	2.06	7.22	5.17	6.75	5.79	3.41	5.58	4.17
2002	1.15	1.64	1.21	3.20	3.91	17.85	4.94	17.61	4.86	17.19
2003	0.86	1.01	1.24	1.47	4.28	2.49	5.16	2.03	5.11	0.86
2004	1.85	1.20	2.74	0.87	4.27	5.92	4.91	8.71	4.84	9.13
2005	4.05	2.94	4.43	2.30	4.43	3.56	4.63	8.41	4.56	8.71
2006	4.89	4.64	5.01	4.29	4.74	2.74	4.91	0.96	4.81	−0.33
2007	2.84	4.62	3.27	6.07	4.14	10.50	4.53	10.07	4.46	10.62
2008	0.03	1.43	0.40	4.89	2.54	21.20	3.05	27.96	2.66	42.80
2009	0.03	0.10	0.51	0.70	3.90	−6.40	4.60	−17.15	4.61	−27.90
2010	0.07	0.12	0.34	0.73	3.30	10.50	4.19	10.04	4.34	8.84
2011	0.00	0.05	0.16	0.57	1.91	18.73	2.69	30.28	2.92	35.87
2012	0.03	0.05	0.18	0.25	1.76	4.94	2.66	3.46	2.94	2.66
2013	0.01	0.03	0.16	0.29	3.04	−7.40	3.77	−12.66	3.96	−15.09
2014	0.01	0.02	0.28	0.21	2.19	11.80	2.58	23.99	2.78	30.19

(*continued*)

Exhibit 7.9. Par Bond Yields (end of year, %) and Returns (during the year, %) (*continued*)

	1 Month		1 Year		10 Year		20 Year		Long	
	Yield	Total Return	Yield	Total Return	Yield	Total Return	Yield	Total Return	Yield	Total Return
2015	0.10	0.01	0.80	0.22	2.32	1.61	2.81	−0.80	3.03	−2.53
2016	0.41	0.18	0.92	0.83	2.48	0.65	2.90	1.27	3.08	1.65
2017	1.23	0.77	1.80	0.63	2.42	3.31	2.60	8.38	2.75	10.17
2018	2.40	1.79	2.64	1.89	2.70	0.42	2.88	−1.16	3.02	−2.45
2019	1.46	2.12	1.62	3.01	1.93	9.73	2.28	13.03	2.39	16.33
2020	0.05	0.43	0.10	1.87	0.92	11.53	1.43	17.50	1.66	19.20
2021	−0.02	0.04	0.41	−0.03	1.48	−3.04	1.92	−6.17	1.90	−4.29
2022	4.00	1.39	4.71	−0.75	3.85	−16.40	4.19	−27.22	3.99	−32.43
2023	5.56	5.08	4.77	4.88	3.89	3.35	4.22	3.53	4.03	2.40
2024	4.11	5.36	4.20	5.02	4.58	−1.40	4.88	−4.21	4.80	−8.45
2025	3.44	4.03	3.52	4.42	4.18	8.41	4.80	5.88	4.86	3.60

Source: Author calculations. CFI par bond yields and returns calculated from CFI forward rates database. Forward rates estimated from CRSP Treasury bond prices using CFI methodology, as discussed in Chapter 8.

Key Takeaways

- We extended our earlier CFI work, using spline methods to estimate forward interest rates, which we then used to estimate US Treasury yield curves and synthetic US Treasury bond returns across the yield curves.
- Bond yields generally rose over roughly the first half of the period, reaching a peak above 15% for long bonds in September 1981. Then, yields fell until the early 2020s. These trends created negative returns in excess of yield in the earlier period (1926–1980) and positive returns in excess of yield in the later period (1981–2025).
- Overall, the average income returns were 3.21% for short bonds (one-month maturities) and 4.79% for long bonds (20 years), providing a historical horizon premium of 1.58%.
- Total returns over the 1926–2025 period were approximately the same as the yields. The yield in 1926 was similar to the yield in 2025, so returns in excess of yield are near zero over the whole period.
- Most bond return volatility comes from the change in bond yields and is related to a bond's modified duration or interest rate sensitivity: As yields rise and fall, bond prices fall and rise.

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CHAPTER 8. TREASURY BOND YIELD AND RETURN METHODOLOGY

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We seek to estimate the yields and returns for US Treasury bonds, notes, and bills over 1926–2025. We use a method that first extracts monthly forward-rate yield curves from actual US Treasury security prices and then, from these yield curves, creates synthetic securities based on the work of Coleman, Fisher, and Ibbotson (1989, 1993). We began this effort in collaboration with the late Lawrence Fisher in the 1980s. In recognition of this partnership, we call the results of our study, presented in Chapter 7 and discussed in this chapter, the Coleman Fisher Ibbotson (henceforth CFI) database and methodology. Treasury yield curves are useful not only for understanding the Treasury market itself but also for pricing most other US dollar–denominated bonds based on spreads over the Treasury curve.

The resulting bond data include three components:

- Monthly estimated US Treasury forward rates (yield curves)
- Par bond riskless yields for selected maturities (one, three, and six months; 1, 2, 3, 5, 7, 10, and 20 years; and the longest maturity) and monthly returns for those maturities
- The ability to calculate (using the estimated yield curves) the present value (PV) for any arbitrary US dollar "riskless" (nondefaultable) cash flows and instruments. For example, one can calculate yield curves for par bonds, zero-coupon bonds (zeros), or annuities or price any set of riskless streams of US dollar cash flows over the last hundred years.

To produce the estimated forward rates and par bond yields, we use the underlying bond prices in the CRSP bond data file, which was itself created by Fisher at the University of Chicago. The CRSP data contain prices and characteristics for all market-traded bonds from December 1925 to the present. Collectively with Fisher, however, we recognized that translating the raw prices into forward yield curves could enable the data to be used to value all types of standardized bonds (e.g., par bonds for selected maturities) and any arbitrary cash flows (as long as the cash flows are riskless). Here we expand on our earlier work, offering refinements in the splines estimation techniques, taxation adjustments, and probabilistic maturity adjustments based on callability terms.

Goals and Challenges in Estimating Bond Returns

Our goals for US Treasury markets are straightforward: to estimate yield curves and then returns for selected single-bond portfolios with maturities of, say, three months, 2 years, and 10 years.[1] Calculating a return requires "buying" a bond today (say, with a two-year maturity) and "selling" it one month later (when it has one year and 11 months maturity). To be consistent across time, we wish to buy today an exact two-year bond trading at par ($100) and sell the same bond in one month, when the bond will be one month shorter. Using the actual bonds traded is one approach, but generally there will not be exact-maturity bonds for the maturities we want; so, some interpolation method is necessary for calculating synthetic bonds and portfolios.

The approach we take is to estimate a yield curve for each month and, from that estimated curve, price a synthetic two-year bond. Then, a month later, we estimate the new curve and use that new curve to price the original bond (shorter by one month). The benefit of using estimated yield curves for calculating synthetic bonds is that once we have the curves, we have the flexibility to estimate returns across arbitrary bonds (and portfolios) and for different holding periods—we can estimate a three-month return as easily as a one-month return.

As we have emphasized, par bond yields are the most common (and most intuitive) way to display and describe the yield curve. In Chapter 7, we provide exhibits illustrating par yields for a discrete set of points (one month, three months, etc.). The Federal Reserve publishes the H.15 constant-maturity yields for a set of discrete maturities. It is instructive to think of bond returns in terms of these par bond yields and changes in the yields. We can think heuristically of the total return for a two-year bond from January to February being the sum of multiple components:

- Accrued income (earnings from the promised yield over the month)
- Change in the par bond yield for the on-the-run bond: ModDur × ($-\Delta y$), with Δy being the change from January to February for the on-the-run bond
- Return from "rolling down" the yield curve, from two years to one year and 11 months, ModDur × ($-\Delta y$), where now the change is the two-year par bond to the one-year and 11-month par bond for a fixed curve (February)

This decomposition is useful because it highlights why par bond yields for discrete maturities (e.g., 1 year, 2 years, 10 years, such as we provide in Chapter 7 or the Fed publishes in its H.15 data releases) are insufficient for calculating monthly returns. The first and second items, (accrued income and change in the par bond yield) can be approximated from the discrete par bond yields (ours or those from H.15). For a good estimate of the third item (the return from rolling down the yield curve), however, we require more detail: the shape of the curve between 23 months' and 24 months' (two years') maturity. The discrete points in the exhibits in Chapter 7 or the Fed's H.15 data provide too little detail on the shape at and just below two years' maturity. The return resulting from the roll-down can be quantitatively important. The yield curve is generally upward sloping (see Exhibit 7.8), so the return from roll-down will generally be positive. For the decade 2010–2019, the average one-month yield roll-down at a 2-year maturity was

[1] Our detailed tables include a wider range of maturities: one, three, and six months; 1, 2, 3, 5, 7, 10, and 20 years; and the longest maturity. The three maturities quoted in the text are sufficient for illustrating all the issues.

1.5 bps and at 10 years was 1.0 bp. These amounts are not large, but they accumulate over a year to contribute roughly 0.4% and 1%, respectively, to the annualized average return.[2]

The need to calculate synthetic prices for both on-the-run exact-maturity bonds (say, 2 years and 10 years) and the shorter bonds (1 year and 11 months and 9 years and 11 months) forces us to calculate curves that both are flexible (allow variable shapes) and use the market data that are available. The returns we report incorporate that detailed information on the shape of the curve, detail beyond what is available in our par bond tables (or the Fed's H.15 data), which show only discrete points.

The piecewise twisted forward curve methodology we use, discussed in the next section, allows for a flexible curve that can use the rich data available in the markets. **Exhibit 8.1** shows the instantaneous forward rates for December 2021 in Panel A and the resulting continuous par bond curve (blue line) plus the actual bonds (dots) in Panel B. We might consider this line to reflect a typical curve—upward sloping at the short end but flattening somewhat at the longer end. Allowing jumps in the instantaneous forward rates has the benefit that the forward curve is localized: The short and long ends are connected through the relative prices of short- and long-dated bonds, not through the mathematical constraints that are often imposed so that the estimated forward curve is continuous.

Fitting the Treasury curve across time requires a curve methodology that is not only fine grained but also flexible and capable of fitting the wide variety of yield curves actually observed. **Exhibit 8.2** shows par bond curves for December 2022 and 2023. The level and shape of the curves are quite different from each other and from the 2021 curve. In 2022, the curve is steep at the very short end (out to roughly 1 year), inverted from roughly 1.5 to 10 years, and then humped. For December 2023, the curve is fully inverted between 1 and 5 years, is flat between 5 and 10 years, and has a hump at the long end.

Forward Curve Methodology

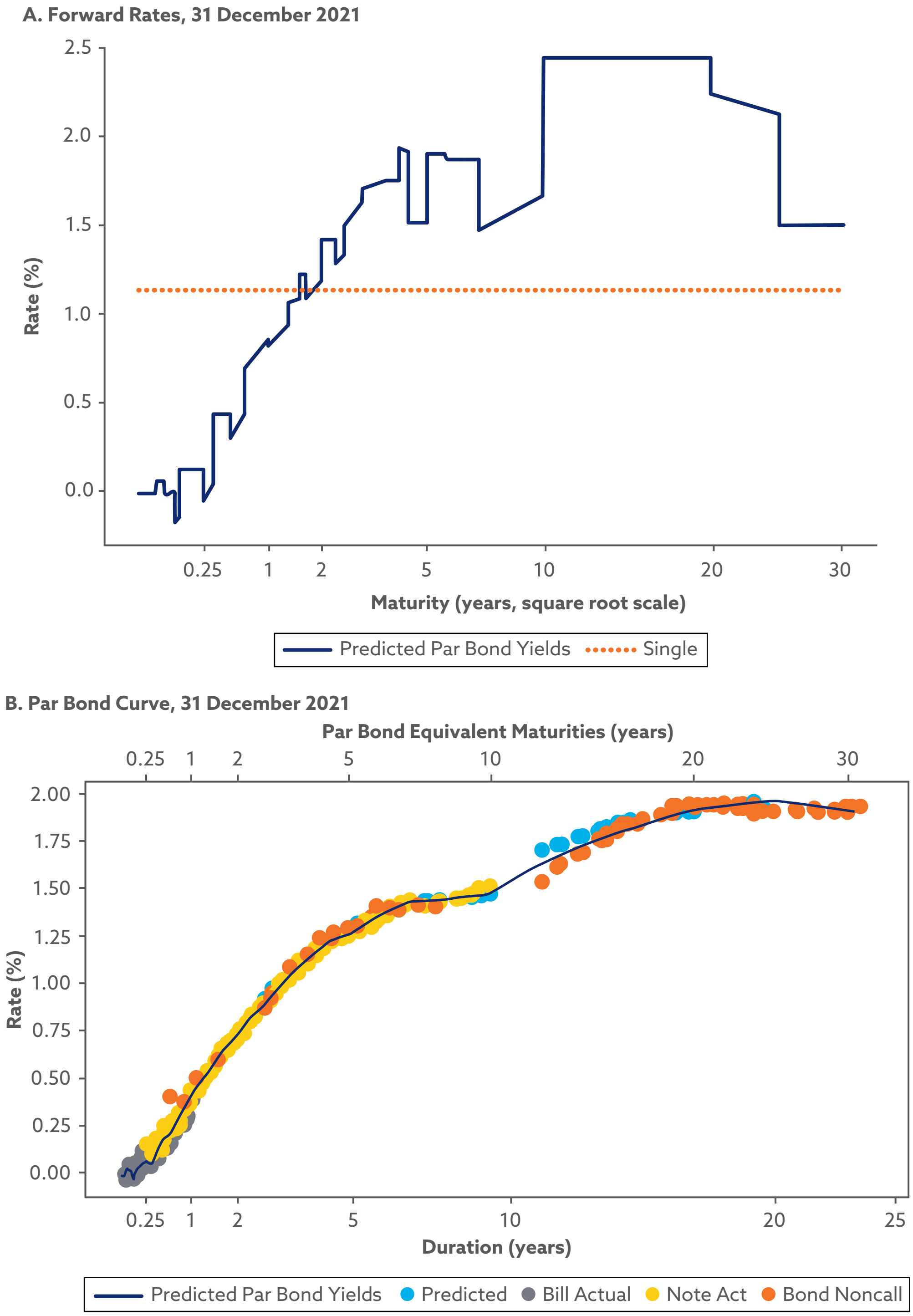
The general approach we use to fit forward curves is split into three components:

- Choosing a parametric functional form for the forward curve: The parametric forward curve translates into a function for the discount factor function for each maturity, $d(t)$. With this discount factor function, we can then calculate the PV of any set of cash flows: $P_0 = \sum_t d(t)C_t + d(T)M$.
- Choosing market data—the bonds—and appropriately describing their cash flow dates and amounts
- Defining and implementing an appropriate objective function and fitting methodology that specifies how to use the market data to fit numerical values for the parameters of the forward curve

Exhibit 8.1 shows an example of the fitted forward curve. For the parametric functional form, we start from the simplest one: instantaneous forward rates that are piecewise constant—that is, assuming that the forward curve is constant between specified breakpoints. Jumps in the

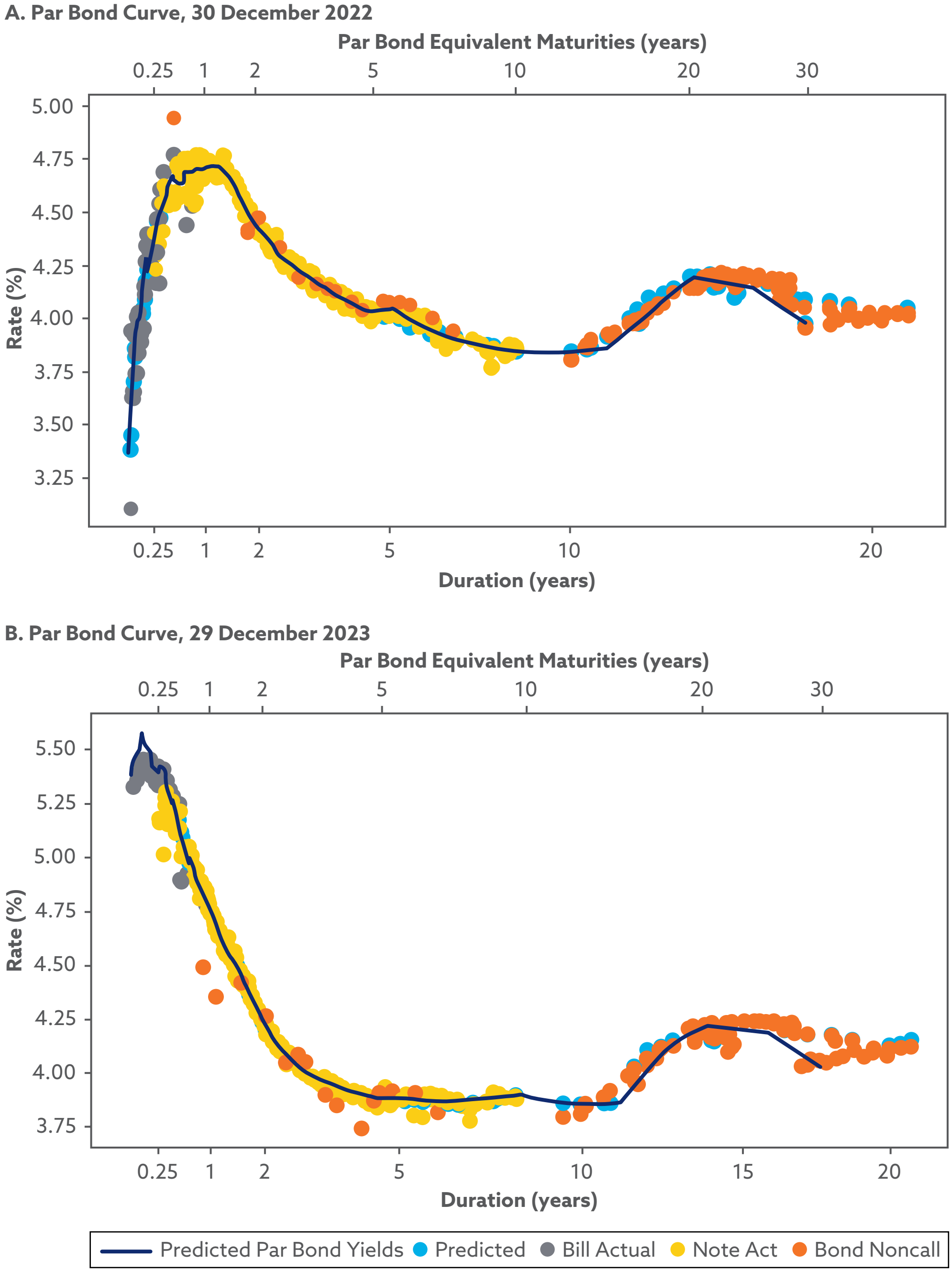
[2] The differences in yield of 1.5 bps and 1.0 bps for the 2- and 10-year bonds, respectively, translate to larger returns because the yield difference needs first to be annualized (multiplied by 12) and then multiplied by the negative duration of the bond.

Exhibit 8.1. Forward Rates and Par Yield Curve for 2021



Source: Author calculations. CFI par bond rates and actual versus predicted yields calculated from CFI forward rates database. Forward rates estimated from CRSP Treasury bond prices using CFI methodology, as discussed in the text.

Exhibit 8.2. Par Yield Curves for 2022 and 2023



Source: Author calculations. CFI par bond rates and actual versus predicted yields calculated from CFI forward rates database. Forward rates estimated from CRSP Treasury bond prices using CFI methodology, as discussed in the text.

instantaneous forward rates do not cause problems with the zero rates or discount factors. As we show in the sidebar, the discount factor and zero-coupon yields (hereafter, zero yields) are functions of the *integral* of the forward curve and thus are always continuous, with jumps in forward rates corresponding to changes in the slope of discount factors or zero rates.[3]

We start with the following breakpoints:

- *Short end:* 7 days, 14 days, 21 days, 28 days, 0.32 year, 0.5 year, 1 year
- *Long end:* 2 years, 3 years, 5 years, 10 years, 15 years, 20 years, 25 years, 32 years

For recent decades, these breakpoints roughly correspond to weekly bills at the short end and on-the-run points for notes and bonds. We then split those periods—entering a new breakpoint—when there are many bonds (at least 25 within a break period and 5 in each of the new periods). As Exhibit 8.1 and Exhibit 8.2 show, this method produces a fine-grained curve when there are many bonds, as occurred in the 2020s. We also allow the forward rates to twist, which further smooths the forward curve without inducing undue oscillation.

Yields and Forward Rates

To properly explain forward rates, we need to get technical. A forward rate is the discount rate or interest rate between two dates in the future. We write the price or PV of a bond today as the future cash flows discounted back to today by a *yield-to-maturity*, discussed earlier:

$$PV = \frac{c/2}{1+y/2} + \frac{c/2}{(1+y/2)^2} + \cdots + \frac{c/2}{(1+y/2)^{2n}} + \frac{100}{(1+y/2)^{2n}}.$$

In addition, when we are considering many bonds trading in the same market (as with the US Treasury market), we want to allow a different yield for different maturities. In its simplest form, this is called the zero yield, z_i, which is different for each maturity. Using the zero yield, we now have

$$PV = \frac{c/2}{1+z_{0.5}/2} + \frac{c/2}{(1+z_1/2)^2} + \cdots + \frac{c/2}{(1+z_n/2)^{2n}} + \frac{100}{(1+z_n/2)^{2n}}.$$

Instead of a separate zero rate for each period (a rate that goes from period *i* back to today), we could also write this in steps, going from today to 0.5, from 0.5 to 1, and so on:

$$PV = \frac{c/2}{1+f_{0,0.5}/2} + \frac{c/2}{(1+f_{0,0.5}/2)(1+f_{0.5,1}/2)} + \cdots + \frac{100}{(1+f_{0,0.5}/2)\cdots(1+f_{n-0.5,n}/2)}.$$

[3] It would seem very natural to generalize piecewise constant to piecewise linear forward rates, continuous across breakpoints but with different slopes. Doing so, however, would produce very poor results. As discussed in Hagan and West (2015), the piecewise linear approach produces oscillations in forward rates and is very nonlocal.

Here, $f_{0.5,1}$ is the *forward* rate or forward yield from ½ year to 1 year, and $f_{n-0.5,\,n}$ is the forward rate from n – 0.5 years to n years. This is a particularly convenient form for fitting and estimating a yield curve because it allows better control and analysis of the yield or forward curve. In our original work (Coleman et al. 1989, 1993), we assumed forward rates were constant between fixed maturity points. Here, we allow the forward rates to twist, and we more flexibly determine the breakpoints, depending on the number of bonds available.

Actual bonds have payments at different dates, not just on half years, and we need to work with a forward rate function $f(u)$ defined over all future maturities u. We need to define the relationships between the forward curve, the discount curve, and the zero interest rate curve:

$$d(t) = \exp\left[-\int_0^t f(u)du\right],$$

$$z(t) = \frac{\left[\int_0^t f(u)du\right]}{t}, \text{ and}$$

$$d(t) = \exp[-z(t) \cdot t],$$

where

$f(u)$ = forward rate function (continuously compounded)

$d(t)$ = the discount factor function for cash at time t, the PV of \$1 due at time t

$z(t)$ = continuously compounded zero rate from today to t

t = maturity from today, so today = 0

If t is measured in years, $f(u)$ and $z(t)$ are both continuously compounded annual rates.

Now the PV (price plus accrued interest) of any bond can be expressed as

$$P_0 = \sum_t d(t)C_t + d(t)M,$$

where

P_0 = price plus accrued interest at time zero

C_t = coupon payment due at time t

M = face amount of bond (usually \$100) due at time T

The price of any bond is now a function of the forward curve, $f(u)$.

Displaying Monthly Par Bond Yields—Macaulay Duration

In Chapter 7 and in the detailed exhibits available in the online appendix, we show annual and month-by-month yields. In the tables, we display the par bond yields for a range of maturities from one month to 20 years. In the graphs, we display both par bond yields *and* the actual-versus-predicted yields for the bonds used in estimation, as in Exhibits 8.1 and 8.2. These graphs show our estimated par bond curve (the blue line), the predicted yields for each bond (light blue dots), and the actual yields for each bond (dots of different colors to denote bills versus notes and bonds).

Each graph contains a wealth of information: the shape of the par bond curve, the quality of fit (any separation between the light blue dots and dots of other colors), and the variety of bonds in the market each month. These graphs also illustrate some of the challenges we face: sharply different levels of yields (for example, roughly 10% in 1978 compared with 4% in 2025); sharply different yield curve shapes (for example, sharply rising at the short end, generally upward sloping in 2021, and inverted in 2023); and challenges with callable bonds containing embedded options (for example, in 1978).

The presence of callable bonds for most of the first 80 years of our sample period compels us to make a slightly unusual choice for our graphs: displaying the yield versus Macaulay duration (using the Macaulay duration for the horizontal scale). For callable bonds, there is really no other good choice, because a callable bond's "maturity" will be some probabilistic combination of time to first call and final maturity. We can, however, use the concept of Macaulay duration (a present-value-weighted measure of the "length" or average time to receipt of cash flows of a bond, in years) and the relation between Macaulay duration and elasticity or modified duration (interest rate sensitivity) to define an option-adjusted Macaulay duration. We first calculate the interest rate sensitivity (modified duration) of the callable bond, which will be lower when the bond has a high probability of call (behaves like a bond to first call) and higher with a low probability of call (a bond to final maturity). We then use the relation

$$\text{ModDur} = \frac{\text{MacaulayDur}}{1+y/2}. \tag{8.1}$$

This "option-adjusted" Macaulay duration, measured in years, allows us to graph both callable and noncallable bonds on a consistent and comparable basis. As an extreme example, the 4.25s of 15 June 1947 (callable 1932) were trading right at par in January and February 1929. First call was 3.3 years, final maturity 18.3 years, and the Macaulay duration roughly 6 years. The Macaulay duration of 6 years for this callable bond corresponded to a par bond with maturity of roughly 6.7 years, even though the final maturity was almost three times that.

Estimation Challenges with Historical Curves—Adapting Forward Curve Methodology

In estimating a yield curve and returns consistently across history, there are a variety of challenges. For the current Treasury market, most of these challenges do not arise: There are many bonds (on the order of 450 bonds outstanding in 2024), they are well distributed across maturities, and all are standardized with no quirks, such as callability. For historical curves, however, this is not the case. To estimate consistent returns, we face these challenges:

- *Curve methodology:* A flexible but robust curve methodology that can be applied across the past 100 years
- *Callability:* The US Treasury issued long-dated callable bonds for most of the period 1925–1984. Through 1955, virtually all long-dated bonds (maturity of 15+ years) were callable, but the portion fell into the 25% range by the 1960s and then rose back to 90% by 1980. **Exhibit 8.3** shows that in 1993, callable bonds still represented more than 35% of bonds with maturities of 15+ years. Any estimation of the long end of the curve must deal with callability.
- *Flower bonds:* Through the 1970s, virtually all long-dated bonds (maturity of 15+ years) were "flower bonds" that could be redeemed at par for payment of estate taxes. This meant that during a period of high interest rates, when low-coupon bonds would normally trade at a deep discount, such a bond would have value above and beyond the discounted value of future cash flows because it could be put (sold) back to the government at par if the owner died.
- *Tax status:* During the 1920s, the Treasury issued mainly partially tax-exempt securities. During the 1930s, it issued mainly fully tax-exempt securities. Starting in the 1940s, it issued fully taxable securities.
- *Sparse data:* In the early years of our sample, there were only a handful of bonds and not very many at the long end. For example, in January 1926, there were 15 usable partially tax-exempt bonds, with one maturing in 1952 and another in 1954—1926 and 28 years' maturity, respectively. But these had calls in 1947 and 1944, which effectively shortened their duration.

Sparse Data, Rich Data, and Choice of Breakpoints

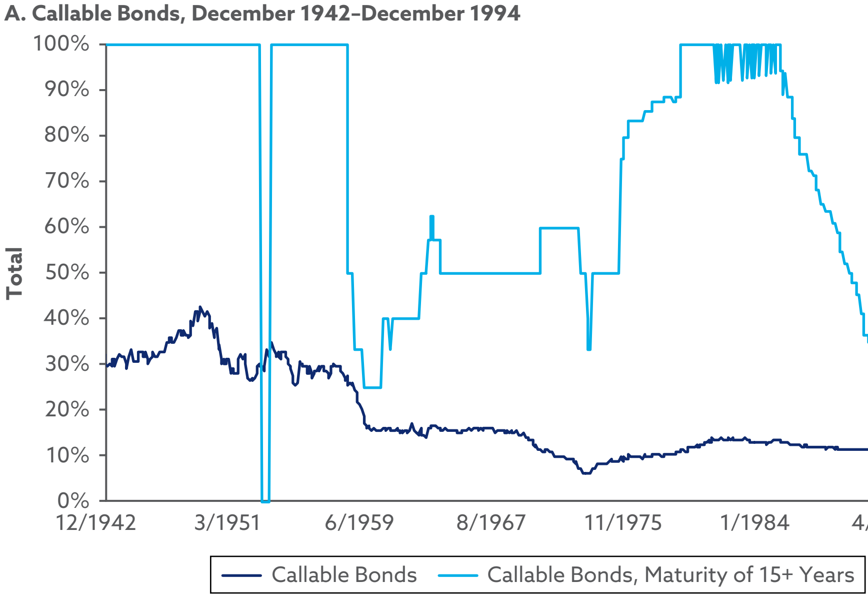
We start with breakpoints, shown previously, that for recent decades roughly correspond to weekly bills at the short end and on-the-run points for notes and bonds. For many of the early decades of our sample, the data are quite sparse. We collapse break periods when there is only one bond in a period. For example, for January 1929, the breakpoints and number of bonds are as follows:

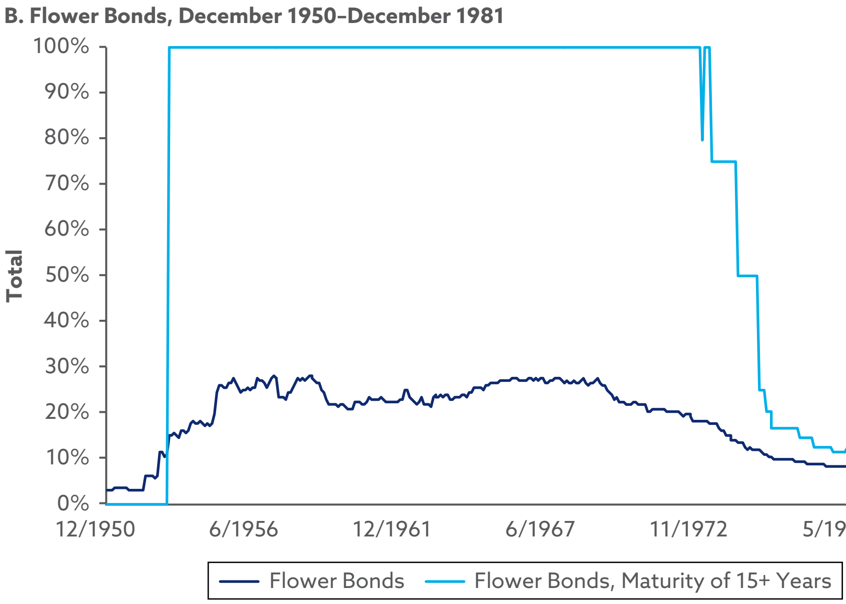
Breakpoints	1–321 days	3.67 years	6.61 years	20.40 years
Number of bonds	4	3	2	5

Callable bonds make the issue considerably more difficult because they are some probabilistic combination of short dated (to first call) and long dated (to final maturity). When there are callable bonds, we use the option-adjusted Macaulay duration to set breakpoints. We first calculate the option-adjusted modified duration using a single rate (flat rate for the whole curve). We then convert the modified duration to an option-adjusted Macaulay duration and then to an equivalent maturity for par bonds (using the estimated single-rate yield). We assign bonds to breakpoint periods (and count the number of bonds in a period) based on their maturity—the actual maturity for noncallable bonds and this "par bond equivalent maturity" for callable bonds.

For recent decades, we have many bonds (more than 350 for the 2020s), allowing us to expand breakpoints. When a break period has more than 25 bonds, we split the period but ensure that both the earlier and later periods contain at least 5 bonds.

Exhibit 8.3. Percentage of Callable and Flower Bonds





Source: Author calculations based on CRSP Treasury bond data.

Tax Status

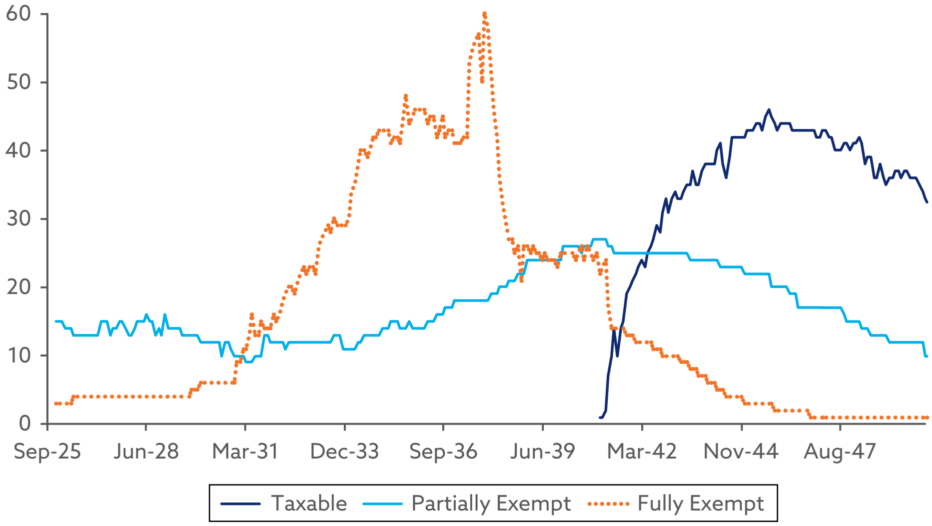
During the 1920s and 1930s, both wholly and partially tax-exempt Treasury bonds were outstanding. Fully taxable bonds appeared in 1940, and all three varieties were being traded until the early 1960s. Among bonds that were similar in other respects, the wholly tax-exempt bonds had the lowest yields and the fully taxable bonds had the highest.

Exhibit 8.4 shows the three regimes. Panel A shows the number of bonds and bills of each type. Panel B analyzes the short end, showing the percentage of all bills (by count) that are in each tax status.

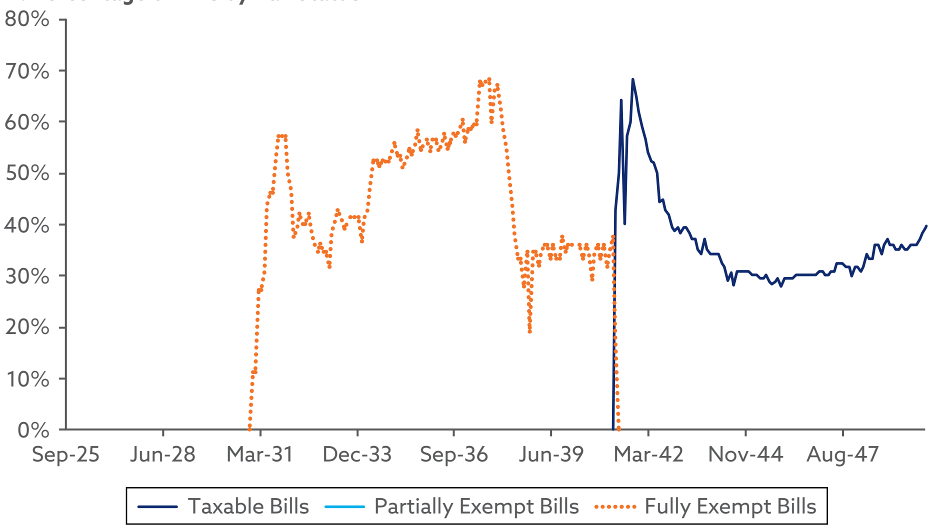
Because yield does depend on tax status, our term structure estimates treat each class separately. Our estimates are not very reliable, however, unless the class includes both short-term and long-term bonds.

Exhibit 8.4. Bonds and Bills by Tax Status, December 1925–December 1949

A. Number of Bonds and Bills by Tax Status



B. Percentage of Bills by Tax Status



Source: Author calculations based on CRSP Treasury bond data.

Exhibit 8.5. Curve Regimes

	Estimated Curves	Curve Overlap	Bond Returns	Return Overlap
Partially exempt	Dec. 1925–Dec. 1932		Jan. 1926–Dec. 1931	
Fully exempt	Jan. 1930–Dec. 1942	Jan. 1930–Dec. 1932	Jan. 1932–Dec. 1941	Dec. 1931–Jan. 1932
Fully taxable, flower	Jun. 1941–Dec. 1973	Jun. 1941–Dec. 1942	Jan. 1942–June 1973	Dec. 1941–Jan. 1942
Fully taxable	Jan. 1973–Dec. 2025	Jan. 1973–Dec. 1973	Jul. 1973–Dec. 2025	Jun. 1973–July 1973

We therefore estimate three separate sets of yield curves:

- **Partially tax exempt, 1925 through 1932:** Before 1930, we have no real choice except to fit a partially exempt curve, although this does not include any short bills.
- **Fully tax exempt, 1930 through 1942:** Starting in 1930, we can estimate a fully exempt curve. In 1931, the long ends of the curves are not too different but, of course, the short ends are different because there are no partially exempt bills. For December 1935, again, the long ends are not much different in shape but the short ends are quite different—in fact, the rates for the short-end fully taxable curve are negative, with bills slightly positive and short-dated notes negative.
- **Fully taxable 1940 through 2025:** Beginning in April 1941, there was a variety of both short- and long-dated taxable bonds, enough to fit a curve. Initially, there are no short-end bills, but by June 1941, there is at least one bill.

To produce consistent returns, we overlap the regimes by a month and calculate the returns as shown in **Exhibit 8.5**.

Callable Bonds and European Option Methodology

The US Treasury issued long-dated callable bonds for most of the 1925–1984 period. Panel A of Exhibit 8.3 shows the fraction of all bonds from 1942 to 1994 that were callable, and we can see that for long periods, callables made up all or the majority of bonds with 15+ years to maturity. The PV of such bonds cannot be represented as a simple sum of discounted cash flows. We approximate callable bonds by evaluating the option exercisable on the first (or next) call date. The PV of such a callable bond will then be

$$PV_c(\text{FwdCrv}) = PV_{nc}(\text{FwdCrv}) - \text{Call}(\text{FwdCrv}), \tag{8.2}$$

where

$PV_{nc}(\text{FwdCrv})$ = PV of noncallable bond to final maturity date as a function of the forward curve

Call(FwdCrv) = European call option to first (or next) call date, exercisable into a bond from the first call to final maturity date, calculated as a function of the forward curve

PV_c(FwdCrv) = resulting PV of callable bond

The noncallable bond and the option are valued off the same forward curve. We value the European option using option methodology based on Black and Scholes (1973), modified for valuing bond options (as discussed in the online methodology appendix). We generally use a normal Black–Scholes-type yield option valuation method (assuming yields are normally distributed) because it allows rates to go below zero, which may be important for periods of ultra-low rates, such as during the Great Depression and after 2008 (when a small number of short-dated callable bonds was left over from issuance during the 1980s). Although this is an approximation because callable Treasuries are generally callable at each coupon date—they are Bermudian rather than European options—with this methodology, we can estimate a noncallable forward curve.

In the online appendix, we discuss the valuation of callable bonds in more detail. Here, we focus on the intuition. One way to think of the problem is that we do not know the maturity of the bond, and so we do not know what part of the curve to use: the early (today to first call) or late (call to maturity). A callable bond is somehow a combination of the curve to first call date and the curve from first call to maturity.

Exhibit 8.6, which covers February 1929, illustrates the problem. Two bonds in particular (the 4.25s of 15 October 1938/1933 and the 4.25s of 15 June 1947/1932) are trading just below or just above par. An ad hoc rule ("yield-to-worst") is to use the first call date if the current price is above par (presuming the bond will be called for certain) and the maturity date if the price is below par. Panel A shows the curve using this rule. The two bonds are trading just above par and are treated as maturing in 1938 (9.6 years, 7.9 years duration) and 1947 (18.3 years,12.8 years duration), respectively.

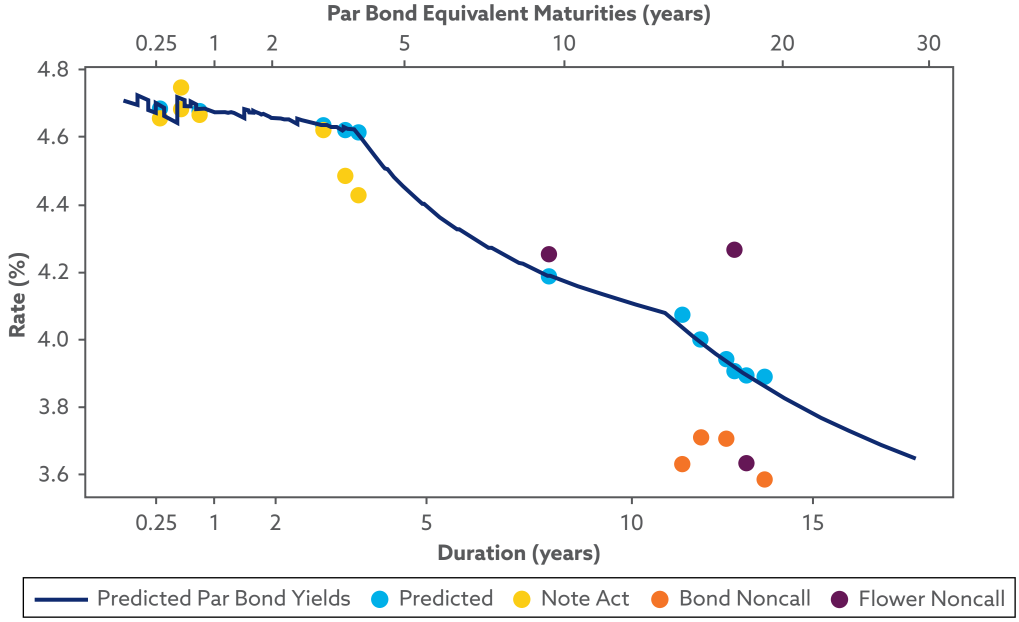
The curve in Panel A presents an issue: The 4.25s of 1947/1932 in particular are trading at a much higher yield than other bonds of similar duration and final maturity. The reason is that the 4.25s of 1947/1932 have a high option value, are trading as a combination of short (3.3 years) and long (18.3 years) maturity, and thus behave "shorter" than their final maturity. With the downward-sloping yield curve, this means they have a yield higher than noncallable bonds with that same final maturity. The other long-dated bonds, although callable, have a low probability of call and are trading more like long-dated bonds, with lower yields (given the slope of the yield curve on that date).

As a result, the yield curve is distorted, with neither the 4.25s of 1947/1932 nor the other bonds fitting well at the long end. The solution to the problem is to use the option formula of Equation 8.2, which treats the bond as a probability-weighted combination of first call and final maturity.

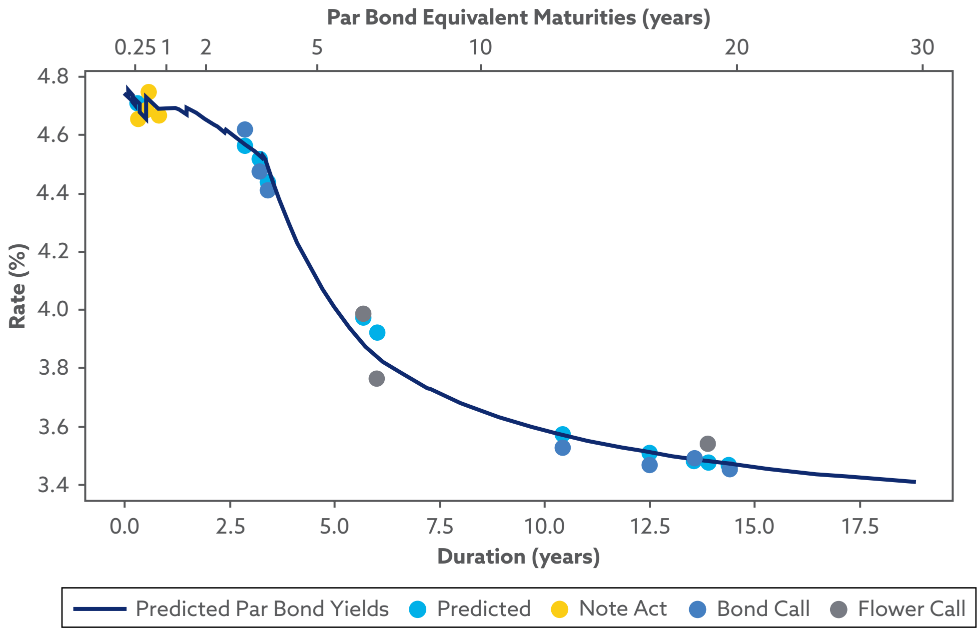
Panel B shows the results. Both bonds are a weighted average of short and long, with Macaulay durations very close to each other (5.7 and 6.0 years). We use an option-adjusted Macaulay duration to represent the length of the bonds because the bond "length" is not clearly defined. The standard definition of Macaulay duration is the present value–weighted time to repayment of cash flows and is defined only for fixed-cash-flow instruments. We can, however, use the relation between Macaulay duration and modified duration—the percentage sensitivity of PV to

Exhibit 8.6. Forward and Par Curve for 1929, Yield-to-Worst and Option-Adjusted

A. Par Bond Curve, 28 February 1929, Yield-to-Worst (%)



B. Par Bond Curve, 28 February 1929, Option-Adjusted



Source: Author calculations. CFI par bond rates and actual versus predicted yields calculated from CFI forward rates database. Forward rates estimated from CRSP Treasury bond prices using CFI methodology, as discussed in the text.

Note: For callable bonds, a normal yield option model is used to evaluate the option to first (or next) call, with an annualized level yield volatility of 0.005 (decimal) or 0.5 percentage point, which translates into roughly 3 bps per day.

changes in yield, MacDur = ModDur(1 + y/Freq)—to define an option-adjusted Macaulay duration for the callable bonds.

Panel B of Exhibit 8.6 graphs the yields versus option-adjusted Macaulay duration, and the bonds line up nicely. The two 4.25% bonds fit right in the middle, with duration around six years, between the shorter bonds with higher yield and longer bonds with lower yield.

Flower Bonds

The US Treasury issued bonds from 1943 to around 1968 that could be redeemed at par ($100) for the payment of estate taxes upon death of the owner. This instrument is effectively a put held by the owner of the bond—an option to put the bond back to the government at $100 upon death of the owner. These are known as "flower bonds" because of the association with flowers given at funerals. Exhibit 8.3 shows that prior to 1973, all long-dated bonds were flower bonds.

During periods of high interest rates, a normal bond with a low coupon would sell at a discount. During such a period, a flower bond would become valuable because of the effective put: If bought at a discount, it could be redeemed for $100 after the owner's death. Such a flower bond would trade at a premium relative to non-flower bonds and a premium to the discounted present value—the yield would be lower than it otherwise would be.

Not all flower bonds will trade equally as flower bonds. Consider two flower bonds, one with a lower coupon. If the flower option were removed, the two bonds would trade at (roughly) the same yield and the lower-coupon bond would have a lower price (larger discount). With the flower option, that larger discount provides a larger value to flower bond buyers, who will choose the lower-coupon and lower-priced bond over the higher-coupon bond. This higher demand will push the price of the lower-coupon bond up (and yield down) relative to the higher-coupon bond. When the lower-coupon bond is trading at a lower yield (higher price), we can conclude that the lower-coupon bond is trading with a larger flower component. In any month, we can examine all flower bonds and determine which are trading with the largest flower component—so-called flower bonds *par excellence*. Larry Fisher, the originator of the CRSP US Treasury bond database, created a list of flower bonds *par excellence*, which we used in our original Coleman et al. (1989, 1993) books and which we have updated slightly.

The lack of non-flower bonds and the rising rates during the 1960s and early 1970s makes estimating the long end of the curve challenging. The best we can do prior to 1973 is to use our list of flower bonds (given in the online appendix) to exclude flower bonds *par excellence*. This produces a curve where the long end is contaminated to the least degree possible with the flower bond effect. In 1973, the Treasury started to issue long-dated non-flower bonds (the 6.75s of 15 February 1993 issued in January 1973 and the 7s of 15 May 1998/1993 issued in May 1973). Starting in July 1973, we exclude all flower bonds and move to a non-flower curve. For returns, we create a series using flower bonds up to June 1973 and excluding flower bonds starting in July 1973 (but using the non-flower curve for June 1973 to calculate the return for July 1973).

Multiple Clienteles: 1968, Bonds, and Flowers

In the 1960s, the US Treasury curve appeared to be trading with multiple clienteles: short-end bills, medium-term notes versus bonds, and long-term flower bonds. The problem appeared to result from a 4.25% cap on bond coupons (with the Fourth Liberty Loan Act in September 1918, Congress restricted the maximum coupon for bonds but not notes), together with rising yields by the late 1960s (up to 7% for the long end by 1969, well above 4.25%). The cap effectively precluded the Treasury from issuing long-dated bonds, and between 1965 and 1971, the Treasury did not issue bonds but issued only notes with maturity up to seven years.[4] Older and lower-coupon bonds seem to have traded at a premium (lower yield) to notes with the same maturity, presumably because of scarcity of bonds. We try to manage this issue by weighting notes more heavily than bonds during this period in our nonlinear least-squares fitting. This means our curve is effectively a note curve in the intermediate part of the curve (two to seven years).

Key Takeaways

- The Coleman Fisher Ibbotson data include monthly US Treasury forward rates, continuous par bond yield curves, par bond returns of any selected maturity or duration, and other yield curves and returns as desired—for example, zero coupon, annuity, and so on—in that any "riskless" US dollar cash-flow stream can be priced over the 1926–2025 period.
- The CRSP government bond file of raw US Treasury bonds, notes, and bills is used to estimate forward interest rates with piecewise twisted forward rate functions (splines) covering the short term (seven days) to the long term (up to 32 years).
- Forward rates are used to estimate par bond yield curves over different tax regimes (partially tax exempt for 1925–1932, tax exempt for 1930–1942, and fully taxable for 1940–2025), with flower bonds (issuance 1943–1968) in which the lowest dollar prices are distorted because they could be used to pay estate taxes at par and callable bonds (issuance 1925–1984) whose maturities are option adjusted. After 1988, all US Treasury bond issued were noncallable and fully taxable, but previous issuances still existed.
- Par bond returns are calculated from the monthly continuous yield curves for selected maturities and durations, with returns consisting of the income, the modified duration times the negative yield change, and the gain or loss from rolling down the yield curve as the bonds shorten their maturity each month.

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[4] In 1967, Treasury notes were redefined (by statute) to mature in one to seven years (instead of five), and in 1971, Congress authorized issuance of $10 billion of higher-coupon bonds. In 1988, Congress eliminated the 4.25% coupon limit.

CHAPTER 9. THE EQUITY RISK PREMIUM

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Why We Care About the Equity Risk Premium

Why do we care about the equity risk premium? Why is it often described as the most important variable in finance? And why does so much effort go into estimating it, both historically and as a forecast?

The simple answer is that the equity market is the most important capital market—it is where change in the wealth of the world occurs on the margin—and the equity risk premium (ERP) is the *price of risk* in that market. Understanding the price of equity risk—that is, the additional return that people expect on the margin for assuming an additional unit of equity risk—enables us to unravel puzzles in practically every branch of finance.

Applications of the Equity Risk Premium

The ERP is the key element of the expected return on equities (the remainder of that return consisting of the riskless rate). Estimates of the expected ERP are useful in a large number of applications, some of which we will describe in further detail later in this chapter:

- asset allocation (between equity and fixed-income asset classes),
- financial planning, including projection of the long-term growth of wealth and determination of appropriate saving and spending rates,
- determination of the cost of equity capital, essential in corporate valuation settings, capital budgeting, and other aspects of corporate finance, and, overarching all of the above,
- as the crucial input to the capital asset pricing model (CAPM), which estimates the expected return on a security or portfolio conditional on knowing its beta (i.e., its systematic risk, the portion of the security's total risk that is correlated with the risk of the overall market).

Expected Return Does Triple Duty

The central place of the ERP in finance is illustrated by the "triple duty" nature of expected returns, of which the ERP is the most variable and most interesting part. In the hypothetical construct that economists call a perfect capital market, (1) the *expected return* on a risky security, (2) the *cost of capital* faced by a firm issuing that security, and (3) the *discount rate* appropriate for reducing the future cash flows from that security to their present value (or market price) are all the *same number*.

Because information about securities is imperfect and costly, as well as because of taxes, transaction costs, and differences in investors' tastes and preferences, however, the capital market is obviously not perfect—far from it! As a result, this triple equality does not hold precisely in practice. It is, however, a useful framework for linking the various aspects of finance in which the expected ERP is used.

Principal Approaches to Estimating the Expected ERP

There are four broad categories of approaches to estimating the expected ERP:

- historical,
- demand oriented,
- supply oriented, and
- surveys.

We begin with the historical approach taken by Roger Ibbotson and Rex Sinquefield (1976a, 1976b) in their classic work, the semicentennial of which we are celebrating in this book. Moreover, during much of the time since their original work, the historical model was the dominant way of estimating the ERP.

The Historical Return Approach

One of the most important reasons why Ibbotson and Sinquefield (1976a, 1976b) investigated the historical total returns on US equities starting in 1926 was simply that no one knew what the relative long-run rates of return on the principal asset classes had been. Cowles (1938) and Fisher and Lorie (1964) had collected long-run stock market returns, but they had no riskless or reference asset with which to compare them. Ibbotson and Sinquefield, by calculating return *differences*, homed in on the realized equity risk premium and other premiums discussed in Chapter 2.

Ibbotson and Sinquefield's original articles and subsequent updates (Stocks, Bonds, Bills, and Inflation®, hereafter SBBI®) revealed that the realized ERP in the United States had been quite large over the period studied, enough to justify a large allocation to stocks for investors with typical risk preferences. In fact, some of the shift in investor behavior from a fixed-income-dominant to equity-dominant investment allocation over the last half century can be attributed to Ibbotson and Sinquefield's findings.

Using Historical Returns for Forecasting

But knowing what happened in the past is of limited usefulness unless that information tells us something about the future. How is an accurate measure of the past, or realized, ERP helpful for understanding future outcomes? One possibility is that the historical record is representative of what can happen and is likely to happen in the future—in terms of risk as well as return. A statistician would call such a process "stationary."

In their early works, Ibbotson and Sinquefield proposed a forecasting method based on the premise that the ERP is stationary. We call this approach the historical method or historical model. To justify it, Ibbotson and Sinquefield argued that past realizations of the ERP are a good guide to the future because of the following:

- There is no compelling evidence that either the amount of risk in the market or the price of risk (defined earlier) has changed systematically over time or would be expected to change materially in the future.
- Over time, investors conform their expectations to what is proven to be realizable in financial markets, so historical returns are at least a plausible guide to investors' expectations.[1]
- A history as long as 1926–1974 (initially) or, better yet, 1926–2025 (today) contains most of the event types and economic conditions that investors should expect in the future. These types of events, including bull and bear markets, crashes, periods of stability, high and low inflation, wars, recessions, financial crises, and so forth, have been reflected in market returns that are averaged together to form the historical return data. Thus, the historical or realized ERP is a good guide to what investors can expect in the future.

At the time of Ibbotson and Sinquefield's original work, other means of estimating the expected (future) ERP, such as the dividend discount model, had produced forecasts that were way too low. A better method was needed.

Although many investors now expect that the US ERP will be lower in the future than in the past century, the past provides a helpful framework and baseline for developing future expectations.

Applying the Historical Model

Applying the historical, or what Ibbotson and Sinquefield called the "future equals past," model is conceptually simple. The expected value, or mean, of the ERP in the future is equal to the average ERP realized in the past. If you simply want a point estimate of the expected ERP, then according to this model, you are done. But risk, as well as return, must be taken into consideration in any forecast. Ibbotson and Sinquefield's 1976 articles and SBBI® assume that the *probability distribution*, as well as the mean, of the realized ERP will be the same in the future as it was in the past.

Adjustments can be made to the historical model. An example is in Chapter 20, wherein the US historical returns are modified by making an international adjustment because the United States was the best-performing country rather than a typical country. Another adjustment might be to take out the increase in the price-to-earnings ratio (P/E) that occurred in the United States in the past century, and we make this adjustment in what we call the adjusted historical model, which we cover later in this chapter, in the section on the supply of returns.

[1] See Ilmanen and Maloney (2026) for a thorough treatment of how investors form return expectations.

The Supply and Demand for Returns: An Introduction

We now provide a brief description of the supply and demand framework introduced by Ibbotson, Diermeier, and Siegel (1984) and Diermeier, Ibbotson, and Siegel (1984). This background is needed to understand the rest of this chapter.

In these two articles, the authors introduced the concept of the demand for returns (what return investors require in order to take the risks inherent in a given security) and the supply of returns (the cash flows that corporations provide to their stockholders and other capital providers). Although the traditional finance literature refers to the supply and demand for *capital*, we flip this concept around, both in this discussion and in a rich vein of literature that developed in the wake of the 1984 articles: We regard buyers of securities as demanders of capital market *returns* and sellers or issuers as suppliers of those returns. Analyzing the supply and demand for returns in this way sheds greater light on the questions we are trying to answer in this book.

The Demand for Returns

The concept of an equity risk premium arises from the demand side of this equation. If investors are risk averse, they require a higher return from investing in risky assets than from holding safe ("riskless") ones. That difference is the ERP if the risky asset under consideration is an equity index and the riskless asset is a Treasury bill, note, or bond.[2]

Capital Asset Pricing Model

The CAPM, developed by William Sharpe (1964) and several other researchers at about the same time,[3] formalizes this relationship. The CAPM says that the expected return on a risky security is equal to the riskless rate plus the security's beta (a measure of its market risk, the part of its total risk that is correlated with movements of the equity market index) multiplied by the ERP:

$$E(r_p) = r_f + \beta_p(\text{ERP}), \tag{9.1}$$

where

$E(r_p)$ is the expected return on security or portfolio p

β_p is the beta of security or portfolio p

r_f is the risk-free rate

ERP is given by $E(r_m) - r_f$—that is, the expected return on the market index minus the riskless rate

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[2] This chapter refers often to US Treasury securities or government bonds. The same concept would apply, however, if we were discussing these topics for other countries. Generally speaking, we are referring to government securities issued by countries whose sovereign debt is largely regarded as free of default (or riskless).

[3] The CAPM was developed in the early 1960s by Sharpe (1964), Treynor (1962), Lintner (1965a, 1965b), and Mossin (1966). For a good historical perspective on the development of the CAPM, see Perold (2004).

The CAPM does not specify how the ERP should be estimated; instead, it assumes one can obtain the needed estimate from a separate, independent source. The challenge posed by the CAPM's need for an ERP input is the original reason why researchers sought to obtain an accurate estimate of the (future or expected) ERP. Even though the CAPM is no longer the only equilibrium model of asset returns that practitioners use, it remains centrally important to the problem of estimating the expected ERP. By recognizing that investors require an additional return for investing in risky as opposed to riskless assets, the CAPM sets up the question of *why* a (nonzero) ERP exists, as well as what the right number is.[4]

Popularity Asset Pricing Model

Another demand-side approach, merging ideas in the CAPM and in Ibbotson et al. (1984), is the popularity asset pricing model (PAPM) of Ibbotson, Idzorek, Kaplan, and Xiong (2018). Covered in Chapter 18 of this book, the PAPM merits a brief summary here. In the PAPM, the demand for an asset reflects asset characteristics to which a given investor is attracted or by which they are repelled, including not only risk and return but also such characteristics as liquidity (or lack thereof), tax treatment, reputation of the company, and ethical or environmental considerations. Aggregating across investors, the more popular or well liked the asset is, for any of these reasons, the *lower* the expected return (because the asset's popularity has caused its price to be bid up to a level that reduces future returns).

Mehra–Prescott or Pure Utility Theory Model

A demand-side approach exists that does result in a numerical estimate of the expected ERP, although it is rarely used in practice. The work of Mehra and Prescott (1985) looks outside the financial markets to utility models with reasonable risk-aversion parameters to ascertain what investors would rationally demand, or require, in order to take on the risk of equities instead of riskless assets. These authors based their method on the observed price of risk in macroeconomic settings, but their ERP estimates are an order of magnitude lower than those obtained through the other methods described here, so we do not pursue this method any further.

The Supply of Returns

Supply models of the expected ERP measure what corporations offer to would-be investors in terms of expected cash flows (distributable profits). The classic dividend discount model (DDM) of Graham and Dodd (1934) is an example of a supply model because it takes as an input the cash flows to the investor from the corporation. Ibbotson and his coauthors have contributed to enhancements and modifications to the DDM (see, e.g., Diermeier et al. 1984; Ibbotson and Chen 2003; Straehl and Ibbotson 2017), thus adding to the supply-model literature. This subsection discusses these works, along with contributions from other authors that are supportive of this general approach.

Supply-based models of the ERP have become increasingly influential in the last generation and have emerged as a complement to Ibbotson and Sinquefield's historical approach. In general,

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[4] Note that the CAPM is a single-period model, generally requiring a short-term estimate of the ERP (one that is derived by subtracting the yield on a short-term reference or "riskless" asset). This chapter focuses on long-term estimates of the ERP.

supply models have in common the characteristic that they use information from the real economy, rather than market prices as is the case with purely historical models.

The intense interest in supply models in the late twentieth and early twenty-first centuries emerged when many analysts noticed that the historical model was producing overly high ERP estimates. The work of Ibbotson and Chen (2003), described later, is an example, but movement in the direction of supply models began earlier, with Campbell and Shiller (1988), Fama and French (1988), and Jeremy Siegel (1994). In the current century, the works of Shiller (2000), Asness (2000, 2003), Arnott and Bernstein (2002), Cochrane (2011), and Ilmanen (2011) stand out as landmark efforts. Support for supply models continued to increase in the wake of the market collapses of 2000–2003 and 2007–2009.[5]

Diermeier, Ibbotson, and Siegel (1984): A Quick and Dirty Supply Model

The first and most basic supply model is that of Diermeier et al. (1984). The authors started with the observation that equity total returns must equal dividend yields plus the growth rate of dividends. This latter quantity cannot in the infinitely long run exceed the growth rate of the overall economy or else dividends would crowd out all other economic claims. Diermeier et al. completed the model, which we now regard as a "quick and dirty" estimate, by asserting that the expected equity total return equals the dividend yield minus new issues net of share buybacks plus the GDP growth rate as a proxy for dividend growth. The ERP is the expected equity total return minus the riskless rate.

Grinold and Kroner (2002) and Grinold, Kroner, and Siegel (2011) embellished this model, adding new data on buybacks in light of their dramatically increased importance in recent decades.[6]

Ibbotson and Chen (2003): The Adjusted Historical Model

One potential flaw of the historical model is that it implicitly projects forward the very substantial past increase in the valuation ratio (P/E) of the market over 1926–2025 indefinitely into the future. Because such a further rise is unlikely to happen again starting at today's high valuations, one can adopt an *adjusted historical model* instead: Take the historical results and subtract that part of the return attributable to the rise in P/E.

As of this writing, the historical 1926–2025 arithmetic mean ERP, based on the S&P 500 and predecessor indices and using long-term bonds as the reference asset, was 6.4%. Subtracting the arithmetic mean annual rate of P/E expansion, which was 1.1%, we arrive at an expected arithmetic mean ERP of 5.3%.[7] This is the current result using the adjusted historical method.

The adjusted historical method can be regarded as a type of historical model or as a supply-related model. Ibbotson and Chen (2003) showed that at least with respect to past returns,

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[5] Laurence Siegel (2017, pp. 9–12) provided more detail on this movement in a section called "Time-Varying Premia and the DDM Counterrevolution." The supply models we have discussed, as well as those covered in Siegel (2017), have become prominent—even dominant—in ERP estimation as practiced by investment managers and in corporate finance and valuation settings in the twenty-first century.

[6] Chen and Obizhaeva (2022) provided a good literature review on the rising importance of buybacks.

[7] The 1.1% estimate of annual P/E expansion was calculated by Ibbotson and Chen (2003) as the compound annual growth rate of Shiller's CAPE (see footnote 10) over 1926–2025. This estimate differs from the one shown in the "Implementation Illustration" section, which is based on three-year average S&P 500 earnings.

the adjusted historical model is consistent with a supply approach. They outlined six different ways of decomposing historical equity returns. One of those ways (which they called the earnings model) decomposes the historical equity return into four components: income return, inflation, growth in real earnings per share (EPS), and growth in the P/E. The adjusted historical ERP sums the first three components but leaves out the growth in P/E.

Ibbotson and Chen noted that the historical capital gain return of the stock market equals EPS growth plus P/E expansion—so if we take out P/E expansion, we are looking only at information from corporations (the real economy). A supply-side input is thus inherent in the adjusted historical model.[8]

Reflecting the influence of the supply side, the output of the adjusted historical model has been labeled the "supply-side ERP" in various Ibbotson Associates and Morningstar publications and has been referred to as such in court cases and other legal and regulatory contexts.[9] It is the method used in the "Implementation Illustration" section of this chapter.

Straehl and Ibbotson (2017): Adding in Buybacks as a Source of Return

In a follow-on article, Straehl and Ibbotson (2017) enhanced the supply literature by showing that over a longer time period (1871–2014), total cash payouts to the investor—dividends plus share buybacks—are the key drivers of long-run equity returns. They showed that "total payouts per share (adjusted for the … decrease [in the number of shares resulting from] buybacks) grew in line with economic productivity, whereas aggregate total payouts grew in line with GDP" (Straehl and Ibbotson 2017, p. 32). This analysis bolsters the contention that information from the real economy is useful and additive in predicting future stock returns.

Straehl and Ibbotson (2017) also introduced a new valuation ratio, cyclically adjusted total yield (CATY). This measure adds buybacks to dividend payments to arrive at an improved measure of cash flow to the investor, which they called *total yield*. The authors showed that CATY "predicts

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[8] The remainder of the historical total return is the dividend yield, which is also partly sourced in the real economy. The dividends themselves come from corporations, but the dividend *yield* involves dividing by a market price, so the adjusted historical model is only partly a supply model. Stated another way, the "supply-side ERP" is a historical method with an adjustment based on the idea that the P/E expansion over the last century is unlikely to be repeated, and it reconciles to the supply-side model outlined in Ibbotson and Chen (2003) when applied historically. When applied to the future, these two models can diverge because the earnings or dividend growth estimates may come from a different source than historical stock returns.

[9] Specifically, the adjusted historical estimate by Ibbotson Associates and Morningstar consists of the "historical equity risk premium minus [the change in] price-to-earnings ratio calculated using three-year average earnings" (Ibbotson Associates 2005, p. 258). This estimate has emerged as one of the most frequently used ERP estimates in US Delaware Court of Chancery appraisal cases.

The Delaware Court of Chancery is often the forum of shareholder disputes in the United States, with valuation disagreements at the core of many of these cases. Accordingly, the business valuation and appraisal communities and investment advisers engaged in pricing mergers and acquisitions pay close attention to the inputs used in those valuations, including cost-of-capital-related decisions. The Delaware Court of Chancery has expressed in some cases a preference for using a supply-side ERP that is identical to the adjusted historical method described in this chapter. The first time the court decided in favor of the supply-side ERP (rejecting the historical ERP also published in the SBBI) was in April 2010 in the case Global GT LP v. Golden Telecom, Inc., 993 A.2d 497 (Del. Ch. 2010; https://cases.justia.com/delaware/court-of-chancery/137130-0.pdf?ts=1462311681). A sequence of court decisions that adopted the same approach followed. Nevertheless, the parties of any case are still advised to support their assumptions, and the "supply-side ERP" should not be automatically presumed to be the accepted method by the court.

changes in expected returns at least as well as the … CAPE" (Straehl and Ibbotson 2017, p. 32).[10] Given the decreased importance of dividends and greater prevalence of buybacks in recent years, we expect CATY to outperform CAPE (cyclically adjusted P/E) even more as a forecaster of future returns than it has in the past.[11]

Implied ERP

Yet another supply-based model of the expected ERP was set forth by Damodaran (2008), whose "implied ERP" is conceptually based on the DDM. It begins by solving for an implied cost of equity capital (i.e., expected total return on equity), which is the sum of the riskless rate and the ERP. This implied cost of equity capital is the discount rate that equates the present value of consensus expected earnings (or dividends and buybacks) for a stock market index with the current level of that index. The implied ERP is then obtained by subtracting the current yield on the riskless asset.[12]

Surveys of the Expected ERP

Setting aside economic modeling, one way to find out what people expect from the markets is to ask them. Thus, surveys have become an alternative or supplement to the historical, supply, and demand approaches.

Surveys of expected returns have been around for a long time, and one in particular has gained traction among certain communities of investors, corporations, and advisers. Since 2009, Pablo Fernandez and his coauthors have conducted an annual survey of finance and economics professors, which was expanded to include analysts and corporate managers in 2010. In these surveys, respondents are asked what ERP they are using to calculate the *required* return to equity in different countries at that point in time. Since 2013, with the exception of 2016, the annual survey has also asked for the riskless rate assumption being used along with the reported ERP.

Fernandez (2004, 2023) portrays the ERP as embracing four different concepts: historical, expected, required, and implied ERP. In the context of the CAPM, he says, the model assumes that the required ERP is the same as the expected ERP.

The survey has gained some acceptance as a benchmark for ERPs, given its breadth of coverage, particularly outside the United States and among some US multinational corporations and private equity investors that need to value foreign operations. For example, the 2026 survey (Fernandez, Habibian, and Acín 2026) reported riskless rates and ERP results for 97 countries.

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[10] CAPE was developed by Robert Shiller at Yale University. It divides the current price on the S&P 500 by the trailing average of 10 years of inflation-adjusted earnings, smoothing out economic cycles.

[11] An unpublished paper (Siegel 2018), with a funny title ("She Caught the CATY and Left Me a Mule to Ride," a riff on a lyric from a Blues Brothers song), provides more color on CATY and adds a third source of cash flow to the investor: cash takeovers of companies in the index by companies (including private equity funds) not in the index. In Siegel's interpretation, this last source of cash boosts the supply-side estimate of the ERP by a not insignificant 0.6%.

[12] In his application of the DDM model, Damodaran assumes that the long-term growth rate for S&P 500 earnings (the perpetuity growth rate after the fifth year) is equal to the 10-year US Treasury yield. The basis for such an assumption is weak and during times of market dislocations may result in distorted ERP estimates.

Unfortunately, these surveys do not make clear whether the ERP forecast being solicited is of the arithmetic or geometric mean or relative to bonds or bills. The absence of this information makes the survey results difficult to interpret.

Issues in Numerical Calculation of the ERP

Measuring the ERP—the (past or prospective) difference between the returns on two assets or asset classes—sounds simple, but it is not. In this section, we examine some of the issues involved in calculating the ERP.

Arithmetic vs. Geometric Mean Differences (Risk Premiums)

One of the most contentious issues is whether the *arithmetic mean difference* or the *geometric mean difference* is the relevant measure for the ERP. As mentioned in Chapter 2, both are relevant but for different applications. Before exploring the calculation of *differences* between asset return series, let us first recall from Chapter 3 the distinction between the arithmetic and the geometric average (mean) rate of return on a *single series*. The arithmetic mean is the simple average of the periodic (say, annual) returns on an asset; the geometric mean is the compound rate of return that equates the beginning and ending values of an investment in that asset.

Chapter 2 reported that the Ibbotson Large Cap stocks total return index had an arithmetic mean return of 11.8% and a geometric mean return of 10.1% over the 1926–2025 period.[13] Over the same period, 20-year US Treasury bonds, which have less risk (a lower standard deviation), had an arithmetic mean total return of 5.4% and a yield return of 4.9%. The corresponding geometric mean total and yield returns were both 4.9%. The long-horizon arithmetic average ERP over this full-century period was thus 11.8% − 4.9% = 6.9%—that is, the arithmetic mean stock total return minus the arithmetic mean bond yield return.

When two arithmetic means are being compared, only the arithmetic difference (for example, $R_{A,Stocks} - R_{A,Bond\ Yield}$) is relevant. That calculation is how we arrived at the 6.9% arithmetic mean estimate for the ERP relative to bonds. To compare two geometric means, however, one could choose either the arithmetic difference between them, $R_{G,Stocks} - R_{G,Bonds}$, or the geometric difference, $\frac{1+R_{G,Stocks}}{1+R_{G,Bonds}} - 1$. The geometric difference provides a more precise answer and is always smaller than the arithmetic difference (for time series that have a nonzero variance, which is the case for asset returns).[14] **Exhibit 9.1** shows the ERP and other risk premiums.[15]

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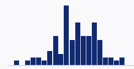
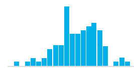
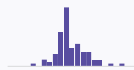
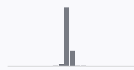
[13] These are summary statistics of annual returns, not annualized summary statistics of monthly returns.

[14] The geometric mean approaches the arithmetic mean when there is little variability in the time series.

[15] The arithmetic means shown are the mean of the risk premium time series created by subtracting the two basic asset class annual returns, and the geometric means shown are the geometric mean of the risk premium time series created as the geometric difference of the two basic asset class annual returns—that is, $\frac{1+r_A}{1+r_B} - 1$, where r_A and r_B are the annual returns on asset classes A and B, respectively. The population standard deviations shown are of the latter time series (the one created by geometric differencing).

Exhibit 9.1. Realized Risk Premiums on Ibbotson Equity and Bond Indices and Real Interest Rates, 1926–2025

	Compound Annual Return	Arithmetic Mean Annual Return	Risk (standard deviation)	
Long-horizon equity RP	4.9%	6.9%	18.4%	
Short-horizon equity RP	6.6%	8.5%	18.7%	
Small-stock RP	0.8%	2.6%	13.1%	
Bond-horizon RP	1.6%	1.6%	1.3%	
Real interest rate	0.3%	0.3%	3.9%	
				–90 0 90

Source: Calculated by the author from Ibbotson Indices data.

Notes: RP = risk premium. The risk measure is population, not sample, standard deviation.

Bonds vs. Bills as the "Riskless" Asset

In Chapters 2 and 4, as well as elsewhere in this book, we chose to use the 20-year US Treasury bond as the "riskless" or reference asset to which risky assets can be compared. The choice of a riskless asset should depend on the time horizon of the person doing the choosing. No asset is completely riskless (the prices of long-term bonds fluctuate; the yields of short-term bills fluctuate).[16] When one is estimating the ERP, however, the default-free bond should match as closely as possible the time horizon of the investor.

Because we are concerned with the picture facing long-term investors, we generally use the 20-year US Treasury bond as a proxy for riskless investing in this book. The maturity of such a bond may reasonably match (as closely as we can with a single bond maturity) a long-term investor's time horizon. In the context of corporate finance and valuation, where businesses are often valued as going concerns, the ERP is also typically estimated relative to a long-term government bond as the proxy for the riskless asset, as discussed later in this chapter.

[16] Treasury Inflation-Protected Securities (TIPS) are sometimes described as truly riskless, but they are not riskless. Although they are indexed 1:1 to the Consumer Price Index for All Urban Consumers (CPI-U), TIPS have risks, as enumerated by Pfau (2011). Importantly, liquidity issues in the TIPS market are well documented, with various authors developing models to estimate the TIPS liquidity premium for the US and other markets. See, for example, Andreasen, Christensen, and Riddell (2021). In addition to the risks listed by these authors, the main measure of inflation used by the US Bureau of Labor of Statistics, the CPI-U, may not match the inflation rate experienced by any given investor.

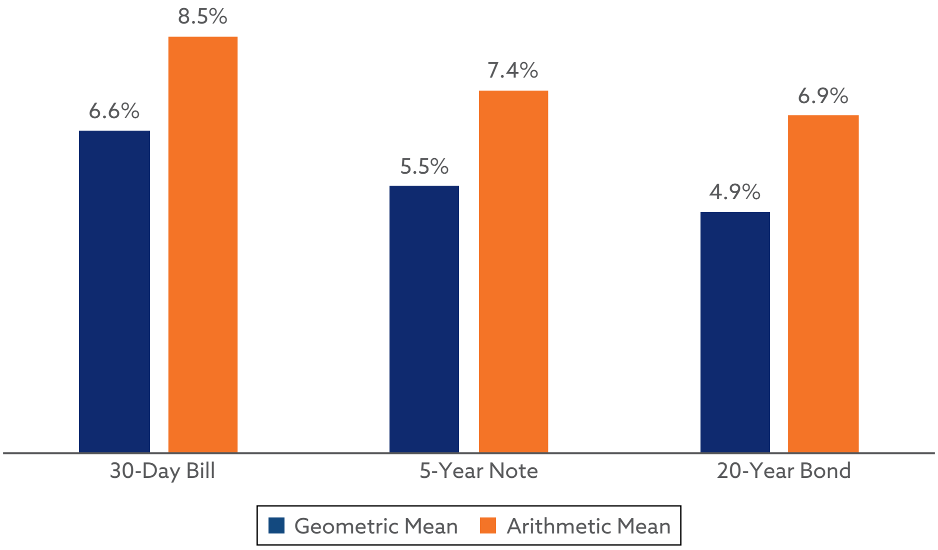
Thus, our entire discussion of the ERP in this book is based on the choice of a 20-year bond as the "riskless" asset. Some investors have other time horizons (or no particular horizon), however, and an ERP calculated on the basis of a different bond maturity can be useful for certain applications.[17]

In **Exhibit 9.2**, we illustrate the concept that realized ERPs will differ depending on the maturity selected for the riskless asset. This important concept is often ignored in practice but can result in significantly different ERP estimates.

Use of Bond Yield vs. Bond Total Return in Calculating the ERP

As was done in SBBI (for example, Ibbotson and Harrington 2020), we use the *yield* on the bond at the time of "purchase," not the total return over the time period the bond is held, as the relevant number to subtract from the equity total return in calculating the ERP. We do that because the yield at time of purchase is the expected return on the bond; any subsequent gains or losses from changes in market yields are *unexpected*. Because we are using measures of the realized ERP to ascertain what investors should and do expect in the future—that is, to make forecasts—we define the realized ERP as the actual return on stocks minus the return that the

Exhibit 9.2. Historical ERP: Geometric and Arithmetic Mean Premiums in Excess of US Treasury Bill, Note, and Bond Maturities, 1926–2025



Sources: Data from Ibbotson Large Cap stocks total return index and 30 Day Treasury Bills, CFI 5 Year T Notes, and CFI 20 Year T Bonds yield indices.

[17] For example, shareholder disputes involving the computation of lost profits or business damages (e.g., for patent or trademark infringement) tend to be focused on a shorter period (i.e., the period when losses/damages were incurred, which is often less than 20 years). In such cases, when quantifying the (present) value of such losses/damages, advisers will often use a maturity on the riskless asset commensurate with the period being evaluated.

investor *expected* on a particular long-term bond (i.e., the income return component, a reasonable equivalent for the expected yield at a given time).

In other words, because we are trying to ascertain what investors expected, we do not subtract the total return that the investor actually earned on the bond because that result includes unexpected surprises. Instead, we subtract the total return that the investor rationally expected at the beginning of the period.[18]

What Historical Period Is Relevant?

As we saw in Chapter 4, the decision of what historical period to use for estimating the ERP involves a tradeoff. The longer the period, the "tighter" the estimate (that is, the standard error of the estimate declines with the square root of the number of years). The farther back one goes in time, however, the more likely the estimate will include data from periods that are irrelevant because they are so long ago.

When the first Ibbotson and Sinquefield studies were published, 1926 to the present (at the time) was already a fairly long period, so investors and others in search of long-term historical data usually used that whole period.[19] There are reasons one might use a shorter or longer period, however. Starting the period after the chaos of the Great Depression and World War II can be defended on the basis of relevance. **Exhibit 9.3** shows how the ERP estimates change as one shortens the period. The average returns fluctuate, but the standard error goes up monotonically as the period becomes shorter.

A longer period has been used to support the claim of stationarity—that the relative returns of equities and bonds, unlike the absolute returns, are close to constant (Siegel 1994). Using more recently collected data, however, McQuarrie (2024) challenged this claim, showing that the realized ERP was lower in the nineteenth century relative to more recent periods (he reiterates this assertion in Chapter 10 of this book). If one links McQuarrie's data with the Ibbotson Indices, the resulting ERP over the whole 233-year period is surprisingly low.

In selecting a historical period, investors should balance the need for relevant data from markets that resemble those of today against the desire to use an ERP that is estimated with a low standard error.

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[18] Not everyone uses this approach to calculate realized ERPs. Some academics instead subtract the total returns on bonds from the realized equity returns when computing realized ERPs. See, for example, Dimson, Marsh, and Staunton (2025).

[19] Prior to September 2008, it was quite common for valuation practitioners to be comfortable using a realized ERP estimate (based on data starting in 1926) that was updated once each year. Following the bankruptcy of Lehman Brothers in September 2008, however, valuation analysts and other practitioners began to question the stability of their ERP estimate. In the aftermath of the 2008 global financial crisis (GFC), other sources of ERP estimates began being used in conjunction with or in lieu of the realized ERP with 1926 as the starting point. Some practitioners continued to use the historical series but began using different period averages as a proxy for the future. These include, for example, long-term averages starting after World War II, after 1957 (when the S&P 500 was created), or after 1963 (following the creation of the Compustat database).

On the institutional investor side, overly high or unstable ERP estimates were typically moderated by blending in supply-side estimates, and this practice began long before the GFC. Some investment bankers use shorter historical periods to calculate realized ERPs.

Exhibit 9.3. Historical (Geometric vs. Arithmetic) ERP in Excess of 20-Year Treasury Yield, Calculated over Various Periods

	Number of Years	Geometric Mean	Arithmetic Mean	Standard Error of Estimate
1926–2025	100	4.9%	6.9%	1.8%
1950–2025	76	5.4%	7.1%	2.1%
1960–2025	66	4.0%	5.3%	2.0%
1970–2025	56	4.3%	6.0%	2.2%
1980–2025	46	5.7%	7.5%	2.4%
1990–2025	36	5.8%	7.7%	2.8%
2000–2025	26	4.0%	5.8%	3.5%

Source: Data from Ibbotson Large Cap stock total return index and CFI 30 Day Treasury Bills, CFI 5 Year T Notes, and CFI 20 Year T Bonds yield indices.

Implementation Illustration

As discussed previously, the Ibbotson and Chen (2003) adjusted historical ERP (removing the growth in P/Es) became known as the "supply-side ERP" in various Ibbotson Associates and Morningstar publications, as well as subsequent publications by Duff & Phelps (later rebranded as Kroll).[20] To this day, practitioners refer to this method in court cases and other legal and regulatory contexts. For the purposes of this section, we will also call this method the "supply-side ERP."

To estimate the geometric mean expected ERP using the adjusted historical model or supply-side ERP, one would

- decompose historical equity returns into income return, inflation, EPS growth, and P/E expansion;
- subtract (geometrically) the rate of P/E expansion; and
- subtract (geometrically) the income return on 20-year US Treasuries.

To estimate the rate of P/E expansion, Kroll, following the example of Ibbotson Associates and Morningstar, uses a three-year average of S&P 500 earnings in the denominator rather than a single year's earnings. This practice smooths earnings volatility resulting from nonrecurring

[20] Morningstar published this estimate from 2006 (after acquiring Ibbotson Associates) until 2013, at which point it discontinued its cost-of-capital-related publications. Duff & Phelps, LLC, a global financial advisory firm, took over the work of updating those annual estimates in 2014. Following the acquisition of Kroll, LLC, in 2018, Duff & Phelps decided to rebrand itself as Kroll, a process initiated in 2021 and completed in 2022. To avoid ambiguity, Duff & Phelps, LLC, should not be confused with the unrelated Duff & Phelps Investment Management, a wholly owned subsidiary of Virtus Investment Partners.

items and changes in profitability and allows the earnings number used in the P/E to better reflect a normalized (long-term) trend. Thus, we have the following:

- Numerator (P): the current level of the S&P 500 index (or an equivalent index)
- Denominator (E): three-year average of index earnings based on (1) last year's reported earnings on the S&P 500, (2) the forecast of the current year's reported S&P 500 earnings, and (3) one-year forward projection of reported S&P 500 earnings

Using this methodology, Kroll's estimate of the compound annual growth rate of the P/E of the S&P 500 (and predecessor indices) from 1926 to 2025 is 0.85% per year.[21] This P/E growth rate can then be subtracted (geometrically) from historical S&P 500 total returns to arrive at an adjusted historical equity return:

$$\text{AHR} = \frac{(1 + \text{TR}_{S\&P\,500})}{(1 + g_{P/E})} - 1, \tag{9.2}$$

where

AHR = adjusted historical estimate of equity returns ("adjusted historical return")

$(1 + \text{TR}_{S\&P\,500})$ = geometric average return of equity index

$g_{P/E}$ = growth rate of P/E of equity index

Using this P/E growth rate of 0.85% and the 10.1% geometric mean return (rounded) on the Ibbotson Large Cap stock total return index for 1926–2025, we estimate an adjusted historical return (which we use as a proxy for the supply-side equity expected return) of $\frac{1 + 10.1\%}{1 + 0.85\%} = 9.2\%$. Then, subtracting (geometrically) the long-term bond yield, we arrive at an estimate of the geometric mean "supply-side" ERP:

$$\text{ERP}_{SS} = \frac{(1 + \text{AHR})}{1 + Y} - 1, \tag{9.3}$$

where

ERP_{SS} = geometric "supply-side" ERP

AHR = adjusted historical return

Y = 20-year Treasury bond yield[22]

In this illustrative example, the resulting geometric average adjusted historical return (or as it is known in practice, the "supply-side" ERP) is

$$\frac{(1 + 9.2\%)}{(1 + 4.9\%)} - 1 = 4.1\%. \tag{9.4}$$

[21] This estimate is from the Kroll Cost of Capital Navigator. Kroll drew historical S&P 500 earnings from two sources: (1) 1925–87 earnings estimated based on Wilson and Jones (2002) data and (2) 1988–2025 reported S&P 500 earnings from S&P Global.

[22] Yield as of 31 December 2025 (rounded).

Summary

We have presented a variety of ways to estimate the equity risk premium, including pure historical, adjusted historical, and other demand- and supply-oriented approaches. The results do not differ radically among the approaches, suggesting that all of them have something to contribute to the dialogue about how to best make this calculation. Most practitioners, in both investment management and corporate finance, use more than one of the methods presented here, including historical and forward-looking estimates and combinations thereof.

Key Takeaways

- The equity risk premium is the key element of the expected return on equities. Estimates of the expected ERP are useful in a large number of applications. These include asset allocation, financial planning, an element of the discount rate used in valuation, determination of the cost of equity capital (for corporate finance purposes), and as the crucial input to the CAPM.
- The expected or future ERP is a forward-looking concept, and no single universally accepted methodology exists for estimating it. It may or may not be equal to the realized or historical ERP.
- There are four broad categories of approaches to estimating the expected ERP: historical, demand oriented, supply oriented, and surveys.
- Most practitioners, in both investment management and corporate finance, use a combination of these methods, including both historical and forward-looking estimates.
- Realized ERPs will differ depending on how they are being measured. Differences arise from (1) the choice of a time horizon, that is, whether the riskless rate is considered to be the yield on a long bond, short-term Treasury bill, that is, some other maturity; (2) the use of geometric versus arithmetic averages; (3) the historical look-back period selected; and (4) the use of total return versus yield return on US Treasuries.
- Ibbotson and Sinquefield's (1976a, 1976b) original work was seminal in establishing a methodology for estimating the ERP and other risk premiums. Over much of the time since their original work, their ERP estimate, using the historical model, was dominant. Although other methods are now used in combination with the original one, their groundbreaking research is the foundation for capital market decisions still being made today.

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SECTION 3

Centuries of US and Global Returns

CHAPTER 10. US STOCKS AND BONDS BEFORE 1926

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Roger Ibbotson and Rex Sinquefield's "Stocks, Bonds, Bills, and Inflation: Year-by-Year Historical Returns (1926–1974)" (Ibbotson and Sinquefield 1976) can fairly be said to have launched the history of capital market returns as we know it today, influencing a generation of future scholars who came of age after its publication. As it became established through the annual publication of increasingly prominent Stocks, Bonds, Bills, and Inflation (SBBI®) yearbooks, historical inquiry began to widen beyond the calculation of risk premiums to include broader questions of what I will call "stationarity." For instance, by the 1990s, one could read in the financial press that since 1926, stocks have returned about 10% per year. Had it always been that way? Or had stock returns been different in the nineteenth century? In the same vein, the twentieth century saw a return on equities about 5 percentage points per year higher than on long-term bonds.[1] Had stocks always beat bonds by that much?

Jeremy Siegel (1994, 2022) gave a preliminary answer based on the early compilers of data that were available to him. He found stationary results back through the nineteenth century, reporting that the long-term return on stocks had always been between 6.5% and 7% in real (inflation-adjusted) terms, corresponding to the 10% nominal return seen in SBBI starting in 1926. And he found that stocks had almost always returned considerably more than bonds over multidecade holding periods. In time, Siegel's narrative came to be widely accepted. In his telling, the complete financial history of the United States appeared to be a superset of the period starting in 1926 that is chronicled in SBBI, not different in any material respect.

Unfortunately, some of Siegel's sources proved to be problematic. He relied on Smith and Cole (1935), Macaulay (1938), and Cowles (1939).[2] More recent data collection has challenged his synthesis.

Return to Primary Sources

New data collection began to gather steam in the late 1990s. Goetzmann, Ibbotson, and Peng (2001) were the first researchers in the 60 years since Cowles (1939) to go back to primary sources for nineteenth century data. They identified a key publication from 1815: *The New York Shipping and Commercial List*.[3] It recorded stock prices on the New York Stock Exchange and starting in 1825 regularly reported dividends. None of Siegel's sources prior to Cowles (1939),

[1] In the formal academic literature, "equity excess return" generally refers to the return in excess of short-term Treasury bills. Here, however, we mean the return in excess of long-term Treasury bonds.

[2] Other compilers drawing on these resources include Ibbotson, Siegel, and Love (1985) and Ibbotson and Brinson (1987, 1991).

[3] The first page of the issue for 21 February 1815 is reproduced in Forsyth (1964, p. 48). It shows stock prices from the day before, with 17 stocks listed, mostly bank and insurance firms, 13 of which included a price, along with four federal bonds and two city issues.

with his 1871 start date, had compiled a dividend series; early editions of Siegel had to infer dividend yields for 1802–1870.

Tabulation of prices and returns compiled by the Goetzmann team first appeared in Goetzmann et al. (2001). In fact, Siegel (2014) switched to their series for the 1825–70 period beginning with the fifth edition of his book.

As decades passed, limits of the Goetzmann et al. (2001) return series began to emerge.

- They did not find sufficient information on the capitalization of the stocks included and chose to use price weighting to calculate their index.
- The dividend record had many omissions.
- In the early years, a good proportion of stock trading took place on the street, after the auction calls on the exchange had identified who might want to buy or sell at what price. Confining the newspaper record to a single publication reporting the official record, as the Goetzmann team did, obscured the extent of early stock trading.
- The team also made the choice to compile only end-of-month prices. Because many stocks in the era did not trade every week or even every month—and certainly not in the official record—the Goetzmann et al. (2001) price record proved quite sparse relative to what could be found using a more relaxed criterion.[4]
- Last, the team projected the twentieth century dominance of the New York Stock Exchange back in time to the beginning. It later became apparent that before the Civil War, New York was only one stock market among several, with stocks listed on other exchanges accounting for the majority.

The next key data collection effort, which became available some years after Goetzmann et al. (2001), was led by Richard Sylla of New York University. Sylla undertook a broader canvas of newspapers back to the 1790s and searched for stock trading records in Philadelphia, Boston, and Baltimore, as well as New York (Sylla, Wilson, and Wright 2005).[5] Notably, the Sylla team also compiled federal, municipal, and corporate bond prices. Finally, the Sylla team took a catholic approach to stock price collection, not confining themselves to official exchange reports, end-of-month trades, or trade prices at all but also accepting bid–ask quotes and dealer price sheets as they appeared. They compiled a roughly weekly price series, with some stocks having an entry almost every week and others featuring a sparser record.

The resulting price record dramatically expanded the pre-1860 compilation of Goetzmann et al. (2001), with dozens of stocks in contrast to their handful and hundreds when they had dozens, as well as good coverage back an additional two decades to the early 1790s across multiple exchanges.

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[4] Thus, the Goetzmann et al. (2001) file has price quotes for only 7 of the 13 stocks with prices in the 21 February 1815 issue of the *New York Shipping and Commercial List*, which would not have been end of month.

[5] There were still other exchanges, and US stocks also traded in London, but these three markets in addition to New York accounted for the bulk of the record.

The new Sylla et al. (2005) record suffered from several of the same limits as the Goetzmann et al. (2001) record, however: There was still no information on share count to allow weighting of returns by market capitalization and in the Sylla case, no dividend compilation at all. The Sylla team also chose to leave the price record in raw form and did not construct an index as the Goetzmann team had done.

Arriving on the scene two decades later, I enjoyed a crucial advantage over previous compilers: the ongoing digitization of (almost) everything. It was no longer necessary to send teams of research assistants into the dusty archives to turn the pages of crumbling newspapers and peruse them one by one in search of a dividend announcement or stock price. Historical newspaper databases had proliferated, with vast quantities of scanned text now searchable by keyword. And not only newspapers: I found almanacs, registers, municipal histories, railroad manuals, and more in one digital archive or another.

Given these new resources, I set out to cull and curate the raw Sylla price data into a capitalization-weighted index of price return, using almanacs and other resources to track down the share counts that had been missing from prior work. I also found that the custom in the early decades was to publish a dividend announcement in the format of what we would call a classified ad. A simple keyword search, pursued across cities and years, in conjunction with early dividend compilations dating to 1819, produced hundreds of additional dividends to supplement those in the Goetzmann et al. (2001) database. Using the newly collected data, I constructed a capitalization-weighted index of total return for a broad stock market index dating from January 1793, which I linked first to the Cowles (1939) record beginning in 1871 and then to the CRSP record at the end of 1925, producing a stock return series now more than 230 years in length (McQuarrie 2024a).

Stock returns are generally best reported on a closing-price to closing-price basis (month-end close in the case of monthly data). In constructing pre-1926 stock returns, however, I found that in many cases, stock prices were reported infrequently, either because the stocks themselves traded infrequently or for other reasons, such as delayed or insufficient reporting. Given these constraints, I had to resort to other methods. Because close-of-year quotes are not always available, any December quote that is available could be out of date and not capture the year-end total return. So, I used January because it does capture the year-end; and to arrive at a January quote, I took an average of the price quotes in January or an average of the January low and high, depending on the source. As a result, returns reported for a given year—say, 1793—are January 1793 to January 1794.

In the spirit of SBBI, I also set out to compile a bond return index that could be compared to the new stock return index, allowing an assessment of the excess return on equities over a much longer timespan. On the first pass, I included corporate bonds, which began to appear in the 1830s and which dominated trading in the US fixed-income markets from the 1880s until World War I (McQuarrie 2024a). However, I received criticism that corporate bonds, with their idiosyncratic risks, were inappropriate in studies of the equity excess return or risk premium. I later redid my bond index to consist exclusively of government bonds, targeting a maturity of

20 years, which could be linked to the SBBI long government bond series that starts in January 1926 (McQuarrie 2024b).[6]

The remainder of this chapter examines these updated two-century records of stock and bond returns in the United States, with a focus on stationarity: what elements stay the same across the December 1925 boundary and what aspects are different or distinctive in the newly compiled pre-1926 record.

Comparability of Pre-1926 and Post-1926 Data

Before proceeding to the new pre-1926 data, the reader needs to be cautioned about the data's comparability to the post-1926 SBBI data compiled by Ibbotson and Sinquefield. The SBBI data begin in 1926 for a reason. Ibbotson and Sinquefield believed that the stock market was different enough in the early twentieth century that collecting data from that period might be fruitless or misleading. To go back yet another 50 or 100 years would mean studying a very different stock market. If anything, the government bond market of the 1800s was even more alien, relative to the vast, liquid twentieth century Treasury market, with its fully populated maturity spectrum and a minimum of risk.

At the beginning of the nineteenth century, the United States was an emerging nation and its bonds, although guaranteed by the full faith and credit of the Treasury, then as now, can hardly be treated as risk-free instruments.[7] There were only a few bonds outstanding at any point, almost all bonds were long bonds at issue, and early bonds had no stated maturity. There were no Treasury bills. Under the gold standard, a Treasury default was both conceivable and something to be feared. A Treasury bond was designed to pay in gold and be redeemed for gold. If the government vaults did not have enough gold—and there were several close calls in the nineteenth century—default would occur, in a way that cannot happen under today's fiat currency, which can be printed as needed. In short, whether issued by the government or not, these bonds should be regarded entirely as *risky* instruments, in no way a proxy for the risk-free rate of return.

The stock returns that follow are, like today's returns, based on the common shares of enterprises that were legally structured in much the same way as today's corporations. Thus, at first glance, the stocks of 1825 look more similar to today's stocks than the government bonds of 1825 do to today's bonds.

But a closer examination reveals a wider gap. By 1926, there was a Standard Statistics index of 90 stocks spread across several dozen sectors, along with well-populated Dow Jones averages separately calculated for industrial, railroad, and utility stocks. A hundred years prior, however, there were just a few dozen banks, each (other than the Second Bank of the United States) a single-branch local bank, along with a couple of canals and a scatter

[6] In this second effort, I drew primarily on the compilation of Hall, Payne, and Sargent (2018), who had assembled and organized federal bond data from the beginning through 1925 using the Sylla et al. (2005) compilation, the *Commercial and Financial Chronicle*, and other sources.

[7] There are also gaps in the series for which municipal bonds had to be substituted for Treasuries (McQuarrie 2024b).

of turnpikes.[8] The entire transportation sector had the capitalization of a single large city bank at that time.

Later, by 1850, banks no longer traded on the exchanges, canals and turnpikes had succumbed to railroads, and the US stock market consisted of a single sector: railroads. Railroad stocks would dominate exchange listings until the 1890s, when industrials began to proliferate. There is a good reason the Dow Jones Industrial Average dates back only to 1896: Before that point, there were not enough industrials trading in New York City to make up an index.

Just as a Treasury bond with no maturity date issued by an emerging nation under the gold standard is very different from a US Treasury bond in 2025, so also a 26-mile single track railroad running between Boston and Lowell, Massachusetts, is very different from a company such as Sears, Roebuck & Co., selling every product imaginable to a nationwide market. And perhaps even more so, a local bank in Philadelphia is different from a global bank, such as JPMorgan Chase.

After some debate, I decided to present the data on stock and bond returns before 1926, for what they are worth, on the theory that it is better to make them available for the reader to scrutinize than to ignore or exclude them—caveat lector.

Equity and Bond Returns Compared

Exhibit 10.1 shows real wealth indices for stocks and bonds, assuming an investment of $1 in January 1793 held through December 2023, with a vertical line drawn at 31 December 1925.

It is apparent at a glance that stock and bond returns look very different on either side of the year-end 1925 line. On the more familiar right side, stocks return far more than bonds, as the two wealth lines diverge. Stock wealth accumulated through the first 150 years was about double that of bonds, but over the most recent eight decades, the wealth gap in favor of stocks grew to almost 300 times.

In the nineteenth century, the performance of stocks and bonds resembled a horse race, with one moving ahead and then the other. Only after 1900 did stocks move into an apparently permanent lead, except for the bottom of the Great Crash in 1932. And only after World War II did the return on stocks soar far above the return on bonds.

Exhibit 10.1 indicates that the excess return on stocks has not been stationary over time. Note that I am not referring here to the equity risk premium (ERP) as defined in this book; the realized ERP is the total return on stocks minus the *yield*, not the total return, on bonds (see Chapter 9).

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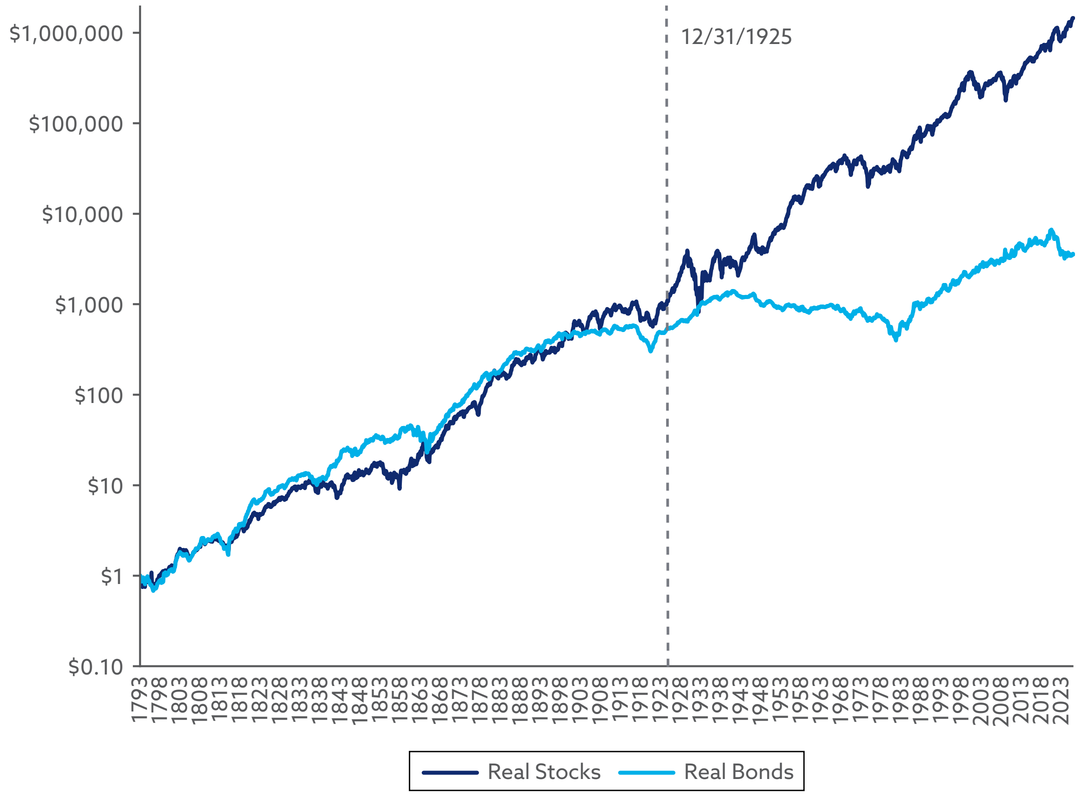
[8] There were also insurance stocks, especially in New York (see Goetzmann et al. 2001). I excluded these in McQuarrie (2024a) out of concern that the Great Fire of December 1835—which caused the bankruptcy of nearly all the fire insurance firms in the city, with share prices going to zero—would depress market returns in a way that might not be pertinent to the present day. Subsequently, I found that on a total return basis, adding back the insurance sector would have only mildly depressed reported market returns, by 0.07 percentage points annualized over 1799–1845 (McQuarrie 2025).

Exhibit 10.1. Stock and Bond Returns, January 1793–December 2023



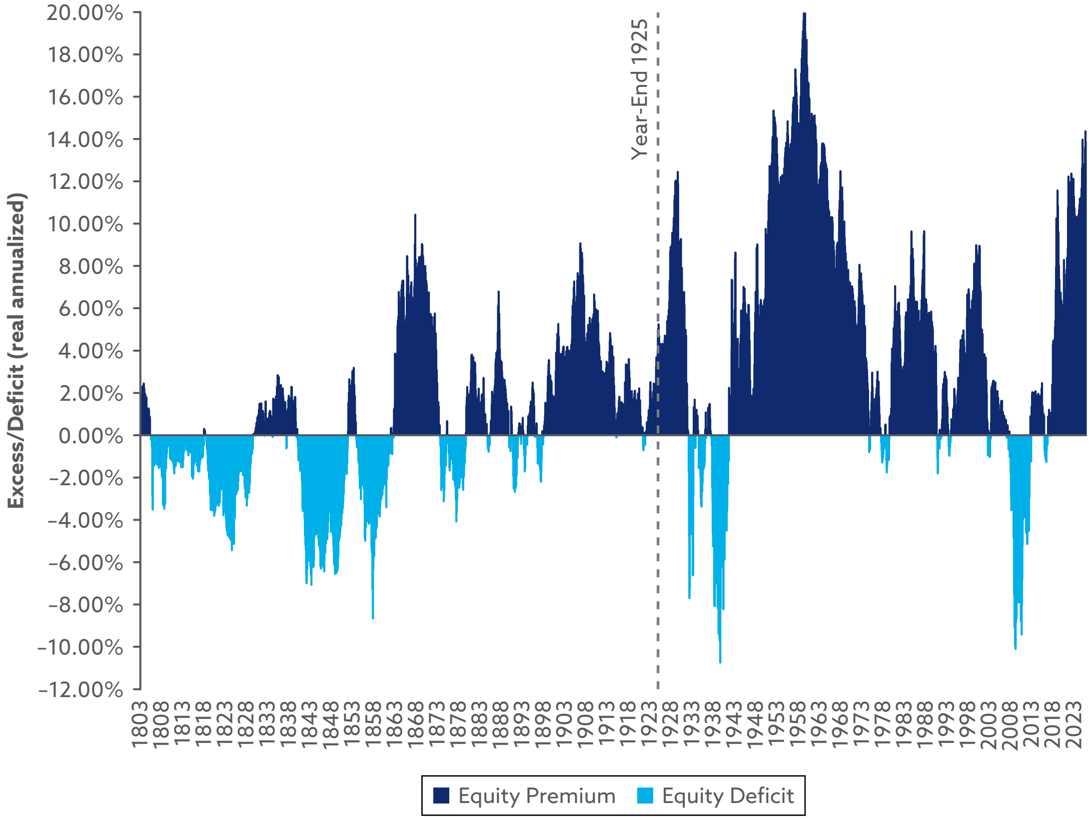
Sources: McQuarrie (2024a, 2024b).

Notes: These are the stock returns from McQuarrie (2024a), re-expressed monthly, and the long government bond returns from McQuarrie (2024b), collected at a monthly frequency. These are real returns, deflated by the Warren and Pearson (1935) index of wholesale prices until 1913 and the CPI thereafter. Note that McQuarrie (2024a), like Siegel (1994) and unlike SBBI, uses the CRSP total market index for stock returns starting in 1926, not the S&P 90 or S&P 500. Government bond returns in this exhibit are lower before and after 1900 than the corporate bond returns used in McQuarrie (2024a). The *y*-axis is a logarithmic scale.

Exhibit 10.2 provides a more fine-grained exploration of how the excess equity return has fluctuated. For this exhibit, the annualized real return on stocks and bonds was computed over the trailing 120 months, and then the bond return was subtracted from the stock return. There are 2,652 such rolls.

It was already apparent in Exhibit 10.1 that December 1925 does not mark the exact turning point or change in regime. Exhibit 10.2 indicates more clearly that the regime change occurred at about the turn of the century, as stocks moved into the lead after decades of underperforming bonds. The 10-year excess or deficit of the equity return looks quite different before and after 1900. During the nineteenth century, an equity *deficit*, in which stocks returned less than bonds over the trailing 120 months, was about as common as an excess. The cumulative excess equity return did not turn positive until just after 1900. Before then, given an anchoring

Exhibit 10.2. Historical Equity Premium over the Trailing 120 Months, January 1803–December 2023



Sources: McQuarrie (2024a, 2024b).

in January 1793, there had been a cumulative equity deficit. Stocks in the nineteenth century suffered setbacks after the Panic of 1819, the Panic of 1837, the Panic of 1857, the Panic of 1873, and the Panic of 1893. As Exhibit 10.1 showed, each time stocks came close to overcoming bonds, a panic got in the way, until about 1900.

After 1900, substantial equity deficits have occurred only in times of great crisis, as in the 1930s or in 2007–2009. Even modest equity deficits, such as the one in the late 1970s, are uncommon relative to the nineteenth century experience. Conversely, an excess return on equities, as expected by theory, became the norm, and several of the bars in Exhibit 10.2 after 1900 stretch higher than anything seen in the nineteenth century, such as for the 10 years ending in 1959—a blowout where the excess equity return reached almost 20 percentage points. Even when not so extreme, after 1900, equity excess returns are common, sometimes persisting for decades, in stark contrast to the nineteenth century experience.

Inflation

The results in Exhibit 10.1 are in real terms, after adjusting for inflation. One possible explanation for why the pre-1926 results look so different is the very different behavior of price inflation under the gold standard that prevailed until February 1934 in the United States. The course of prices across the watershed event of the end of the gold standard is so different that two charts are required, given that the second requires a scale 7 times that of the first. Panel A of **Exhibit 10.3** shows the course of inflation from 1793 to 1934. During the War of 1812 and the Civil War, prices doubled or even tripled but then fell back to the starting point. Over the entire 141 years, the value of the inflation index was confined between 0.70 and 2.40 (January 1793 = 1.0).

World War I saw the same tripling of prices. In contrast to the War of 1812 and the Civil War, however, that price peak was never entirely undone, declining only 40% from the 1920 peak to the 1933 low. The nineteenth century pattern of abrupt inflation during war and slow and relentless deflation during peacetime had been broken. In fact, President Franklin Roosevelt's purpose in devaluing the dollar was to break the deflationary spiral.

Exhibit 10.3. Inflation and Deflation During and After the Gold Standard Era

A. Gold Standard Era, January 1793–February 1934

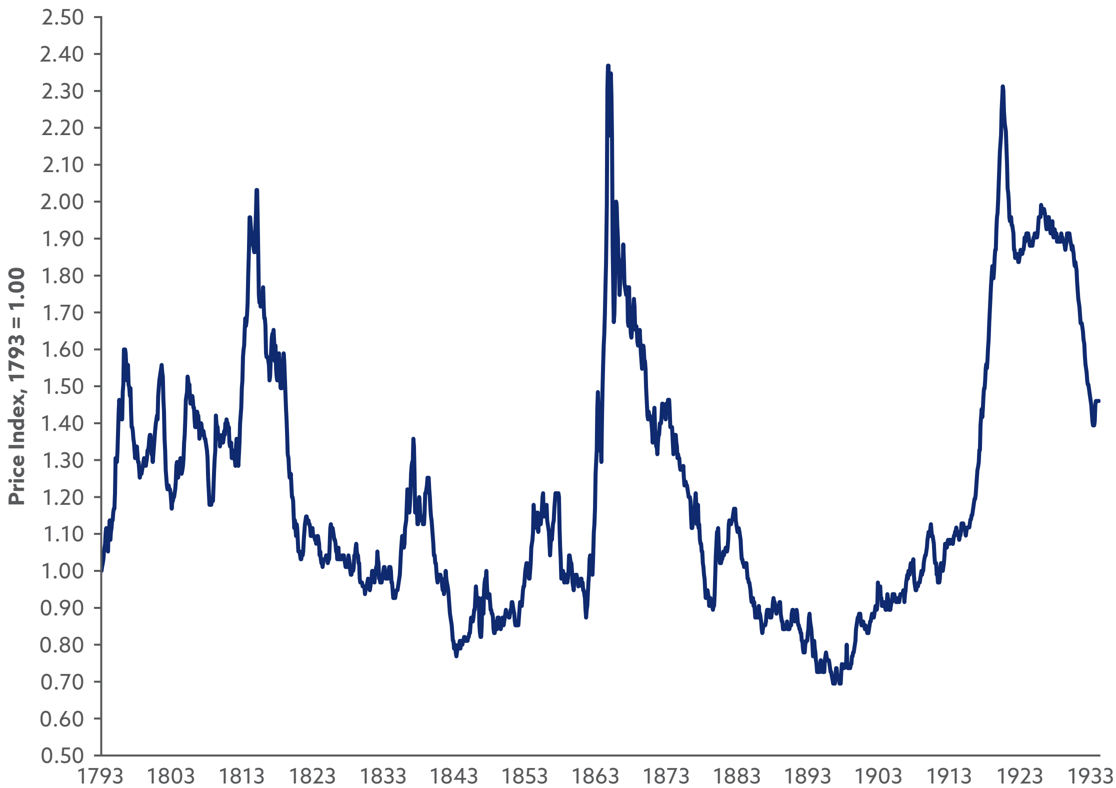
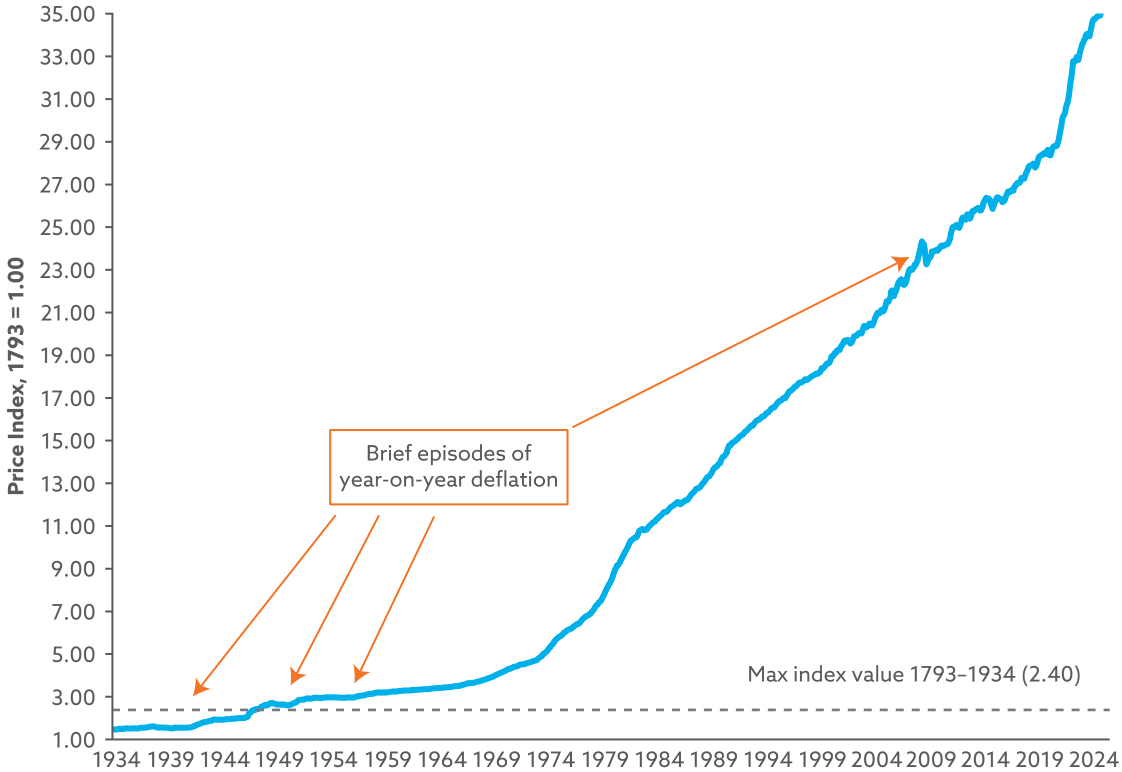


Exhibit 10.3. Inflation and Deflation During and After the Gold Standard Era (*continued*)

B. Fiat Currency Era, 1934–2025



Sources: Series CPIAUCNS obtained from FRED. Calculations by the author.

Note: The four deflationary episodes saw maximum 12 month drops of 4.11%, 2.87%, 0.74%, and 2.10%.

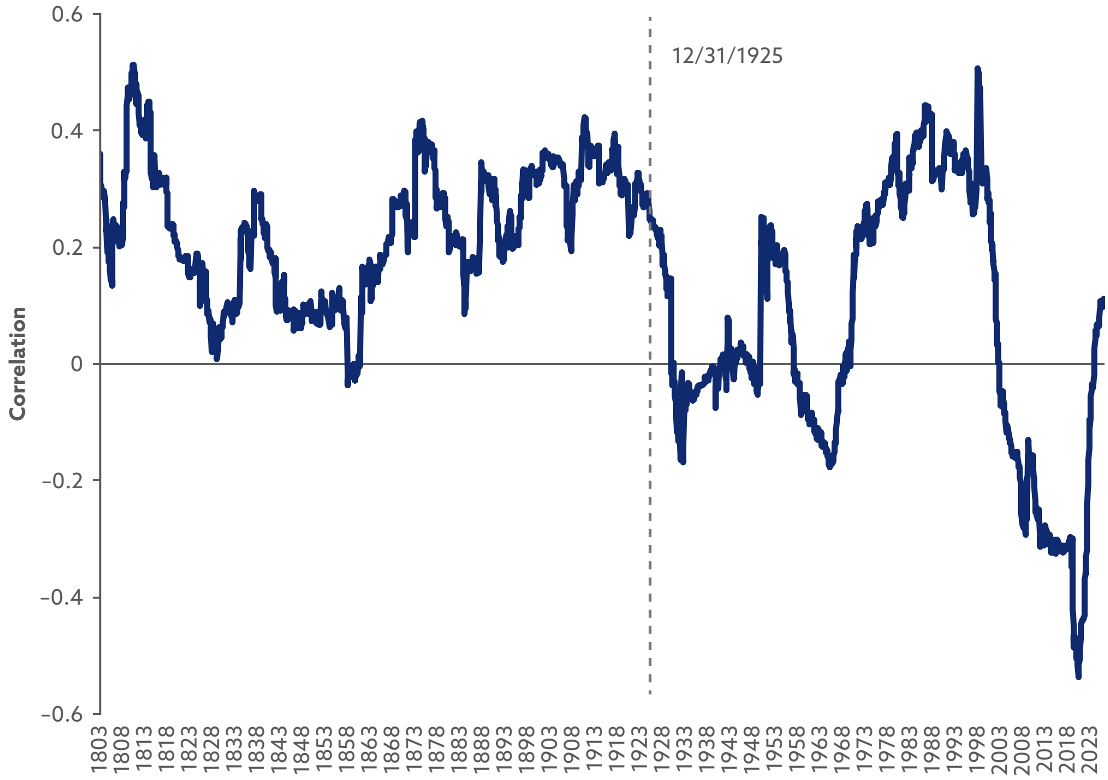
Under the fiat currency in force since 1934, the pattern of inflation looks very different (Panel B of Exhibit 10.3). With the exception of a few brief episodes, deflation has been banished. Prices only go up, at a pace that varies. The regime has changed. It appears that deflation cannot be sustained in a fiat currency system.

In a two-century view, the presence of sustained deflation emerges as a condition required for an excess return on equities (McQuarrie 2026).

More Evidence of Nonstationarity

Exhibit 10.4 shows the correlation between stocks and bonds over the trailing 120 months, with the chart again divided before and after 1926. As with the equity excess return over bonds, a change of regime seems to have occurred. Before about 1926, the stock and bond correlation varied within a relatively tight range centered on r = 0.20, with only a few

Exhibit 10.4. Correlation Between Stocks and Bonds over the Trailing 120 Months, January 1803–December 2023



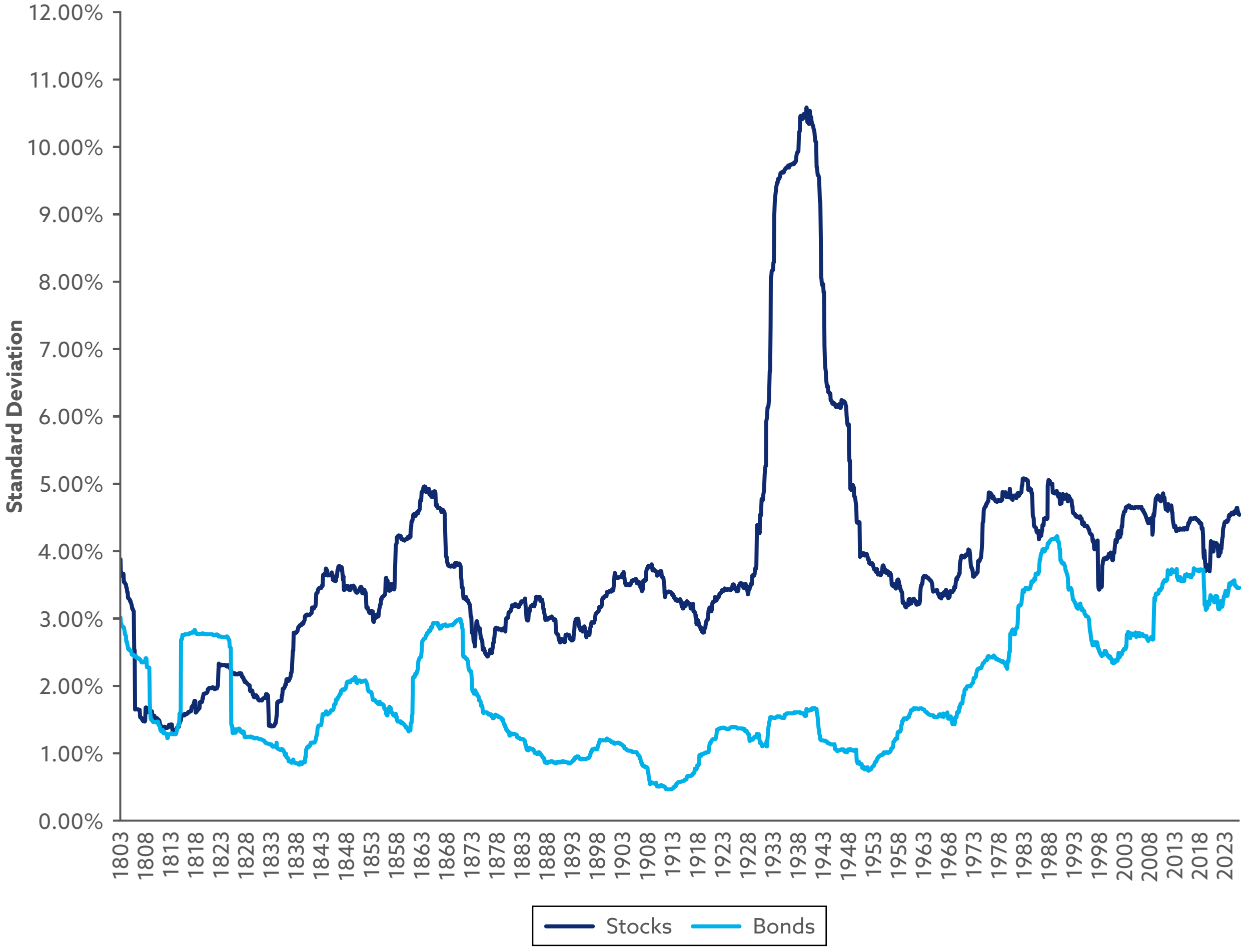
Sources: McQuarrie (2024a, 2024b).

cases where it fell toward zero. After 1926, the correlation began to swing more and more wildly, dropping well below zero, then surging, then dropping even further below zero, then surging, and then plunging again, with abrupt changes in direction over the course of a brief interval.

Clearly, the stock–bond correlation has not been stationary over the trailing two centuries, even when measured over 120 monthly observations. And as with the equity excess return, there appears to have been a change in regime.

Exhibit 10.5 shows the standard deviation of stock and bond returns over the trailing 120 months. There is again evidence of nonstationarity, but the picture is more complex, especially for stocks. Taking the simpler bond pattern first, one can observe a long stretch of very low volatility across the decades before and after 1900, punctuated before and after by sharp upswings and downswings, some associated with wars and some not. In recent decades, bond volatility has been sustained at levels seldom seen in the past.

Exhibit 10.5. Standard Deviation of Stock and Bond Returns over the Trailing 120 Months, January 1803–December 2023

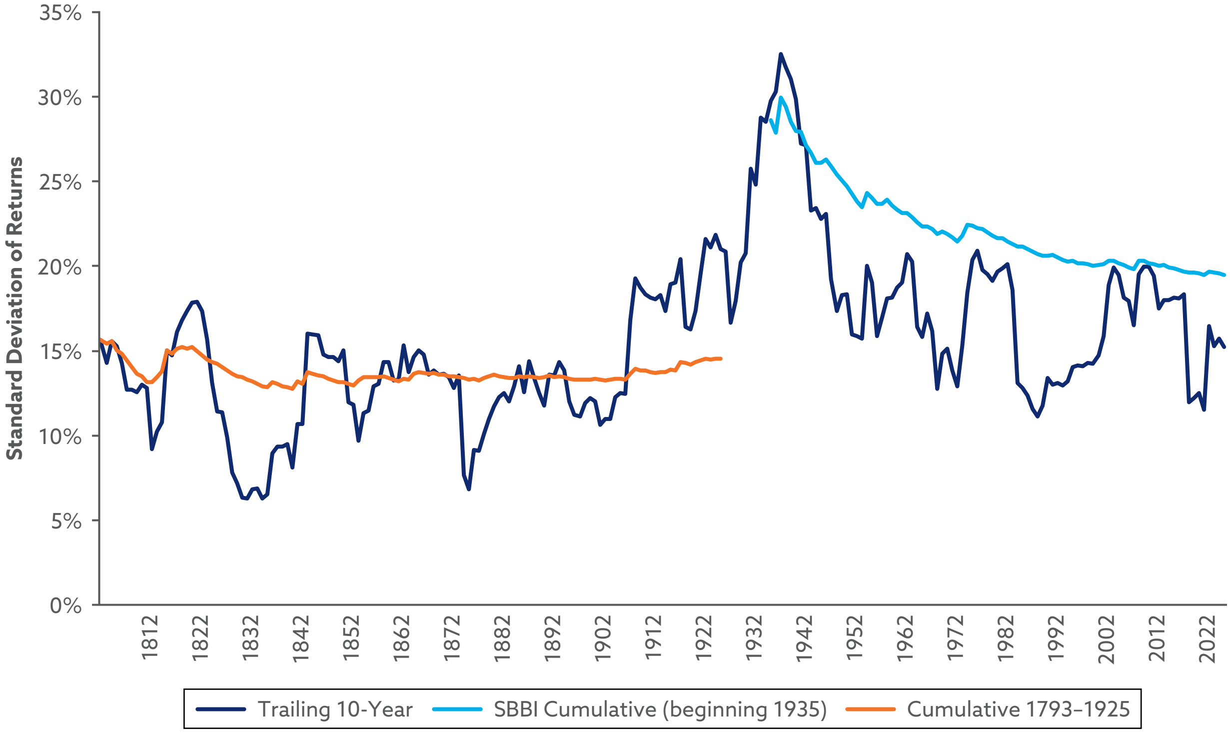


Sources: McQuarrie (2024a, 2024b).

Notes: These are monthly standard deviations. See Exhibit 10.6 for an annual representation for stocks.

Stock volatility is the puzzle. The stock line gives the impression of a rude gesture. To probe further, **Exhibit 10.6** reverts to the more familiar pattern of the standard deviation (SD) of annual returns, now over the trailing 10 years.

Exhibit 10.6. Annual Standard Deviation of Returns on Stocks Before and During the SBBI Period, January 1803–December 2023



Sources: McQuarrie (2024a, 2024b).

The orange line in Exhibit 10.6 shows the volatility of stocks over the first 133 years as it would have appeared to an observer as of year-end 1925. That volatility measure is itself volatile over any given 10-year period (dark blue line) but averages on the low side, under 15%. Then, beginning in the 1920s, volatility soared to a peak never before seen. Stocks went way up from 1924 to 1929, way down from 1929 to 1933, way up from 1933 to 1936, and then suffered one of their worst single-year plunges in 1937.

The light blue line picks up the story as it would appear to an observer whose time horizon began at the end of 1925 (i.e., one who had only the SBBI data available). The first estimate of trailing 10-year volatility available to that observer is December 1935, the leftmost value on the light blue line. Realized volatility rather quickly declines after the 1930s (dark blue line), reaching the low nineteenth century levels by the 1960s. But the light blue line, which shows average volatility anchored to a 1926 start, stays high for a long time. Observers who could only observe data starting in 1926 readily concluded that stocks were by their nature very volatile, with a standard deviation on the order of the 22% initially reported in Ibbotson and Sinquefield (1976). In fact, a truncated history made it impossible to see how that estimate of long-run volatility was biased upward by a single outlier event.

The standard deviation results show the biasing power of a short but extreme regime shift. Not even 100 years' time has sufficed to dilute out the extreme volatility of the 1930s. The nonstationarity of stock volatility parallels that of the equity excess return, with the one-off blowout around 1959—an equity excess return of 20 percentage points per year over 10 years—likewise acting to bias the 100-year estimate of the equity excess return over 1925–2025.

Limitations of Pre-1926 Data

In this section, I examine the shortcomings of stock and bond data prior to 1926.

Stocks

The first stock data limitation is statistical: Estimates of stock return prior to 1926 are at best monthly, and the monthly observation is often not a closing price but an average of prices in the month, with monthly return based on a comparison of those two monthly averages. The trade record was too sparse and spotty to permit anything more exact.[9] This procedure tends to blunt measured variance (Schwert 1990). Variance is further blunted by the use of interpolation to fill gaps in the price data. Generally speaking, analyses that require precise estimates of the volatility of point-sampled prices cannot be performed on pre-1926 stock data as currently compiled.[10]

The second limitation concerns imprecision more broadly. The ex-dividend date is not observed prior to 1926. Prices averaged over the month may thus include with-dividend and ex-dividend prices. There may also have been no trade in the stock for several months, requiring interpolation. As noted, the Sylla et al. (2005) series that I curated contains a mix of "prices." Almost all the raw entries are paired, representing a bid–ask spread, the weekly high or low, or some other combination, rather than a single closing trade price. These too are averaged, further obscuring the exact character of short-term price movements.

The third limitation is the small number of stocks trading at most points in the nineteenth century. Cowles (1939) started in 1871 with 48 stocks and did not include 100 until about 1900. McQuarrie (2024a) started with 4 stocks in 1793, had dozens by about 1802, and had more than 100 briefly during the 1830s. After trading in bank stocks dried up following the Panic of 1837, there were only railroad stocks, again with a few dozen to start, increasing to more than 50 by the 1860s.

A concomitant limitation concerns sectors. The McQuarrie index is mostly a single-sector index for the first three decades (banks), briefly a two-sector index in the 1830s and 1840s (banks and transportation), and once again a single-sector index through the Civil War (railroads). From the beginning, Cowles sought a three-sector index—railroads, utilities, and industrials—hence the choice of the 1871 start point, as far back as Cowles thought he could go and still have three sectors. His effort succeeded, but only if one accepts a canal as a utility and a coal mine as an

[9] For what it is worth, Cowles (1939) also took monthly prices to be the midpoint of the high and low price, and Shiller's (2015) version of the S&P indices continues that procedure to the present day.

[10] A promising avenue for research on volatility would be to return to the raw Sylla et al. (2005) data, which are often weekly, and develop an estimation procedure that respects the warts and flaws in those data, such as varying frequency of observation and many missing values.

Exhibit 10.7. Detail of Bonds Included in US Government Bond Returns, 1793–2023

Bond Name	Period Included	Maturity Range	Notes
Hamilton 6s	1793–1816	?	No maturity date
War 6s	1816–1824	?	The bond issued in 1813 with redemption "after 1826" was used until redemption seemed certain
Hamilton 3s	1824–1829	?	Better trading record than the 4.5s and 5s
Philadelphia 5s	1829–1843	?	Best trading record among the nondefaulting, highly rated municipal bonds in Sylla et al. (2005)
US 6s issued 1842–43	1843–1848	20–15	Replaced to extend maturity
US 6s maturing 1868	1848–1859	20–9	Held until nine years remaining, waiting for 5s of 1874 to become available
US 5s maturing 1874	1859–1862	15–12	Replaced after a higher-coupon, longer-maturity bond became available
US 6s maturing 1881	1862–1871	19–10	Held until 10 years to maturity; alternatives were callable
US Consol 6s due 1888	1871–1877	17–11	Swapped out at 11 years because new 4.5s outperformed from the outset
US 4.5s due 1891	1877–1880	15–11	Later swapped for a similar coupon and much later maturity
US 4s due 1907	1880–1896	27–11	Later swapped for a much longer maturity
US 4s due 1925	1896–1902	29–23	Held until yield gap under municipals widens
S&P municipals	1902–1908	10	Returns calculated from yields according to Shiller's formula; maturity imputed not observed
NYC 4.5s of 1957	1908–1919	49–38	Observed price, liquid trading, and longer maturity argued for replacement of Standard & Poor's municipals
Fourth Liberty bonds (4.25s due 1938, callable 1933)	1919–1923	19–15	Most suitable of the new Liberty bonds
4.25s due 1952, callable 1947	1923–1926	29–26	Extend maturity

Source: McQuarrie (2024b).

Notes: See McQuarrie (2024b) for more details. All periods run from January to January.

industrial. Only after 1900 can multiple sectors, as we would use the term today, be identified on the NYSE, with multiple subgroups of industrials.

Bonds

The situation is somewhat better for the government bond data, which are typically end-of-month prices. But even here, there are numerous instances where linear interpolations had to be made across missing months. The fact that Treasury bonds could go months without a recorded trade serves as a reminder of how different the US bond market was before the supply of Treasuries exploded during and after World War I.

A second limitation is that although all bonds in the new series are government bonds, that label obscures the heterogeneity of the constituents (see **Exhibit 10.7**). The Hamilton bonds that anchored the series before 1829 had no stated maturity. President Andrew Jackson paid off the debt in 1835, and that imminent payoff was taken as a given upon his election in late 1828, rendering all federal bonds short term in fact. No long Treasuries were traded again until 1842. A Philadelphia bond series was substituted, also without a maturity date. It was one of the very few municipal bonds with a good price record that did not default or plunge in price to a level indicating an expected default during the crisis of 1837–1842.

After 1842, there is a good record of federal bonds through the end of the century. By 1902, however, the Treasury market had almost dried up, as banks bought Treasuries to secure note circulation, and yields were depressed below economic values (Macaulay 1938). A municipal index with unknown constituents, coupons, and maturities was substituted until 1911, followed by a single municipal issue until 1918, when the Liberty bonds became available. Starting in 1922, the series used the long bond initially included in SBBI and then continued with the SBBI long bond series. As with the SBBI series, the bond index uses one government bond at a time, except in 1902–1911. A bond was replaced whenever the addition would lengthen the maturity back out to near 20 years. The goal was an index of long bond returns comparable to the later SBBI series.

A third limitation concerns early quoting practices. It is unknown which prices were flat and which were with interest.[11] Spreading each coupon across the six months and reinvesting it at the observed month-end price or an interpolation of the price is hardly an exact measure on par with the CRSP Treasury database that starts in 1926.

A final noteworthy characteristic is the focus on long bonds and the commitment to total return as the metric. T-bills did not exist before the 1920s, and short-term Treasuries were rare before 1926. Nor was anything like an intermediate series available; 10-year Treasuries were issued now and then over the decades but never regularly or repeatedly, such that no series could be compiled.[12] No long-duration bond, government or otherwise, can be regarded as risk free. Waves of capital appreciation and depreciation are the order of the day in any refreshed index of long bonds.

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[11] A bond price that is quoted "with interest" includes interest accrued since the last coupon date. A bond price quoted without accrued interest is known as the "flat price."

[12] The 10-year government bond series reported in Shiller (2015) uses a proxy before 1954, when the Constant Maturity series was launched by the Treasury. The proxy measure is particularly problematic before the 1890s because of how the source (Macaulay 1938) transformed the raw data. It is also not without problems on either side of the advent of the income tax in 1913, because it uses a municipal series until 1920. See McQuarrie (2024b) for an extended discussion.

More generally, government bonds in the United States in the nineteenth century must be regarded as riskier than contemporary Treasuries. The United States before 1871 might best be characterized as an emerging market with uncertain prospects. In addition, under the gold standard, government default is always a possibility. Given the many risks, nineteenth century investors arguably should have demanded a higher return from sovereign bonds.

The overall limitation of the bond series reported in this chapter is thus its risky character. That feature makes it unsuitable for calculating the ERP as that term is used elsewhere in this volume.

In sum, the nineteenth century data are sufficiently detailed to provide a rough estimate of the level of returns, to enable comparison of stock and bond returns, and to show nonstationarity between one century and another. But the use of total returns instead of yields and the presence of currency and default risk place the bond series at three removes from what would be required to estimate an equity risk premium.

Annual total returns (nominal) for US stocks and bonds, as well as inflation rates, appear in **Exhibit 10.8** for the reader to study and use.

Exhibit 10.8. Inflation and Annual Total Returns (Nominal) on US Stocks and Bonds

Year*	Stocks	Bonds	Inflation	Year*	Stocks	Bonds	Inflation
A. 1793–1874							
1793	–8.26%	–1.10%	11.58%	1812	10.74%	5.68%	18.11%
1794	20.95%	15.40%	16.98%	1813	7.63%	–0.38%	24.00%
1795	10.35%	–4.69%	13.71%	1814	–8.10%	–11.23%	3.76%
1796	–3.94%	–0.91%	–0.71%	1815	13.56%	36.06%	–17.10%
1797	14.01%	9.60%	–9.29%	1816	4.80%	6.80%	–5.00%
1798	8.84%	10.31%	–2.36%	1817	26.00%	13.18%	–1.97%
1799	6.27%	8.28%	2.42%	1818	–14.63%	0.51%	–5.37%
1800	14.29%	19.33%	10.24%	1819	–5.44%	9.51%	–19.15%
1801	13.88%	16.81%	–10.00%	1820	6.55%	11.63%	–12.28%
1802	14.88%	7.84%	–10.32%	1821	12.24%	4.42%	9.00%
1803	4.40%	2.65%	8.85%	1822	–4.21%	2.69%	–4.59%
1804	0.16%	2.69%	13.82%	1823	7.48%	5.93%	–5.77%
1805	0.14%	7.90%	–2.14%	1824	14.90%	16.29%	–1.02%
1806	11.08%	13.21%	–4.38%	1825	2.29%	–4.32%	6.19%
1807	0.30%	4.38%	–5.34%	1826	5.43%	1.27%	–3.88%
1808	15.46%	12.91%	0.00%	1827	4.01%	10.64%	–1.01%
1809	7.74%	5.49%	3.23%	1828	4.22%	0.58%	4.08%
1810	–2.42%	5.55%	3.12%	1829	5.24%	7.65%	–10.78%
1811	2.78%	3.06%	–3.79%	1830	12.89%	5.18%	0.00%

(*continued*)

Exhibit 10.8. Inflation and Annual Total Returns (Nominal) on US Stocks and Bonds (*continued*)

Year*	Stocks	Bonds	Inflation	Year*	Stocks	Bonds	Inflation
1831	5.03%	5.65%	9.89%	1853	−10.76%	6.43%	9.38%
1832	1.48%	7.19%	−4.00%	1854	−12.07%	0.92%	1.90%
1833	1.06%	2.72%	−4.17%				
1834	10.58%	−0.32%	0.00%	1855	−2.03%	5.11%	0.93%
				1856	14.65%	6.25%	2.78%
1835	11.28%	0.19%	16.30%	1857	−15.00%	0.93%	−16.22%
1836	2.07%	3.88%	14.95%	1858	11.35%	2.00%	2.15%
1837	−2.76%	−0.43%	−8.94%	1859	0.73%	2.31%	−1.05%
1838	9.13%	7.74%	4.46%				
1839	−16.49%	1.61%	−15.38%	1860	18.93%	−1.99%	−2.13%
				1861	4.32%	−9.45%	6.52%
1840	−4.90%	6.91%	−6.06%	1862	75.84%	11.80%	28.57%
1841	−31.24%	6.25%	−3.23%	1863	28.40%	23.50%	21.43%
1842	−5.82%	−3.51%	−15.56%	1864	5.91%	15.39%	45.75%
1843	40.24%	20.27%	0.00%				
1844	10.21%	5.70%	3.95%	1865	4.35%	4.11%	−18.83%
				1866	5.68%	12.83%	−7.18%
1845	6.43%	−0.28%	12.66%	1867	11.47%	11.52%	−6.55%
1846	4.65%	−1.33%	−5.62%	1868	22.91%	8.00%	−1.27%
1847	5.44%	2.34%	1.19%	1869	2.37%	13.22%	−8.39%
1848	−0.61%	16.81%	−2.35%				
1849	2.99%	7.91%	0.00%	1870	1.08%	1.84%	−7.75%
				1871	17.38%	8.96%	1.53%
1850	23.08%	9.12%	4.82%	1872	16.58%	10.11%	2.26%
1851	−3.91%	5.62%	−4.60%	1873	−5.59%	6.81%	−4.41%
1852	20.65%	8.39%	15.66%	1874	4.03%	7.50%	−6.92%
B. 1875–1925							
1875	6.11%	8.86%	−5.79%	1886	10.58%	6.85%	0.00%
1876	−12.43%	−0.23%	0.88%	1887	−2.29%	1.15%	4.76%
1877	−0.98%	0.90%	−15.65%	1888	1.88%	4.90%	−4.55%
1878	15.38%	6.96%	−10.31%	1889	8.20%	−0.21%	−4.76%
1879	47.99%	5.52%	20.69%				
				1890	−5.49%	0.50%	2.50%
1880	26.98%	12.13%	−5.71%	1891	16.80%	−0.30%	−6.10%
1881	0.45%	7.93%	8.08%	1892	5.44%	1.45%	7.79%
1882	2.13%	4.67%	−1.87%	1893	−19.31%	3.42%	−13.25%
1883	−9.16%	7.43%	−7.62%	1894	2.66%	2.21%	−4.17%
1884	−14.52%	1.48%	−10.31%				
				1895	5.46%	−0.39%	1.45%
1885	29.69%	5.41%	−3.45%	1896	0.50%	11.85%	−2.86%

(*continued*)

Exhibit 10.8. Inflation and Annual Total Returns (Nominal) on US Stocks and Bonds (*continued*)

Year*	Stocks	Bonds	Inflation	Year*	Stocks	Bonds	Inflation
1897	20.29%	7.39%	2.94%	1912	7.08%	2.01%	7.29%
1898	29.81%	3.61%	1.43%	1913	−4.89%	4.23%	2.04%
1899	4.06%	6.71%	16.90%	1914	−5.77%	4.09%	1.00%
1900	20.68%	6.59%	−2.41%	1915	31.44%	6.35%	2.97%
1901	19.23%	3.71%	2.47%	1916	9.21%	7.98%	12.50%
1902	8.30%	2.55%	9.64%	1917	−17.38%	−9.20%	19.66%
1903	−17.20%	1.48%	−4.40%	1918	16.93%	10.64%	17.86%
1904	31.53%	4.45%	2.30%	1919	19.05%	0.72%	16.97%
1905	21.73%	2.85%	0.00%	1920	−14.26%	−0.05%	−1.55%
1906	0.61%	1.51%	4.49%	1921	9.28%	16.42%	−11.05%
1907	−24.42%	0.32%	−2.15%	1922	29.29%	6.56%	−0.59%
1908	39.20%	9.25%	3.30%	1923	5.46%	4.61%	2.98%
1909	17.00%	1.22%	10.64%	1924	26.87%	8.53%	0.00%
1910	−3.81%	2.53%	−6.73%	1925	23.59%	7.16%	3.47%
1911	3.52%	4.55%	−1.03%				

Sources: McQuarrie (2024a, 2024b).

*The year designation (say, 1793) refers to the return from January of the stated year to January of the following year, rather than over the stated calendar year. The January price may be the average of the January high and low, an average of January daily prices, or another estimate.

Conclusion

When Ibbotson and Sinquefield (1976) was published, to have compiled a 50-year record of stock and bond returns represented an extraordinary achievement. The authors had good reason to expect that as the sample size of observations increased further, now out to 100 years, increasingly precise estimates of the true expected return on stocks and bonds would be gained.

When Cowles' (1939) work reemerged, adding 55 years to the Ibbotson and Sinquefield (1976) stock record, these expectations were further supported. The decades of additional US data compiled in subsequent SBBI editions did the same. Initial work by Dimson, Marsh, and Staunton (2002), with data out to the peak of the dot-com boom in 2000, was not unsupportive of the idea that return estimates would indeed settle down and become more precise as the quantity of historical data increased.

The situation began to change as Dimson, Marsh, and Staunton (2025) moved to address challenges to the survivorship bias in their initial work, adding more and more stock markets that had performed quite poorly and separating out world ex-US returns, where wealth gained from a long-term investment in stocks proved to be an order of magnitude lower than in the case of the United States.[13]

Confidence in the power of a larger sample size to make estimates more precise was further upended by McQuarrie (2024a, 2024b). These studies showed markedly poorer returns on US stocks prior to 1871 and markedly better returns on US bonds prior to 1900. US returns starting in 1926 have now emerged as quite distinct in a multicentury, multimarket view.

It is questionable whether enlarging a time sample has the same beneficial effect on statistical power as enlarging a sample of people. That effect can only hold true if the underlying process that generates returns is stationary. That appears not to be the case when stock and bond returns before 1926 are compared with more recent returns.

Key Takeaways

- Reasonably good data on US stock and bond returns back through 1793 are now available. The new nineteenth century data suggest that patterns in the data starting in 1926, featured in the original Ibbotson and Sinquefield (1976) study and subsequent SBBI yearbooks, may be unusual rather than typical and may be specific to that era rather than broadly representative.
- The nineteenth century data show a smaller and more variable performance difference between stocks and bonds. For long periods, government bonds had higher returns than common stocks.
- One explanation for the comparatively stronger performance of bonds in the nineteenth century is the very different inflation history in that century. Multiple instances of deflation appear in the earlier record, in which prices fell for over a decade, with a total decline greater than 50% on more than one occasion. No such deflation occurred in the fiat currency period starting in 1934.
- In general, the key elements used in asset allocation decisions have not been stationary across centuries. In addition to stock and bond returns, the correlation between stocks and bonds and their respective standard deviations have varied over a wide range. Nonstationarity calls into question the expectation that longer time samples can lead to more precise estimates of long-term portfolio returns.

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[13] Dimson et al. (2002) had reported only a world index. Because the United States had an approximately 50% weight in the world index, the extent of the contrast between US and international returns was obscured.

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CHAPTER 11. GLOBAL MARKETS OVER THE LAST 126 YEARS

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To understand risk and return, we must examine long periods of history in many countries. We do so because asset returns and especially equity returns are volatile: They vary over time, and different markets experience contrasting financial outcomes. This volatility is readily illustrated by recent history: In 2000, the twenty-first century began with a severe bear market. By March 2003, US stocks had fallen 45%, UK equity prices had halved, and German stocks had declined by two-thirds.

Markets then staged a remarkable recovery, hitting new highs in October 2007, only to plunge again into another epic bear market fueled by the global financial crisis (GFC). Markets bottomed out in March 2009 and subsequently rose, with relatively few setbacks, for more than a decade. Volatility stayed low, with only occasional spikes. When markets are calm, we know there will be a return to more volatile and challenging times, although we cannot know when.

"When" proved to be March 2020. The COVID-19 pandemic sent stocks reeling again, falling by more than a third. Volatility skyrocketed to a level even higher than it did during the GFC. The world experienced its third bear market in less than 20 years. Markets staged a rapid recovery and volatility again fell. However, 2022 saw yet another bear market, with both stocks and bonds falling sharply on inflation and rate hike worries and concerns over the Russia–Ukraine war. Stocks recovered, but in 2025, the "Liberation Day" tariffs sent stocks lower again, although they rapidly regained their poise. In 2026, the world was hit by conflict in the Middle East and renewed uncertainties for long-term investors.

The volatility of markets means that, even over long periods, there can be "unusual" returns. Consider, for example, a global investor at the start of 2000 who looked back at the 10.5% real annualized return on global equities over the previous 20 years and regarded it as "long-run" history that offered guidance for the future. Over the next decade, they would have earned a negative real return of −0.6% per year.

A Long-Term and Global Perspective

Investors who hold equities anticipate reaping a reward for their exposure to risk. At the end of 1999, investors could not have expected, let alone required, a negative real return from equities.

Editor's note: Much of the text in this chapter is adapted from Dimson, Marsh, and Staunton (2026b). This chapter copyright the authors.

If they had, they would have avoided them and equity prices would have been lower. Looking in isolation at the returns over the first 10 or 20 years of the twenty-first century could tell us little about the future risk premium. In the first decade, investors were unlucky, suffering two deep bear markets. This experience served as a brutal reminder that the very existence of the risk for which they sought a reward meant that events could turn out poorly, even over multiple years. In the second decade and beyond, markets recovered quickly from the GFC.

At the same time, the returns over the last two decades of the twentieth century also reveal nothing very useful when considered in isolation. These high returns must surely have exceeded investors' prior expectations and thus provided too rosy a picture of the future. The 1980s and 1990s were a golden age. Inflation fell from its highs in the 1970s and early 1980s, and this trend lowered interest rates and bond yields. Profit growth accelerated, and world trade and economic growth expanded. These dynamics led to strong performance from both equities and bonds.

Long periods of history are also needed to understand bond returns. Over the 40 years until the end of 2021, the Dimson–Marsh–Staunton (DMS) world bond index provided an annualized real return of 6.3%, not far below the 7.4% real return from the DMS world equity index. Extrapolating bond returns of this magnitude into the future would be foolish. With almost continually falling interest rates, those 40 years were a golden age for bonds, just as the 1980s and 1990s were a golden age for equities. In fact, the real return on the DMS world bond index in 2022 was −27%.

Golden ages, by definition, are exceptions. To understand investment risk and return—a key goal of our long-term dataset—we must examine periods much longer than 20 or 40 years. This is because stock and bond returns are volatile, with major year-to-year and even decade-to-decade variation. Very long time series are needed to make inferences about investment returns.

Since 1900, there have been several golden ages and many bear markets; periods of great prosperity and recessions, financial crises, and the Great Depression; periods of peace and episodes of war. Lengthy historical records hopefully balance the good times with the bad times, offering a more realistic understanding of what long-run returns can tell us about the future. This focus on very long-run returns is a recurring theme throughout this volume: see especially Ibbotson, Manninen, and Goetzmann (2026) in chapter 4 and Chambers, Dimson, Ilmanen, and Rintamäki (2026) in chapter 17.

The DMS Dataset

This chapter draws on a long-run history of stocks, bonds, bills, and inflation since 1900. It expands on and updates work reported in Dimson, Marsh, and Staunton (2002, 2021) and in other publications. Our research is primarily based on investment returns for 35 markets (the DMS 35 indices) and five composite indices. For 23 countries, we have a 126-year financial market history starting in 1900, and for another 12 markets, we have data that span at least 50 years.

The DMS 23 consists of two North American markets (the United States and Canada), 10 eurozone countries (Austria, Belgium, Finland, France, Germany, Ireland, Italy, the Netherlands, Portugal, and Spain), six other European countries (Denmark, Norway, Russia, Sweden, Switzerland, and the United Kingdom), four Asia-Pacific markets (Australia, China, Japan, and New Zealand), and one African market (South Africa). Included in the DMS 23 are two countries with 1900 start dates but with long breaks in their histories (Russia and China).

Our dataset also includes a further 12 markets with a financial history of at least half a century. The DMS 12 markets include seven in Asia, one in North America, three in South America, and one in Europe. Additional details and comprehensive data sources are listed in Dimson, Marsh, and Staunton (2026b, chapters 11 and 12). Unlike the DMS 23, these markets' history starts not in 1900 but in the second half of the twentieth century. All 12 were emerging markets at their start dates. However, two (Hong Kong SAR and Singapore) were long ago reclassified as developed markets.

In addition, we monitor 55 additional markets for which we have equity return data for periods ranging from 15 to 50 years. We also have inflation, currency, and market capitalization data but not yet bond or bill return data. These 55 countries, in conjunction with the DMS 35, provide a total of 90 developed and emerging markets (the DMS 90), which we use for constructing our composite equity series: the world, world ex-US, Europe, developed market, and emerging market indices.

Equity Returns Since 1900

Panel A of **Exhibit 11.1** shows the cumulative nominal return from stocks, bonds, and bills, as well as the inflation rate, since 1900 in the world's leading capital market, the United States. Equities performed best. An initial investment of $1 grew to $124,854 in nominal terms by year-end 2025. Long bonds and Treasury bills provided lower returns, although they beat inflation. Their respective index levels at the end of 2025 were $284 and $69, with the inflation index ending at $38. The chart's legend shows the annualized returns: 9.8% for equities versus 4.6% on bonds, 3.4% on bills, and inflation of 2.9% per year.

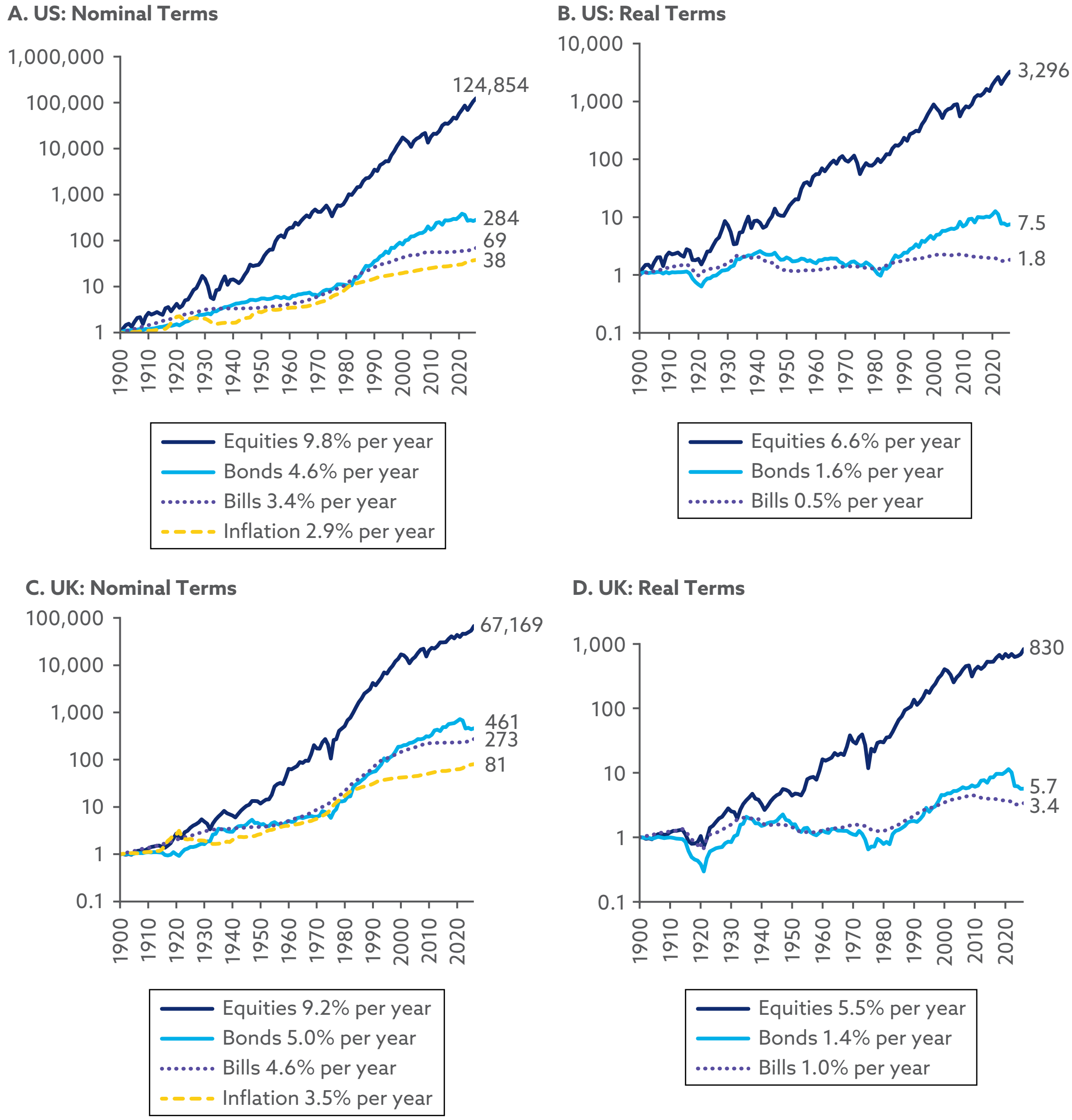
Because US prices rose 38-fold over this period, it is more helpful to compare returns in real terms. The real returns on US equities, bonds, and bills are shown in Panel B of Exhibit 11.1. Over the 126 years, an initial investment of $1 with dividends reinvested would have grown in purchasing power by 3,296 times. The equivalent multiples for bonds and bills are 7.5 and 1.8 times. These terminal wealth figures correspond to annualized real returns of 6.6% on equities, 1.6% on bonds, and 0.5% on bills.

Exhibit 11.1 shows that US equities dominated bonds and bills. There were severe setbacks, of course, most notably during World War I; the 1929–32 Wall Street crash and its aftermath, including the Great Depression; the OPEC oil shock of the 1970s after the 1973 October War in the Middle East; and four notable bear markets so far during the twenty-first century. Each shock was severe at the time. At the depths of the 1929–32 crash, US equities had fallen by 79% in real terms. Many investors were ruined, especially those who bought stocks with borrowed money. The crash lived on in the memories of investors for at least a generation, with many shunning equities.

Panels A and B of Exhibit 11.1 place the 1929–32 crash in its long-run context by showing that equities eventually recovered and gained new highs. Other dramatic episodes, such as the October 1987 crash, hardly register. The COVID-19 crisis, for instance, is imperceptible because the plot shows only annual data; the market recovered and hit new highs by year-end. The bursting of the technology bubble in 2000, the GFC of 2007–2009, and the 2022 bear market are barely discernible. Exhibit 11.1 sets the bear markets of the past in perspective. Events that were traumatic at the time now appear only as setbacks within a longer-term secular rise.

We caution, however, about generalizing from the United States. Over the twentieth century, the United States rapidly emerged as the world's foremost political, military, and economic

Exhibit 11.1. Cumulative Returns on US and UK Asset Classes in Nominal and Real Terms, 1900–2025



Sources: DMS Database, Dimson, Marsh, and Staunton (2026a); Dimson, Marsh, and Staunton (2026b). Not to be reproduced without written express permission from the authors.

power. By focusing on the world's most successful economy, investors could gain a misleading impression of equity returns elsewhere or of future returns for the United States.

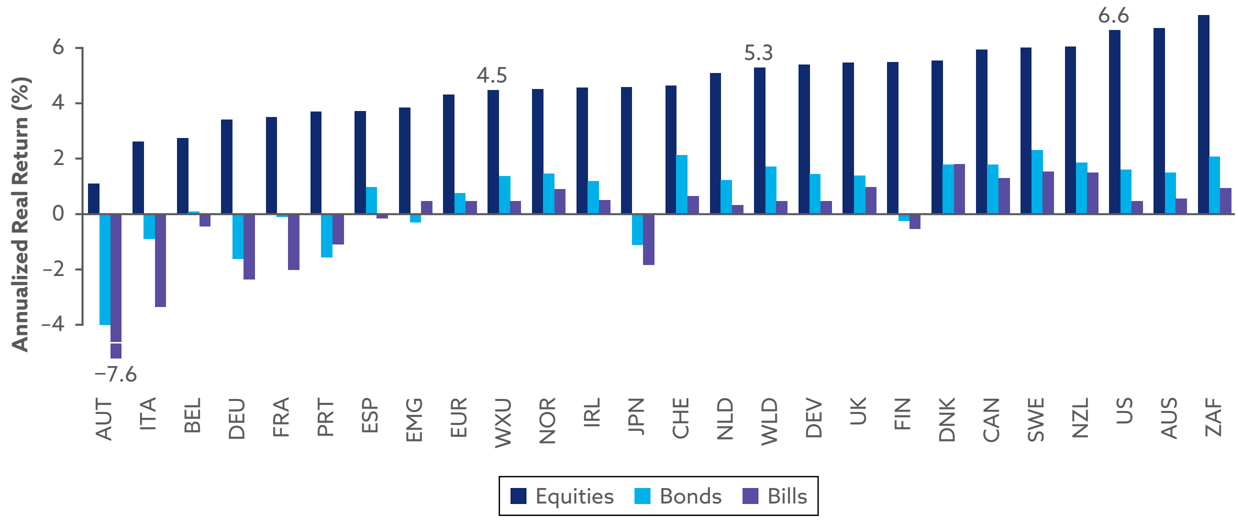
Panels C and D of Exhibit 11.1 show the corresponding charts for the United Kingdom. Panel D shows that although the real return on UK equities was negative over the first 20 years of the twentieth century, the story thereafter was one of steady growth broken by periodic setbacks. Unlike the United States, the worst setback was not during the 1929–32 period but instead in 1973–1974, the period of the first OPEC oil squeeze following the 1973 October War in the Middle East. UK bonds also suffered in the mid-1970s in response to inflation peaking at 24% in 1975.

Exhibit 11.1 shows that investors who kept faith in UK equities and bonds were eventually vindicated. Over the full 126 years, the annualized real return on UK equities was 5.5%, versus 1.4% on bonds. As in the United States, equities greatly outperformed bonds, which beat bills. These returns are high, but they are below those for the United States.

Asset Returns Around the World

Exhibit 11.2 shows annualized real local-currency equity, bond, and bill returns over the last 126 years for the 21 DMS countries with continuous investment histories plus the five composite indices—the world (WLD), world ex-US (WXU), Europe (EUR), developed market (DEV), and emerging market (EMG) indices—ranked in ascending order of equity market performance. The real equity return was positive everywhere, typically around 3%–6% per year.

Exhibit 11.2. Annualized Real Returns (%) on Equities, Bonds, and Bills, 1900–2025



AUT – Austria	ITA – Italy	BEL – Belgium	DEU – Germany	FRA – France	PRT – Portugal
ESP – Spain	NOR – Norway	IRL – Ireland	JPN – Japan	CHE – Switzerland	NLD – Netherlands
UK – United Kingdom	FIN – Finland	DNK – Denmark	CAN – Canada	SWE – Sweden	NZL – New Zealand
US – United States	AUS – Australia	ZAF – South Africa			

Sources: DMS Database, Dimson, Marsh, and Staunton (2026a); Dimson, Marsh, and Staunton (2026b). Not to be reproduced without written express permission from the authors.

Notes: German bonds and bills exclude 1922–1923. WLD = world, WXU = world ex United States, EUR = Europe, DEV = developed markets, EMG = emerging markets.

Equities were the best-performing asset class everywhere. Bonds beat bills in every market except Portugal. This pattern is what we would expect over the long haul because equities are riskier than bonds and bonds are riskier than cash. Our findings thus support one of the lasting laws of finance—the law of risk and return—and the idea that risk bearing should carry an expected reward.

Exhibit 11.2 shows that although most national markets experienced positive real bond returns, seven had negative returns. Mostly, countries with poor bond returns were also among the worst equity performers. Their poor performance arose during the first half of the twentieth century. These were the economies that suffered most from the ravages of war and from periods of high inflation or hyperinflation associated with the wars and their aftermath.

Exhibit 11.2 shows that the United States performed well, ranking third for equity performance (6.6% per year) and eighth for bonds (1.6% per year). These are local-currency real returns, however. As we show later, in common-currency terms, US equities were the world's best performers (closely followed by Australia), and US bonds ranked fourth in the world. This result confirms our earlier conjecture that US returns would be high because the US economy has been such an obvious success story, making it unwise for investors around the world to base future projections solely on US evidence.

The 6.6% annualized real return on US equities contrasts with the 4.5% real US dollar return on the world ex-US equity index. This difference of 2.1 percentage points, when compounded over 126 years, leads to a large difference in terminal wealth. A dollar invested in US equities in 1900 resulted in a terminal value of $3,296 in terms of real purchasing power (see Exhibit 11.1). The same investment in stocks from the rest of the world provided a terminal value of $248, less than 8% of the US value.

A common factor among the best-performing equity markets is that they tended to be resource-rich and/or New World countries. The worst-performing markets were those most afflicted by wars.

Long-Run Real Equity Returns

Exhibit 11.3 provides statistics on long-run real (inflation-adjusted) equity returns. The table shows the 21 countries and five composite indices for which we have continuous histories from 1900 to 2025.[1] The geometric means in the second column show the 126-year compound annual returns, and these are the numbers plotted in Exhibit 11.2. The arithmetic means in the third column show the average annual returns over the 126-year period for each national market or composite index.

The arithmetic mean of a sequence of different returns is always larger than the geometric mean. For example, if a stock doubles one year (+100%) and halves the next (−50%), the investor is back where he or she started and the annualized or geometric mean return is zero. The arithmetic mean, however, is one-half of (100 – 50), which is +25%. The more volatile the returns, the greater the amount by which the arithmetic mean exceeds the geometric mean. This observation is supported by the fifth column of Exhibit 11.3, which shows the standard deviation of each market's returns.

[1]Similar results are available in Dimson, Marsh, and Staunton (2026b) for stock markets that do not have a full 126-year history.

Exhibit 11.3. Real Equity Returns for Indices with Continuous Histories, 1900–2025

Country/Index	Geometric Mean (%)	Arithmetic Mean (%)	Std. Error (%)	Std. Dev. (%)	Min. Return (%)	Min. Year	Max. Return (%)	Max. Year
Australia	6.7	8.2	1.5	17.2	−42.5	2008	51.5	1983
Austria	1.1	5.4	2.7	30.9	−63.2	2008	132.7	1921
Belgium	2.7	5.3	2.1	23.1	−48.9	2008	105.1	1919
Canada	5.9	7.3	1.5	16.7	−33.8	2008	55.2	1933
Denmark	5.5	7.4	1.8	20.6	−49.2	2008	107.8	1983
Finland	5.5	9.2	2.6	29.2	−59.7	1918	161.7	1999
France	3.5	5.9	2.0	22.5	−41.5	2008	66.1	1954
Germany	3.4	8.0	2.7	30.7	−90.8	1948	154.6	1949
Ireland	4.6	7.1	2.0	22.6	−65.4	2008	68.4	1977
Italy	2.6	6.4	2.5	28.0	−72.9	1945	120.7	1946
Japan	4.6	8.9	2.5	28.6	−85.5	1946	121.1	1952
Netherlands	5.1	7.1	1.9	20.8	−50.4	2008	101.6	1940
New Zealand	6.1	7.7	1.7	19.0	−54.7	1987	105.3	1983
Norway	4.5	7.2	2.3	25.9	−53.6	2008	166.9	1979
Portugal	3.7	8.3	3.0	33.2	−76.6	1978	151.8	1986
South Africa	7.2	9.2	1.9	21.3	−52.2	1920	101.2	1933
Spain	3.7	5.7	1.9	21.0	−43.3	1977	99.4	1986
Sweden	6.0	8.1	1.9	20.9	−42.5	1918	67.5	1999
Switzerland	4.6	6.4	1.7	19.1	−37.8	1974	59.4	1922
United Kingdom	5.5	7.2	1.7	19.3	−56.3	1974	100.2	1975
United States	6.6	8.6	1.8	19.8	−38.6	1931	55.8	1933
Europe	4.3	6.1	1.8	19.7	−47.9	2008	75.9	1933
World ex-US	4.5	6.1	1.7	18.8	−46.0	2008	80.1	1933
World	5.3	6.8	1.5	17.3	−42.9	2008	67.8	1933
Developed markets	5.4	6.9	1.6	17.4	−41.3	2008	65.1	1933
Emerging markets	3.8	6.4	2.0	22.6	−63.0	1945	94.0	1933

Sources: DMS Database, Dimson, Marsh, and Staunton (2026a); Dimson, Marsh, and Staunton (2026b). Not to be reproduced without written express permission from the authors.

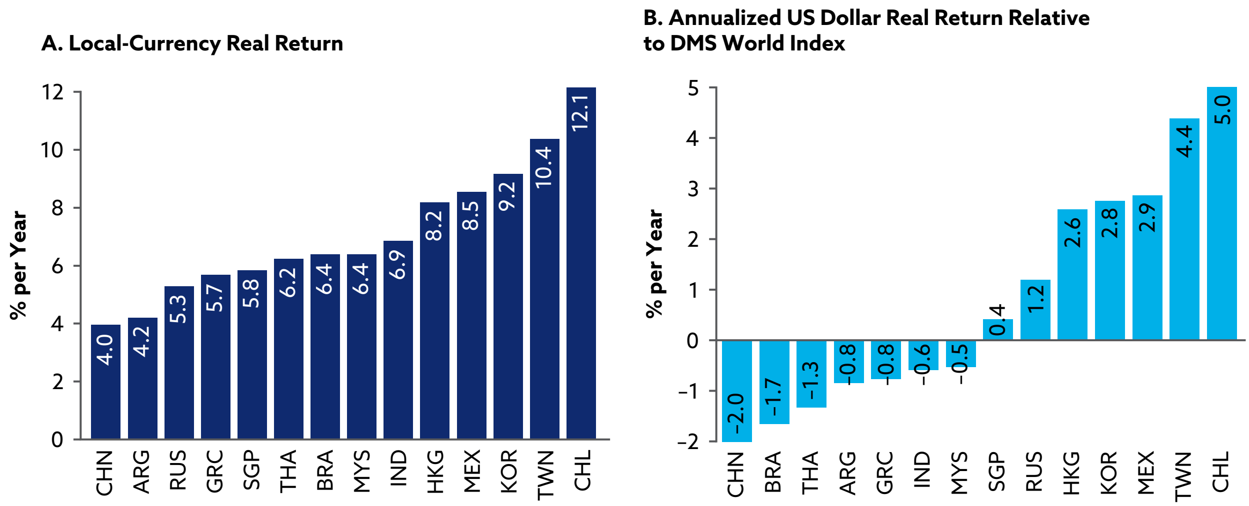
The US stock market's standard deviation of 19.8% places it among the lower-risk markets, ranking sixth after Canada (16.7%), Australia (17.2%), New Zealand (19.0%), Switzerland (19.1%), and the United Kingdom (19.3%). The average standard deviation for the 21 markets in the table is 23.4%. The 17.3% standard deviation for the world index shows the power of global diversification in reducing risk.

The most volatile markets were Portugal (33.2%), Germany (30.7%), Austria (30.9%), Finland (29.2%), Japan (28.6%), and Italy (28.0%). These economies were the most seriously affected by the depredations of war, civil strife, and inflation. In Finland's case, the high volatility reflects its concentrated stock market during some recent periods. Exhibit 11.3 shows that, as one would expect, the markets with the highest standard deviations experienced the greatest range of returns. In other words, they had the lowest minimums and the highest maximums.

Bear markets underline the risk of equities. Even in a low-volatility market, such as the United States, losses can be huge. Exhibit 11.3 shows that the worst calendar year for US equities was 1931, with a real return of –39%. During the 1929–32 crash period, however, US equities fell by 79% in real terms from peak to trough. The worst period for UK equities was the 1973–74 bear market, when stocks fell 73% in real terms from peak to trough and 57% in one year, 1974. For 9 of the 21 countries, 2008 was the worst year. Over intervals of more than a year, many markets have experienced even more extreme returns, both on the downside and the upside.

Panel A of **Exhibit 11.4** shows annualized local-currency real equity returns from the markets for which we have shorter histories. Comparisons are difficult because of their different start dates.

Exhibit 11.4. Annualized Local-Currency Real Equity Returns and Relative Returns over Matching Periods by Market



CHN – China	ARG – Argentina	RUS – Russia	GRC – Greece	SGP – Singapore
THA – Thailand	BRA – Brazil	MYS – Malaysia	IND – Indonesia	HKG – Hong Kong SAR
MEX – Mexico	KOR – South Korea	TWN – Taiwan	CHL – Chile	

Sources: DMS Database, Dimson, Marsh, and Staunton (2026a); Dimson, Marsh, and Staunton (2026b). Not to be reproduced without written express permission from the authors.

In Panel B, we therefore show each country's real US dollar return relative to the return on the DMS world index over the same period.

Exhibit 11.4 shows that the annualized local-currency real returns range from the Chinese Mainland's 4.0% to Chile's 12.1%. Panel B shows that Chile was also the best relative performer, beating the world index by 5.0% per year since its 1960 start date. Taiwan, Mexico, South Korea, and Hong Kong SAR also outperformed strongly.

The worst performer was the Chinese Mainland, which, since its 1993 start date, underperformed the world index by 2.0% per year, despite unprecedented growth in the Chinese Mainland's real GDP since 1990—8.7% per year versus 2.5% for the United States. This serves as a reminder of the lack of a relationship between long-term GDP growth and stock price performance, as documented in Dimson, Marsh, and Staunton (2002, 2014).

Long-Run Real Bond Returns

Exhibit 11.5 shows that the 126 years from 1900 to 2025 were not especially kind to investors in government bonds. Across the 21 continuous-history markets, the average annualized real (inflation-adjusted) return was 0.6% (0.8% excluding Austria's very low figure).[2] Although this return exceeds the average real return on cash by 1.2%, bonds had much higher risk.

Real bond returns were negative in seven of the markets in Exhibit 11.5. German bonds performed worst, and their volatility was even higher than revealed in the table because the statistics exclude 1922–1923. In 1923, hyperinflation resulted in an almost total real loss for German bond investors. In the United States, the annualized real bond return was 1.6%, a little higher than the United Kingdom's 1.4%. These findings suggest that for the full 126-year period, real bond returns in many markets were below investors' prior expectations, with the largest differences occurring in the highest-inflation economies.

Particularly in the first half of the twentieth century, several countries experienced extreme and disappointingly low returns arising from wars and extreme inflation. These low returns were followed by a degree of reversal, with the countries experiencing the lowest returns in the first half of the twentieth century being among the best performers thereafter.

Sweden had the highest long-run real bond return, 2.3% per year, followed by Switzerland and South Africa (2.1%), New Zealand (1.9%), and Canada and Denmark (1.8%). Exhibit 11.5 shows that New Zealand bonds had the lowest standard deviation of returns, 9.0%, followed by Swiss (9.6%) and Spanish (9.9%) bonds.

Since 1900, the average standard deviation of real bond returns across countries was 13.1%, versus 23.0% for equities and 7.5% for bills (these averages exclude Austria). Although bonds have generally been much less volatile than equities, they have experienced some protracted periods of very low or high returns.

In **Exhibit 11.6**, we divide the period from 1900 to 2025 into four subperiods for bond returns: 1900–1949, 1950–1981, 1982–2021, and 2022–2025. We also show the 126-year return from 1900 to 2025. Within each period, we report the annualized return on bonds for the United States, the United Kingdom, Europe, and all 21 markets with continuous histories. For Europe and for the all-market average, we show the average annualized return for the individual countries.

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[2]Similar results are available in Dimson, Marsh, and Staunton (2026b) for bond markets that do not have a full 126-year history.

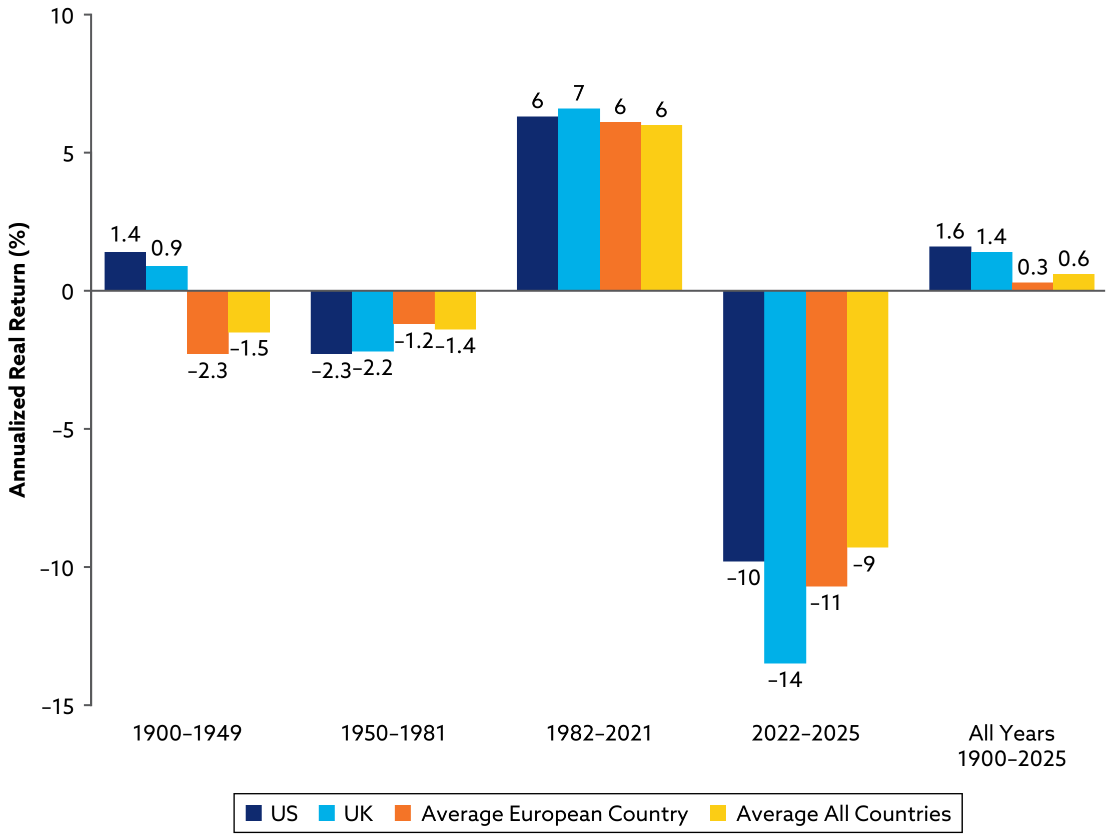
Exhibit 11.5. Real Bond Returns for Indices with Continuous Histories, 1900–2025

Country/Index	Geometric Mean (%)	Arithmetic Mean (%)	Std. Error (%)	Std. Dev. (%)	Min. Return (%)	Min. Year	Max. Return (%)	Max. Year
Australia	1.5	2.3	1.2	13.2	−26.6	1951	62.2	1932
Austria	−4.0	4.1	4.7	52.3	−94.7	1945	484.8	1926
Belgium	0.1	1.3	1.4	15.2	−45.6	1917	62.3	1919
Canada	1.8	2.3	0.9	10.5	−27.7	2022	41.7	1921
Denmark	1.8	2.6	1.2	13.7	−37.0	2022	63.6	1983
Finland	−0.2	1.0	1.2	13.8	−69.5	1918	30.2	1921
France	−0.1	0.8	1.2	13.2	−43.5	1947	35.9	1927
Germany*	−1.6	1.1	1.4	15.8	−100.0	1923	62.5	1932
Ireland	1.2	2.3	1.3	15.1	−37.2	2022	61.2	1921
Italy	−0.9	0.5	1.4	15.4	−64.3	1944	40.0	1996
Japan	−1.1	1.3	1.7	19.0	−77.5	1946	69.8	1954
Netherlands	1.2	1.8	0.9	10.4	−38.3	2022	32.8	1932
New Zealand	1.9	2.3	0.8	9.0	−23.7	1984	34.1	1991
Norway	1.5	2.1	1.0	11.7	−48.0	1918	62.1	1921
Portugal	−1.6	0.0	1.6	18.1	−45.1	1923	90.6	1986
South Africa	2.1	2.6	0.9	10.4	−32.6	1920	42.1	1921
Spain	0.8	1.3	0.9	9.9	−34.8	2022	36.2	1993
Sweden	2.3	3.1	1.1	12.8	−37.0	1939	68.2	1921
Switzerland	2.1	2.6	0.9	9.6	−25.9	2022	56.1	1922
United Kingdom	1.4	2.2	1.2	13.7	−38.5	2022	59.4	1921
United States	1.6	2.1	0.9	10.7	−30.6	2022	35.2	1982
Europe	0.8	2.1	1.5	16.3	−53.7	1919	72.9	1933
World ex-US	1.4	2.4	1.3	14.6	−46.8	1919	76.7	1933
World	1.7	2.3	1.0	11.2	−32.1	1919	46.8	1933
Developed markets	1.4	2.0	1.0	11.1	−33.5	2022	34.7	1933
Emerging markets	−0.3	1.7	1.7	18.5	−76.4	1949	87.3	1933

Sources: DMS Database, Dimson, Marsh, and Staunton (2026a); Dimson, Marsh, and Staunton (2026b). Not to be reproduced without written express permission from the authors.

*German means, standard deviation, and standard error are based on 124 years, excluding 1922–1923.

Exhibit 11.6. Real Bond Returns over Subperiods, 1900–2025



Sources: DMS Database, Dimson, Marsh, and Staunton (2026a); Dimson, Marsh, and Staunton (2026b). Not to be reproduced without written express permission from the authors.

In the first half of the twentieth century, annualized real bond returns were positive but quite low in the United States and the United Kingdom; and they were negative in Europe and when averaged across all countries. These disappointing returns largely resulted from high inflation during and in the aftermath of the two world wars. There were, however, periods in the first half of the twentieth century when investors enjoyed high real bond returns, especially the deflationary period from 1926 to 1933 (see Dimson, Marsh, and Staunton 2026b).

The second set of bars in Exhibit 11.6 shows real bond returns from 1950 to 1981. Returns were negative in the United States and the United Kingdom and, on average, across Europe and all 21 markets. A major culprit was the inflationary 1970s.

The next subperiod shown in Exhibit 11.6 covers the four decades from 1982 to 2021. Over this period, real bond returns were astonishingly high. This was the golden age of bonds. In the early 1980s, governments started to tackle inflation using short-term interest rates as a policy instrument. This approach succeeded in reducing inflation, inflationary expectations, and the risk premium bond investors require for inflation risk, thereby boosting bond prices.

Over time, real interest rates also fell from their high levels in the early and mid-1980s, giving a further boost to bond prices. During the early twenty-first century, bonds benefited from their safe-haven status, from policy interest rates being kept low to support economies, and from quantitative easing. Investors became used to these high returns, but projecting them into the future was clearly inappropriate. This is another example of the importance of looking at long periods of history to understand markets. Even a period of four decades can be misleading if naively extrapolated.

The final subperiod shown in Exhibit 11.6 covers annualized real bond returns from 2022 to 2025. For investors who had grown used to high bond returns and who saw bonds as a safe asset, the returns in 2022 were shocking. The real returns on long-term US and UK bonds were −31% and −39%, respectively. The average return across European countries was −35%, while across all 21 countries it was −31%. Eight countries, including the United States, the United Kingdom, and Switzerland, experienced their worst year ever, as did the DMS developed market index. The era of easy money was over, and inflation and rising real interest rates had taken their toll. The year 2023 was better, but 2024 was disappointing.

The final set of bars in Exhibit 11.6 shows the full 126-year record. Since 1900, the average annualized real bond return across the 21 countries with continuous histories was just 0.6%, with disappointing returns in many markets.

Bill Returns and Real Interest Rates

Treasury bills are an important asset class. They indicate the return on cash and provide a benchmark for the riskless rate of interest. **Exhibit 11.7** shows the annualized real (inflation-adjusted) returns on bills—the realized short-term rate of interest, adjusted for inflation—in the 21 countries and five composite indices for which we have continuous histories from 1900–2025.[3]

Since 1900, US and UK short-term bill investors earned annualized real returns of 0.5% and 1.0%, respectively. Investors in eight countries—Austria, Belgium, Finland, France, Germany, Italy, Portugal, and Japan—earned negative real returns. Almost all of them experienced high inflation at some stage.

For Germany, Exhibit 11.7 excludes 1922–1923, and its full 126-year record is far worse than recorded because in 1923, German bill (and bond) investors lost virtually everything. Although we can generally regard short-dated government bills as riskless, this assumption ceases to be true during hyperinflation. More recently, investors re-learned during the eurozone debt crisis from 2009–2012 that even sovereign bills of developed countries can carry credit risk.

In the first half of the twentieth century, little relationship existed between interest rates and inflation in the United States or elsewhere. From the 1950s onward, however, they have generally had a close relationship. In every country, a breakpoint in the real rate of interest occurred at the end of the 1970s, with real rates thereafter being appreciably higher. A second breakpoint happened in 2008, when rates fell sharply.

[3] Similar results are available in Dimson, Marsh, and Staunton (2026b) for markets that do not have a full 126-year history.

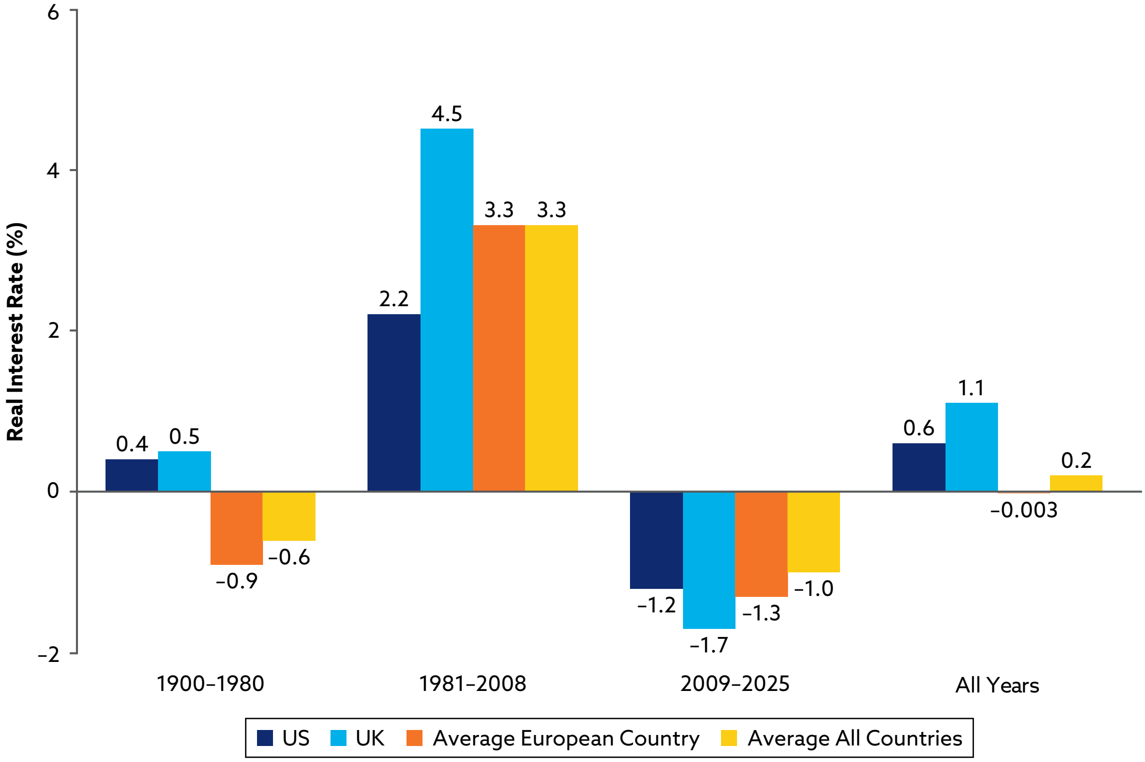
Exhibit 11.7. Real Bill Returns/Interest Rates for Countries with Continuous Histories, 1900–2025

Country	Geometric Mean (%)	Arithmetic Mean (%)	Std. Error (%)	Std. Dev. (%)	Min. Return (%)	Min. Year	Max. Return (%)	Max. Year
Australia	0.6	0.7	0.5	5.1	−15.5	1951	18.5	1921
Austria	−7.6	−3.9	1.6	17.8	−96.4	1922	12.2	1931
Belgium	−0.4	0.4	1.1	12.2	−46.6	1941	69.0	1919
Canada	1.3	1.4	0.4	4.7	−12.5	1947	27.1	1921
Denmark	1.8	2.0	0.5	5.9	−15.8	1940	25.1	1921
Finland	−0.5	0.4	1.0	11.2	−69.2	1918	19.9	1919
France	−2.0	−1.6	0.8	9.1	−38.5	1946	29.7	1921
Germany*	−2.4	−0.6	1.1	12.6	−100.0	1923	38.8	1924
Ireland	0.5	0.7	0.6	6.4	−15.5	1915	42.2	1921
Italy	−3.4	−2.4	1.0	10.9	−76.6	1944	14.2	1931
Japan	−1.8	−0.4	1.2	13.1	−77.5	1946	29.8	1930
Netherlands	0.3	0.4	0.4	4.8	−12.7	1918	19.6	1921
New Zealand	1.5	1.6	0.4	4.5	−8.1	1951	21.1	1932
Norway	0.9	1.1	0.6	6.8	−25.4	1918	31.2	1921
Portugal	−1.1	−0.6	0.8	9.3	−41.6	1918	23.8	1948
South Africa	0.9	1.1	0.5	5.8	−27.8	1920	31.9	1921
Spain	−0.2	0.0	0.5	5.6	−24.3	1946	11.9	1921
Sweden	1.5	1.7	0.6	6.4	−23.2	1918	42.7	1921
Switzerland	0.6	0.8	0.4	4.7	−16.5	1918	25.8	1922
United Kingdom	1.0	1.1	0.5	6.1	−15.7	1915	43.0	1921
United States	0.5	0.6	0.4	4.4	−15.0	1946	17.6	1921

Sources: DMS Database, Dimson, Marsh, and Staunton (2026a); Dimson, Marsh, and Staunton (2026b). Not to be reproduced without written express permission from the authors.

*German means, standard deviation, and standard error are based on 124 years, excluding 1922–23.

Exhibit 11.8. Real Interest Rates over Subperiods, 1900–2025



Sources: DMS Database, Dimson, Marsh, and Staunton (2026a); Dimson, Marsh, and Staunton (2026b). Not to be reproduced without written express permission from the authors.

Exhibit 11.8 focuses on these three periods: 1900–1980, 1981–2008, and 2009–2025. It shows the arithmetic average annual real rate of interest in each period (and for the full 126 years) for the United States and the United Kingdom and the average for all European and DMS markets with continuous 126-year histories. In the United States, the average real interest rate was 0.4% from 1900 to 1980, compared with 2.2% from 1981 to 2008 and −1.2% since then. In the United Kingdom, the pre-1980 average annual real rate was 0.5%, versus 4.5% from 1981 to 2008 and –1.7% since 2009.

The average annual real interest rate was clearly very low—indeed, negative—following the GFC. Since 2022, real interest rates have risen. Investors are now asking whether real rates have returned to normal, which raises the question, What is normal? Unfortunately, many investors' view of normality is heavily conditioned by the period before the crisis. Exhibit 11.8 suggests, however, that although the very low post-GFC real rates were clearly not normal, neither were the very high real rates over the 28-year period before the financial crisis. This is yet another example of the need to look at very long periods of history to gain perspective on important current investment questions.

Emerging vs. Developed Market Returns

Emerging markets tend to be associated with rapid growth and hence are often perceived as offering investment rewards higher than in developed markets. We explore whether this has been the case over the last 126 years by comparing the performance of the DMS emerging market and developed market indices, for both equities and bonds.

The DMS emerging markets equity index is constructed from the DMS 90 database. Starting in 1900, markets are classified as emerging or developed at the beginning of each year. All markets for which we have data and that are deemed to be emerging are included in the index, weighted by each market's capitalization. From the start of MSCI's emerging markets index in 1987, we adopt its annual classification to determine which markets were developed. We do not use MSCI index values. Prior to 1987, we use our own algorithm to determine which markets were developed. This is based on GDP per capita, as described by Dimson, Marsh, and Staunton (2026b).

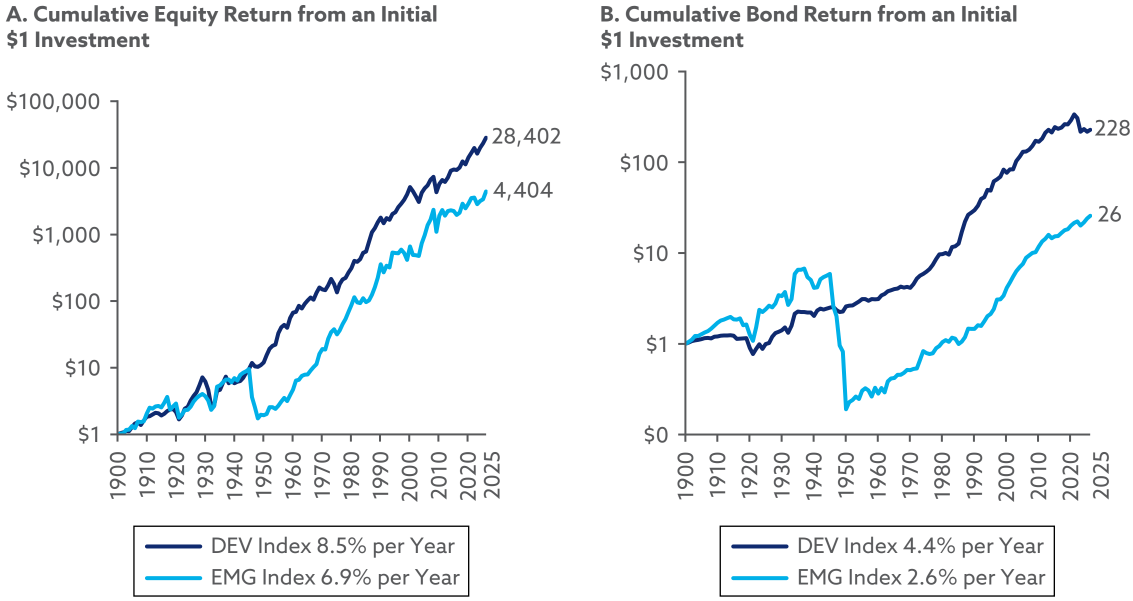
We do not distinguish between emerging, frontier, other, or unclassified markets. Our focus is simply on the split between markets that are deemed developed and those with developing status. We group together all the latter markets as a single cohort and refer to them generically as "emerging." In 1900, the DMS emerging markets equity and bond indexes were based on seven countries. We add other markets once return data become available. Thus, we add Brazil in 1951, India in 1953, Greece in 1954, Chile in 1960, South Korea and Hong Kong (now Hong Kong SAR) in 1963 (until the latter moved to developed status in 1977), Singapore in 1966 (until it moved to developed status in 1980), Mexico in 1969, Malaysia in 1970, Argentina, Thailand, and Zimbabwe in 1976, and so on. We continue bringing other markets into the emerging market index until we reach 2025. Markets leave if they are promoted to developed status. By 2025, the number of constituents in the emerging markets equity index had grown to 66 countries.

The DMS developed markets index is created using the same rule. This index had 16 constituents in 1900 and was joined by Finland in 1932, Argentina in 1960 (until it moved to emerging status in 1976), Japan in 1966, Spain in 1974, Hong Kong (now Hong Kong SAR) in 1977, Singapore in 1980, Luxembourg in 1982, Portugal in 1998, Greece from 2002 to 2013, and Israel in 2011. The developed markets index is computed annually based on all markets deemed to be developed at the start of the year in question. The indices are estimated in common currency—namely, US dollars—although they can readily be converted to an alternative common currency. These indices enable us to compare emerging and developed market performance over the full period of 126 years spanned by the DMS database.

The long-run performance of emerging versus developed market equities is plotted in Panel A of **Exhibit 11.9**. Emerging markets outperformed early in the twentieth century but were hit badly by the October 1917 revolution in Russia, when investors in Russian stocks lost everything. Emerging markets underperformed in the global bull market of the 1920s but were less severely affected than developed markets by the subsequent crash. From the mid-1930s until the mid-1940s, they moved in line with developed markets.

From 1945 to 1949, emerging market equities collapsed. The largest contributor was Japan, where equities lost 97% of their value in US dollar terms. Another contributor was China, where markets finally closed in 1949. Other markets, such as Spain and South Africa, also performed poorly following World War II. Nor were the 1950s kind to emerging market investors, when poor returns from Brazil contributed to underperformance.

Exhibit 11.9. Long-Run Returns on Emerging and Developed Market Equities and Bonds, 1900–2025



Sources: DMS Database, Dimson, Marsh, and Staunton (2026a); Dimson, Marsh, and Staunton (2026b). Not to be reproduced without written express permission from the authors.

After 1960, emerging markets staged a long fight back, albeit with periodic setbacks. From 1960 to 2025, their annualized return was 10.9%, versus 9.6% from developed markets. This gain was insufficient, however, to make up for their precipitous decline in the 1940s. The full 126-year graph shows that the terminal wealth from an initial investment of $1 in emerging markets was $4,404. This amount is appreciably below that of developed markets, which had a terminal value of $28,402.

The annualized return from investing in emerging markets over 1900–2025 was 6.9%, compared with 8.5% for their developed counterparts. The DMS world index, which includes every stock market in the DMS 90 in every year for which data are available, had an annualized return of 8.4% over that period. For a global investor, the impact from including or excluding particular emerging markets has been small. The rules for market classification and the dangers of survivorship bias also have a negligible impact on estimated equity returns or premiums.

The long-run performance of emerging versus developed market bonds is plotted in Panel B of Exhibit 11.9. These long-run bond indices are constructed using the same principles as the equity indices but are based on the 35-market DMS 35 dataset because we do not yet have bond data for the supplementary 55 (almost entirely emerging) markets. The emerging market bond index thus has fewer constituents, starting with seven markets in 1900 and ending with 16 in 2025.

Exhibit 11.9 shows that emerging market bonds were ahead of developed market bonds until the 1940s, when they plummeted. As with emerging market equities, the largest contributor to this decline was Japan, where bonds lost 99% of their value in US dollar terms. Another contributor was China. Spanish bonds also performed poorly in the wake of the Spanish Civil War.

A recovery followed in the second half of the twentieth century. Emerging market bonds outperformed developed market bonds from 1950 to 2025, with the same being true for start dates of 1960 and 1980 (but not 1970). Emerging market bonds have also outperformed DM bonds over the last 40, 30, 20, and 10 years. Over the full 126 years, they gave an annualized US dollar return of just 2.6%, compared with 4.4% for developed market bonds. These returns are nominal, and after adjusting for US inflation, a US investor in emerging market bonds would have lost money in real terms, with an annualized real return of −0.3%, versus +1.4% for developed market bonds. These results are unsurprising, given the crises of the 1940s and the high inflation rates since then in many countries.

Twenty-First Century Returns

The twenty-first century is now 26 years old. Our first book on global investment returns (Dimson, Marsh, and Staunton 2002) reported on a century of data since 1900. We can now compare investment returns over the entire period—more than a century and a quarter—since 1900. **Exhibit 11.10** shows asset returns for the 21 markets with a continuous long-term history. For comparability across countries, the annualized real returns on stocks, bonds, and bills are shown in common currency (US dollars). We also show annualized inflation.

American exceptionalism is clear: The United States enjoyed the highest equity returns (ranked first in the rank column), and US bonds were in fourth place. The last two columns show that stocks were the best asset class everywhere, while bills were the worst (except in Portugal, where bonds performed the worst).

Despite the recent spike in inflation, the twenty-first century has predominantly been a period of low inflation. The average annualized inflation rate for the 21 countries over the last 26 years was just 2.2%, compared with 5.6% over the twentieth century. The average annualized bill return was also lower, at −0.4% compared with −0.6% over 1900–1999. These results reflect the long period of very low and sometimes negative short-term nominal interest rates. Over the last 26 years, the annualized real return on the world bond index was 1.1% higher than it was during the twentieth century. This result is attributable to the steady decline in real interest rates—which reversed in 2022.

The annualized real return on the world equity index was 1.6 percentage points lower over the last 26 years than during the twentieth century. Four notable bear markets in 26 years, two of them among the deepest in history, have contributed to this.

The annualized US real equity return was 5.2% over the last 26 years, and although lower than the 7.0% over the preceding 100 years, this return is still excellent. US equities ranked ninth among the 21 markets, but apart from Australia, the markets that ranked higher were small. Twenty-first century global equity performance was driven by the United States, and over the last 26 years, the world ex-US index gave an annualized return of just 2.9%. Equity returns in Germany, France, Japan, and the United Kingdom for the same period were all disappointing.

Exhibit 11.10. Real Common-Currency Returns on Stocks, Bonds, and Bills for Indices with Continuous Histories, 1900–2025

Country/Index	Real USD Equity Return (% per year)	Rank	Real USD Bond Return (% per year)	Rank	Real USD Bill Return (% per year)	Inflation (% per year)	Best	Worst
Australia	6.5	2	1.3	10	0.3	3.7	Equities	Bills
Austria	0.3	21	−4.7	21	−8.3	12.0	Equities	Bills
Belgium	3.1	19	0.5	14	−0.1	4.9	Equities	Bills
Canada	5.7	5	1.6	5	1.1	3.0	Equities	Bills
Denmark	5.8	4	2.1	2	2.1	3.6	Equities	Bills
Finland	5.4	8	−0.3	15	−0.6	6.7	Equities	Bills
France	3.2	18	−0.4	16	−2.3	6.5	Equities	Bills
Germany*	3.5	17	−2.4	20	−3.1	4.5	Equities	Bills
Ireland	4.6	12	1.3	9	0.6	4.0	Equities	Bills
Italy	2.6	20	−0.9	17	−3.4	7.6	Equities	Bills
Japan	4.4	14	−1.3	18	−2.1	6.3	Equities	Bills
Netherlands	5.3	10	1.4	6	0.5	2.9	Equities	Bills
New Zealand	5.6	7	1.4	7	1.0	3.6	Equities	Bills
Norway	4.4	13	1.4	8	0.8	3.6	Equities	Bills
Portugal	3.7	16	−1.6	19	−1.1	7.0	Equities	Bonds
South Africa	6.2	3	1.2	11	0.1	5.0	Equities	Bills
Spain	3.7	15	0.8	13	−0.2	5.4	Equities	Bills
Sweden	5.7	6	2.0	3	1.2	3.3	Equities	Bills
Switzerland	5.3	9	2.8	1	1.3	2.1	Equities	Bills
United Kingdom	5.0	11	1.0	12	0.6	3.5	Equities	Bills
United States	6.6	1	1.6	4	0.5	2.9	Equities	Bills
World ex-US	4.5		1.5					
World	5.3		1.7					

Sources: DMS Database, Dimson, Marsh, and Staunton (2026a); Dimson, Marsh, and Staunton (2026b). Not to be reproduced without written express permission from the authors.

*German bond and bill returns are based on 124 years, excluding 1922–1923.

Despite this uneven performance, global investors in world equities enjoyed creditable returns over the period since we published our first study of long-term asset returns (Dimson, Marsh, and Staunton 2002). Over the last 26 years, they have enjoyed an annualized real US dollar return of 4.0% and an equity premium relative to bills of 4.7%.

Conclusion

Real equity returns since 2000 have been strong but below their historical averages. Four notable bear markets in 26 years have provided a timely reminder of the considerable risk involved in equity investment. Investors were spoiled by high returns in the 1980s and 1990s, when equities seemed to guarantee high returns.

We have stressed the importance of taking a long-term view when seeking to understand the nature of risk and return in the world's markets. It is important because equity and bond markets are volatile. We have shown that in the long run, equity returns have dominated bond and bill returns. Over the 126 years since 1900, equities have outperformed bonds, bills, and inflation in all 21 markets for which we have a continuous history.

For the world as a whole, equities have outperformed bills by 4.8% per year and bonds by 3.5% per year. This result provides a reassuring reminder that in the long run, there has been a reward for taking the higher risk of investing in stocks. Similarly, riskier bonds have outperformed close-to-riskless bills, again indicating a reward for risk. In our most recent Yearbook (Dimson, Marsh, and Staunton 2026b), we looked more closely at these risk premiums and estimated how large we can expect them to be in the future.

Key Takeaways

- Many people consider the long term to be 10 or 20 years. But markets are volatile, and longer periods are needed to understand the risk and return from stocks and bonds. Over the last 126 years, equities dominated government bonds, while bonds outperformed Treasury bills. In the long run, the law of risk and return therefore held: The riskiest assets provided the highest return, and riskless bills gave the lowest return.
- The US stock market has done especially well. However, we caution against extrapolating from the American experience. We quantified the long-run investment performance of 35 different stock and bond markets and presented local-currency returns adjusted for each market's inflation. In a comparison of investment performance since 1900 in common currency, the United States had the highest stock market return and Switzerland had the highest bond market return.
- Developed markets dramatically outperformed emerging markets. Over the period since 1900, a diversified developed market equity portfolio would have grown to more than six times the value of a diversified emerging market equity portfolio. Over the same 126-year interval, a diversified developed market bond portfolio would have grown to more than eight times the value of a diversified emerging market bond portfolio.

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[4]Extensive additional references and data sources are provided in Dimson, Marsh, and Staunton (2026b, pp. 291–300).

CHAPTER 12. THE LONDON MARKET, 1870–1929

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Introduction

The London Exchange was an important public capital market through much of the nineteenth and twentieth centuries. *The Investor's Monthly Manual* (*IMM*) published monthly price records and related information for many of the domestic and international securities that traded on the London Exchange over a 60-year period from 1869 to 1929. We constructed UK and ex-UK capitalization-weighted return indices for corporate stocks, bonds, preferred shares, municipal bonds, and sovereign debt. We matched corporate securities of various types by firm to test the implications of contingent claims theory for the risk and return of subordinated claims. We find a realized equity return of more than 6% and an equity risk premium of more than 3%. We also document significant differences in mean and standard deviation conditional on relative position in the firm's capital structure.

The Investor's Monthly Manual

The Investor's Monthly Manual was a statistical supplement to *The Economist*, published monthly from 1864 to 1870 and less frequently through 1930. The purpose of the supplement was not to provide a continuous, comprehensive, and consistent historical record for posterity but, rather, to be useful to market participants and observers of the day. As such, it is not an official record of securities traded on the London Exchange, but it is nevertheless extensive, with more than 9,000 securities and more than 1.5 million security/month observations. An ongoing project at the International Center for Finance at the Yale School of Management has made the digitized security-level price and dividend data available for research.

Testing Capital Structure Theory

The London capital market provides a rich dataset to test a basic hypothesis about the relative risk and return of structured claims on the value and cash flows of corporations. The stocks, bonds, preferred shares, and other contingent securities for each firm are listed together in the manual, making it possible to inspect the entire capital structure without matching across disconnected data sources.

Contingent claims theories of the firm (e.g., Black and Scholes 1973; Merton 1974; Bhamra, Kuehn, and Strebulaev 2010) make sharp predictions about the relative risk and expected return of corporate securities, conditional on priority position. Equity represents the most junior claim, followed by preferred shares and corporate debt, with senior debt enjoying priority in default states. Because junior claims absorb losses in adverse states and exhibit greater exposure to firm-value volatility, they are inherently riskier and more sensitive to macroeconomic shocks and should earn higher expected returns.

Although Modigliani and Miller (1958, 1963) emphasized that leverage reallocates risk without altering total firm value, the contingent claims framework clarifies how this reallocation generates a strict hierarchy of risk and expected returns across claims. We test this prediction using long-horizon realized returns as proxies for expected returns.

Stocks, Bonds, Bills, and Inflation

Ibbotson and Sinquefield (1976a) is a landmark article in the application of modern portfolio theory to the practice of investment management. It was motivated in part by the need to calculate the risk, return, and correlations for the major US asset classes that dominated institutional investment portfolios at the time. Their analysis was particularly valuable to professional investment managers, who had only recently adopted quantitative methods of portfolio optimization. What was lacking at the time were reliable inputs to the mean–variance model. Ibbotson and Sinquefield (1976a) showed that despite the turbulent performance of equities in the early 1970s, the long-term perspective demonstrated that equity investors could have earned a substantial premium over bonds.

In a companion article, Ibbotson and Sinquefield (1976b) developed a decomposition of expected returns based in part on capital structure theory and in part on the theory of factor premiums. They postulated a small stock premium, an equity premium, a default premium, a horizon (term) premium, and a real (inflation-adjusted) return. The authors found that each of these premiums was positive over the 50-year sample, consistent with the hypothesis that investors require compensation for holding each type of risk. They showed how to use this building block model to forecast future asset class returns via simulation methods.

We do not use precisely the same premiums as Ibbotson and Sinquefield (1976b). First, we forgo the calculation of a small stock premium. Although market commentators in the late nineteenth and early twentieth centuries recognized some shares as more speculative than others, they did not typically differentiate on the basis of capitalization; late twentieth-century interest in small stocks as an asset class stems from the foundational academic research on factor premiums by Banz (1981) and Reinganum (1981).

Instead, we calculate two additional premiums: a preferred share premium, which we call a *priority premium*, and a municipal bond premium over long-term government bond returns. The prevalence of preferred shares in the *IMM* database gives us more power to test whether seniority in the corporate capital structure is associated with lower realized returns. The prevalence of municipal bonds in the database allows us to test a different but interesting hypothesis—whether UK government debt at the time had a lower risk and return than municipal debt had. Finally, we calculate an equity risk premium in two ways: using long-term government debt and a proxy for the short-term riskless security.

Methodology

The London market listed and traded securities of issuers from all over the world, enabling us to compare the performance of UK-only portfolios with that of ex-UK portfolios. We construct annual cap-weighted indexes of each corporate asset class based on the securities issued by the 100 largest companies each year. To do this, we identified the 100 largest firms by equity capitalization at the end of each year. We then found the corporate bonds and preferred shares of these firms.

We calculated a cap-weighed equity return, a cap-weighted bond return, and a cap-weighted preferred share return over the next year. We calculated premiums by taking the differences between these indexes. We used December prices to calculate capital appreciation and price returns. We summed the dividends over the year to calculate income returns and added price return and income return together to calculate total return. If prices were missing for the December issue, we used the price from the latest available month. Because not all companies in a given year have bonds or preferred shares trading, these asset classes may contain fewer securities. This approach has the benefit of measuring the stock–bond premium on the same companies.

Both domestic and foreign municipal debt are represented in our sample, as is foreign sovereign debt. For each of these asset classes, we calculated cap-weighted indexes. For domestic long-term debt, we formed portfolios of long-term government bonds consisting of consols and other long-maturity Treasuries. It is difficult to find a perfect proxy for a short-term riskless security available to investors. UK Treasury bills did not exist over much of the period of analysis; we followed other authors and used the UK prime commercial bill rate. Inflation and production data are from the Bank of England website.

Summary Statistics

Exhibit 12.1 reports summary statistics for three sets of data: the UK only, world ex-UK, and world portfolios. The exhibit reports the results over the full 60-year time period (1870–1929) for the geometric annual return (GM), arithmetic annual return (AM), standard deviation (SD), and Sharpe ratio (SR), where the commercial bill rate is taken to be the riskless rate.

The annual arithmetic mean return for the UK equity index over the 60-year period is 7.34%. This figure is significantly lower than the large-cap US index return over the post-1925 period documented by Ibbotson and Sinquefield (1976a) and the post-1900 period studied by Dimson, Marsh, and Staunton (2023) for UK equities. The volatility of the returns from the pre-1930 equity data is lower as well, however: 7.77% compared with equity index volatility near 20% for most twentieth-century markets. This risk difference may result from the fraction of income return versus capital appreciation. Much of the return in the *IMM* period (1865–1929) was from dividends, and although variable, they were smoother than price changes. As a result, the Sharpe ratio for the *IMM* sample, measured conservatively by using the commercial paper rate as the riskless rate, is 0.45.

Notice the near-monotonic decline in both the risk and return of the basic series in the UK market as one proceeds through the capital structure. The preferred stock return is lower than the common stock return, the corporate bond return is lower than the preferred stock return, the municipal bond return is lower than the corporate bond return, and the government bond

Exhibit 12.1. Asset Returns by Category for the UK, World Ex-UK, and World Portfolios

Asset Class	GM	AM	SD	SR	*t*-Statistic
A. United Kingdom					
Common stock	7.06	7.34	7.77	0.45	7.32
Preferred stock	4.01	4.18	6.01	0.08	5.38
Corporate bond	3.50	3.62	4.90	−0.01	5.71
Municipal bond	3.27	3.36	4.36	−0.06	5.97
Government bond	2.78	2.88	4.39	−0.16	5.08
Commercial paper	3.66	3.67	1.19	–	23.84
Inflation	1.00	1.18	6.31	–	–
B. World Excluding United Kingdom					
Common stock	5.62	6.01	9.09	0.25	5.12
Preferred stock	5.21	5.39	6.04	0.27	6.90
Corporate bond	4.47	4.57	4.70	0.17	7.54
Municipal bond	5.12	5.21	4.37	0.31	9.24
Government bond	4.54	4.64	4.52	0.19	7.96
C. World					
Common stock	6.62	6.88	7.35	0.41	7.25
Preferred stock	4.38	4.49	4.87	0.15	7.14
Corporate bond	3.72	3.82	4.61	0.03	6.41
Municipal bond	3.88	3.95	3.88	0.06	7.89
Government bond	3.89	3.96	3.88	0.06	7.91

Notes: All returns are annualized percentages; *t*-statistics are for the AM. The commercial paper and inflation series are available only for the United Kingdom.

return is lower than the municipal bond return. The only surprise is the higher commercial paper rate compared with the government bond return. Odlyzko (2016) argues that the high price of UK consols in the nineteenth century resulted from their role as a benchmark safe asset in the global capital market.

The monotonic relationship among UK corporate securities does not hold for the other portfolios. For example, Panel B of Exhibit 12.1 shows the summary statistics for the ex-UK portfolios. The common stock return and the Sharpe ratio for the world ex-UK portfolio are both much lower relative to the UK portfolio. Interestingly, the returns to ex-UK preferred stock, municipal bonds, and government bonds are all higher relative to the UK asset classes. The returns across all the ex-UK asset classes are compressed.

Summary statistics differ somewhat for the world portfolio, which was constructed by applying the top 100 rule to equities from the entire sample of companies listed in the *IMM* database. The common stock row for the world category represents the annual average return to a capital-weighted portfolio of the largest stocks reported in the *IMM* database each year, and as before, the preferred stock and corporate bonds are those issued by these same top 100 firms. Ex-UK government bonds represent the returns to a cap-weighted portfolio of sovereign debt of more than 20 countries.

Exhibit 12.2 shows the market share by asset class over the 60-year period and the total capitalization of the market. The market grew fourfold from 1870 to 1929, with long periods in

Exhibit 12.2. Market Share of UK Securities by Asset Class and Total Market Capitalization, 1870–1929

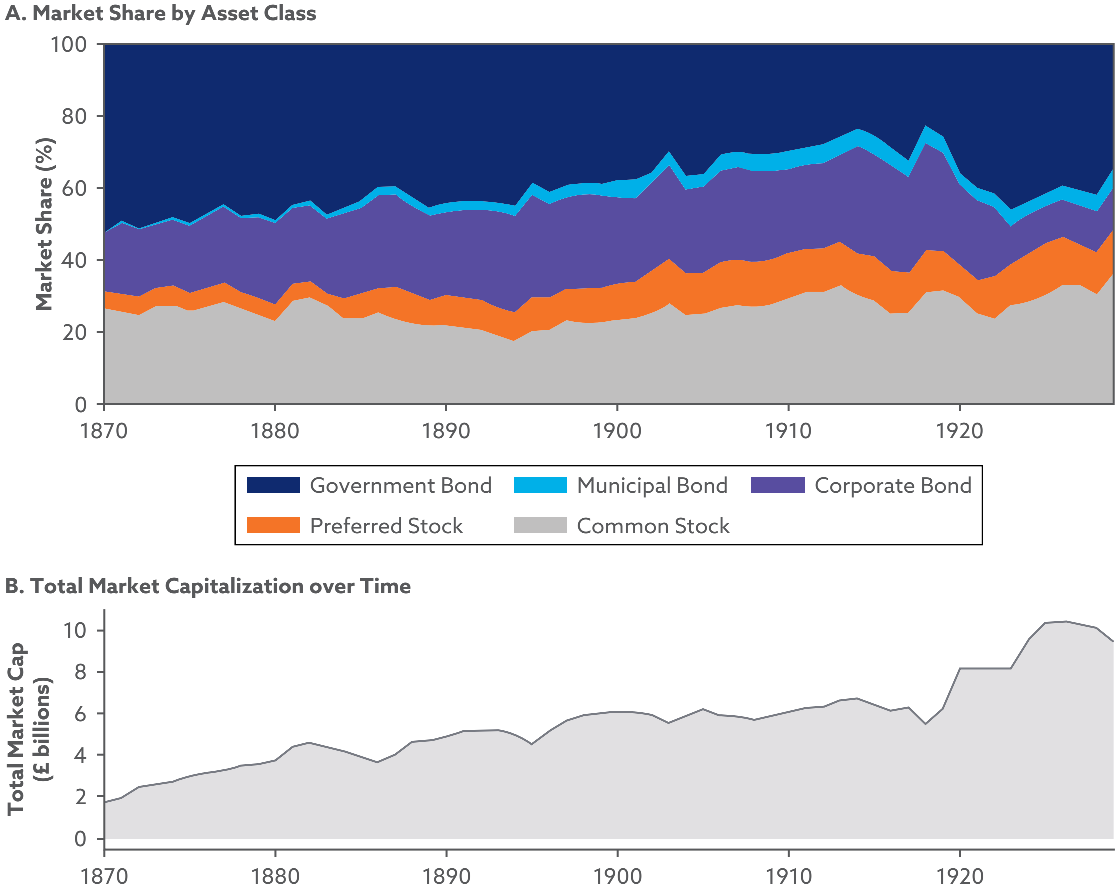
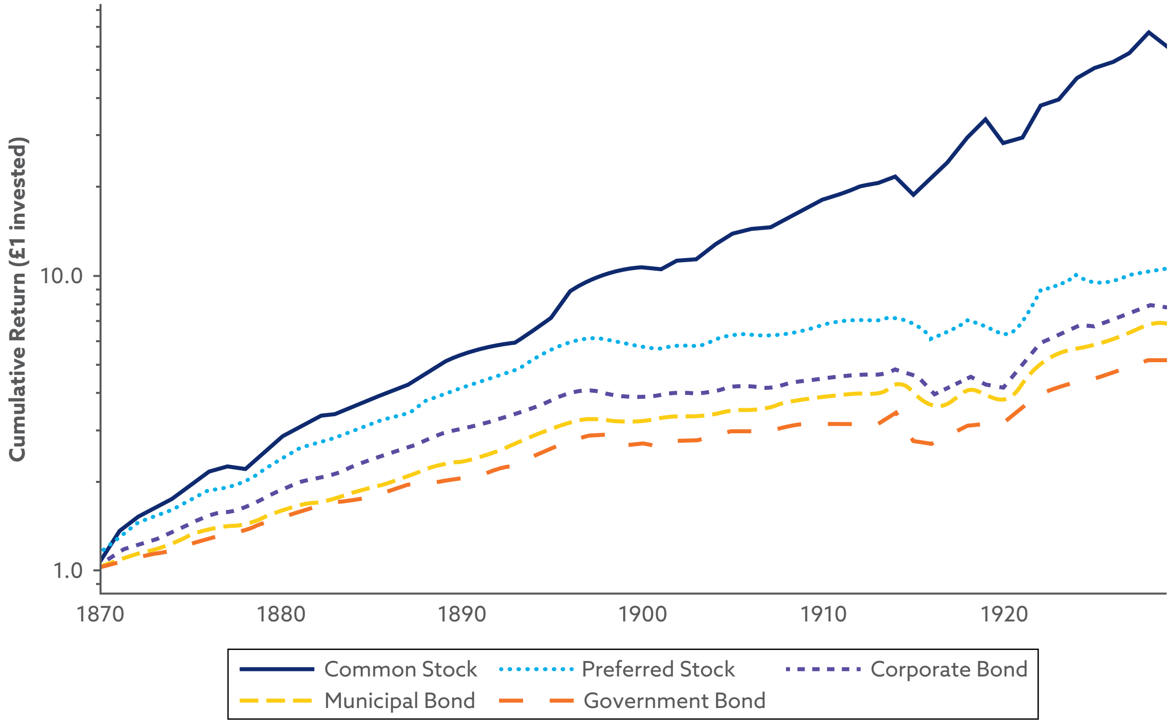


Exhibit 12.3. Cumulative Total Returns by UK Asset Class, 1870–1929



which the capitalization growth was under 3%. This finding is consistent with consumption of a substantial component of total return each period. The exhibit also shows that the fraction of common stock remained fairly stable, growing only slightly in the 1920s.

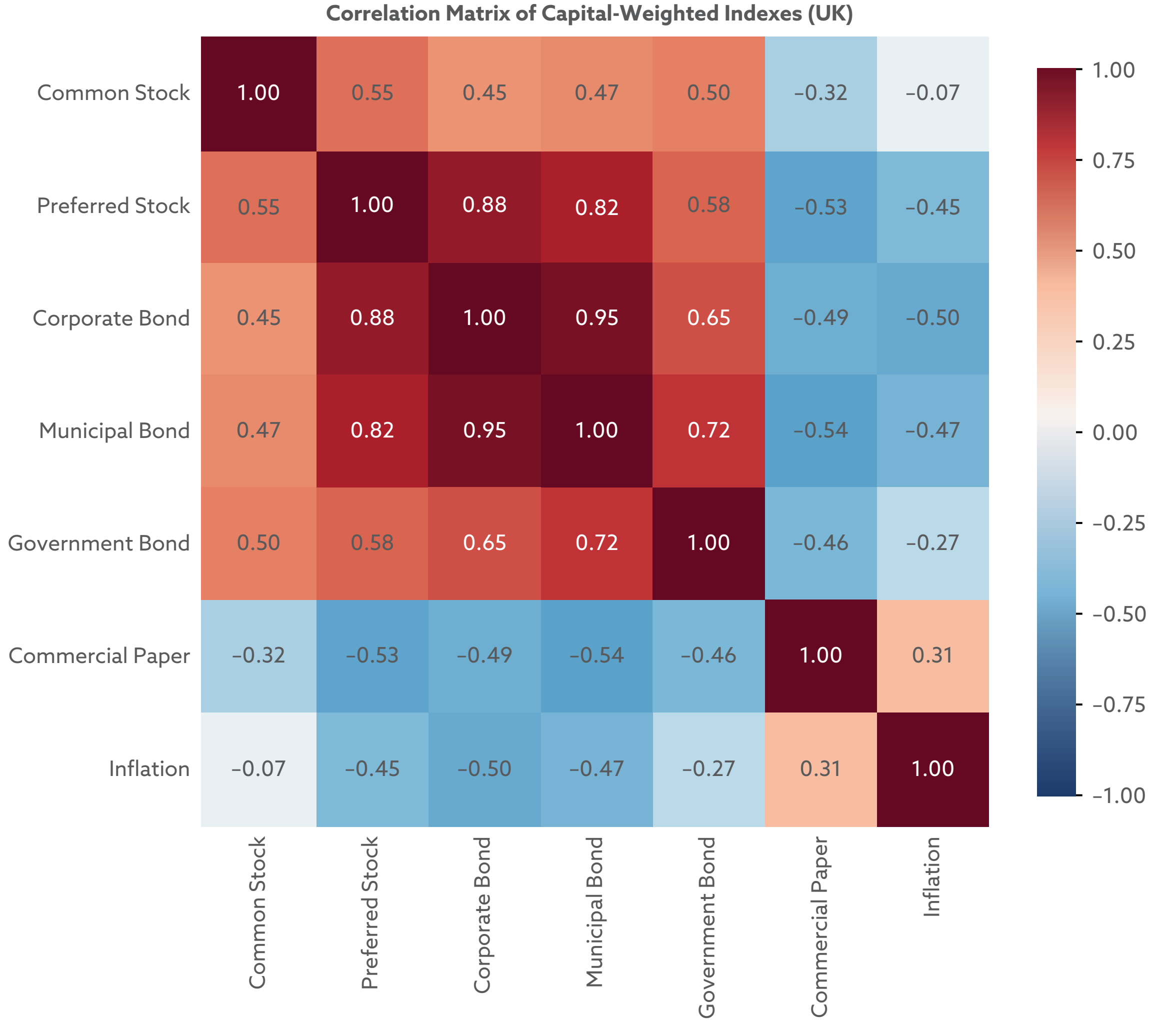
Exhibit 12.3 shows the 60-year cumulative return for stocks, the various corporate asset classes, and long-term government bonds. The risk–return tradeoff for equities versus senior securities is clear, as is the sensitivity of equities to shocks, such as World War I, the recession of 1920–1921, and the crash of 1929.

Exhibit 12.4 is a color-coded correlation matrix of asset class returns, with positive correlation in red and negative correlation in blue, coded as a heat map. Notice that UK equities are highly (but not perfectly) correlated with non-UK equities, moderately correlated with fixed-income securities, and negatively correlated with commercial paper and inflation. Among fixed-income securities, preferred stock and corporate bonds are highly correlated, as predicted by theory.

Risk Premiums

As described previously, premiums are calculated as the difference between the annual return series of two value-weighted portfolios (one for each asset type). For corporate securities, conditioning on the set of top firms each year largely controls for cross-sectional firm

Exhibit 12.4. Correlation Matrix of Capitalization Indexes by Asset Class (UK Portfolio)



differences in underlying risk and provides an accurate test for the significance of corporate risk premiums. **Exhibit 12.5** shows these various premiums.

For the UK portfolio, the equity risk premium is computed two ways: first with respect to the returns on commercial paper and second with respect to returns on a portfolio of long-term UK government bonds, mostly consols. The latter may be appropriate given the similar duration of cash flows from equity and long-term bonds, as well as the fact that the British consol was a reference security; during the period of our data, it was widely regarded as a safe investment. The equity premium over commercial paper is 3.7% and over government bonds is 4.5%, both with *t*-statistics greater than 3. Similarly, the equity premium over all other corporate securities is statistically significant.

Exhibit 12.5. Premium Estimates by Category for the UK, World Ex-UK, and World Portfolios (Full Sample)

Premium	GM	AM	SD	*t*-Statistic
A. United Kingdom				
Equity – commercial paper	3.34	3.68	8.23	3.46***
Equity – long-term government bond	4.25	4.46	6.72	5.14***
Equity – all corporate securities	3.23	3.45	6.74	3.96***
Priority (preferred stock – corporate bond)	0.52	0.56	2.92	1.49
Default (corporate – government bond)	0.66	0.74	3.93	1.45
Municipal – government bond	0.43	0.49	3.25	1.16
Horizon (government – commercial paper)	−0.92	−0.79	5.05	−1.21
B. World Excluding United Kingdom				
Equity – commercial paper	1.90	2.35	9.50	1.91*
Equity – long-term government bond	1.05	1.37	8.08	1.31
Equity – all corporate securities	0.79	1.03	6.97	1.15
Priority (preferred stock – corporate bond)	0.59	0.81	6.72	0.94
Default (corporate – government bond)	−0.13	−0.07	3.57	−0.15
Municipal – government bond	0.52	0.57	3.23	1.36
Horizon (government – commercial paper)	0.84	0.98	5.11	1.48
C. World				
Equity – commercial paper	2.90	3.21	7.84	3.17***
Equity – long-term government bond	2.72	2.92	6.29	3.59***
Equity – all corporate securities	2.56	2.72	5.85	3.61***
Priority (preferred stock – corporate bond)	0.61	0.67	3.60	1.45
Default (corporate – government bond)	−0.18	−0.14	2.73	−0.41
Municipal – government bond	−0.03	−0.01	1.96	−0.06
Horizon (government – commercial paper)	0.19	0.29	4.54	0.50

Notes: All premium estimates are stated in annualized percentages. * and *** denote significance at the 10% and 1% levels, respectively.

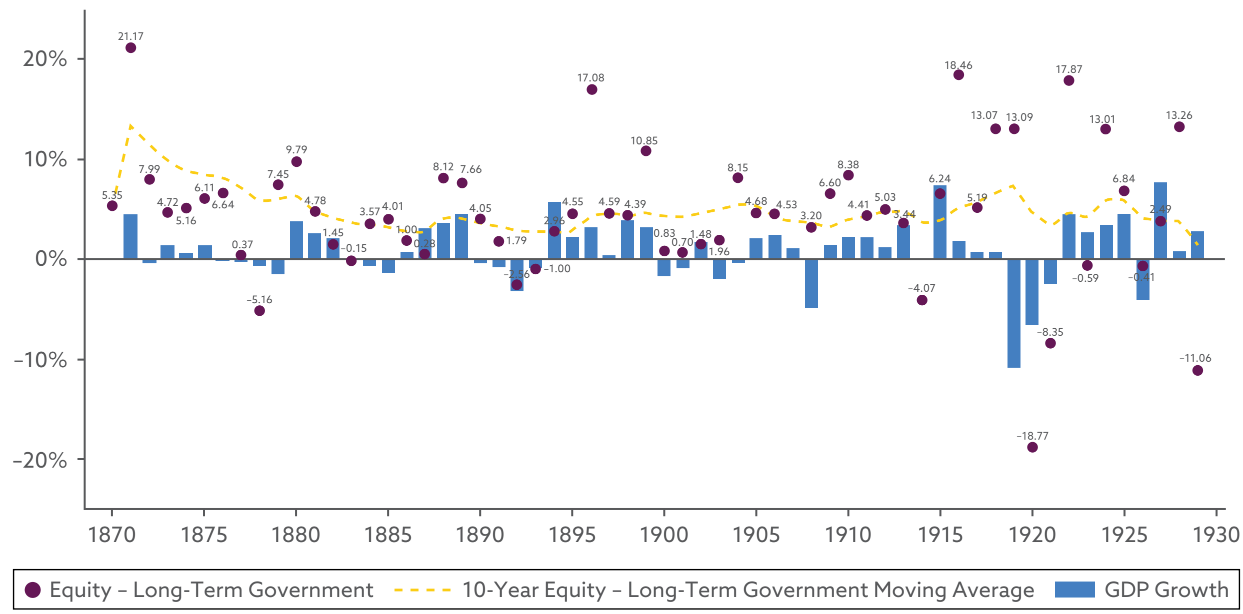
Consistent with theory, the priority premium of preferred stock returns over corporate bond returns is positive, at about 0.52%. The difference in corporate bond returns and long-term government bond returns measures the realized default premium, which is about 0.66%. Chambers, Dimson, Ilmanen, and Rintamäki (2024) surveyed the literature on long-run asset returns and reported that investment-grade corporate bonds have historically offered a credit premium of roughly 1% per year over government bonds across several markets and periods.

Dimson, Marsh, and Staunton (2024) devoted a special chapter to corporate bond returns across countries in the *UBS Global Investment Returns Yearbook 2024*. Our estimate of the default premium in the *IMM* data is broadly consistent with these findings. The only premium with an unexpected sign is the horizon premium.

Exhibit 12.6 plots the annual equity risk premium with respect to government bonds. Purple dots are the annual realized premium, the dashed yellow line is the 10-year backward-looking rolling equity risk premium, and the blue bars are annual UK GDP growth. In most years, the equity risk premium is positive, particularly in the years before World War I. Negative values are associated with recessions or near-zero GDP growth, consistent with equity market exposure to macroeconomic risk.

The rolling 10-year equity premium shows that stocks beat government bonds over every decade-long period in the sample. Exhibit 12.5 shows the relationship is a statistically significant one. The smallest 10-year spread was the final one, ending in 1929. It is noteworthy that 1930

Exhibit 12.6. Equity Risk Premium over Bonds for the Top 100 UK Firms, Backward-Looking 10-Year Moving Average, and Percentage Change in UK GDP, 1870–1929



Note: The risk premium is measured as the difference between the capitalization-weighted index of top 100 UK firms by size and the return to an index of long-term UK government bonds was the last year *The Economist* published *The Investor's Monthly Manual*. The sample ended as the Great Depression began.

McQuarrie (2024) argues that over the very long run, stocks do not always beat bonds, documenting episodes in both the United States and the United Kingdom during which bonds outperformed equities, even over extended holding periods. The consistently positive rolling 10-year equity premium in the *IMM* data suggests that at least in the pre-1930 UK market, the equity risk premium was reliably positive at the decade horizon. This result stands in contrast to the postwar experience in some markets where bonds periodically dominated.

Conclusion

The Investor's Monthly Manual is a record of an important and liquid capital market during its historical peak. We use it to test whether the premiums for a hierarchy of the seniority of corporate claims are consistent with theory; that is, subordinate claims should have a higher risk and thus a higher expected return. We use long-term realized returns over 60 years to test the higher-risk hypothesis and the long-term mean return over the period as a proxy for expected returns. We also tested the statistical significance of these premiums, as well as that of the equity risk premium, with respect to proxies for the riskless rate; long-term government bonds, which have a similarly long duration of future cash flows to corporate cash flows; and a commercial paper rate, which is typically of 30–60 days' duration.

The empirical evidence provided by UK firms strongly supports theoretical predictions about subordinated versus senior claims. Junior claims are more volatile and more sensitive to macroeconomic shocks. The evidence from the ex-UK firms is not significant but generally consistent in sign relative to UK firms.

One potential concern about these results is that we calculated the premiums using data recorded during the heyday of the London capital market. The data stopped in 1930, after the crash year of 1929. This may bias our estimate of the equity risk premium upward. For an investor in 1929 looking back over nearly a lifetime of financial securities performance, however, the relative risk and return of corporate securities with a hierarchy of claims on cash flows and firm value accords well with what later financial theory would predict.

Key Takeaways

- Equity investors in the London market between 1870 and 1929 were consistently compensated for risk. The equity premium over long-term government bonds averaged 4.5% per year, similar to modern evidence for developed markets over the twentieth century.
- The realized returns to equities, preferred shares, corporate bonds, and government bonds decline monotonically with seniority, consistent with the predictions of contingent claims theory.
- The equity premium comoved with the real economy, confirming that equity risk reflected exposure to macroeconomic shocks and was not just noise.

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CHAPTER 13. AN INDEX OF COMMODITY FUTURES RETURNS SINCE 1871

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Introduction

Commodity futures have long played a pivotal role in the global economy, facilitating price discovery and risk management across sectors ranging from agriculture to energy and industrial production. Despite their economic significance, the classification of commodity futures as a distinct asset class remains a subject of debate. To qualify as an asset class, Sharpe (1992) emphasizes shared risk–return characteristics and common responses to economic forces as key criteria.

Although commodity futures share common attributes, such as providing price insurance and exposure to inflation-sensitive assets, their classification as a distinct asset class hinges on whether they exhibit consistent risk and return characteristics over time. This question is fundamentally empirical, requiring a long-term analysis of historical performance across a variety of economic regimes.

This chapter documents the returns to a broadly diversified index of commodity futures, covering more than 150 years of economic, financial, and institutional development. The analysis is based on a uniquely constructed dataset that draws from exchange yearbooks when available and relies extensively on newspaper archives to fill gaps in coverage. By including both active and obsolete contracts, the resulting index reflects the evolving structure of futures markets and captures the performance of a broad array of commodities, many of which are no longer traded today.[1]

This chapter is organized as follows. We begin by defining the return earned by an investor in commodity futures and discuss how it differs from the return on holding physical commodities. We then discuss the data and the construction of our commodity futures index. Next, we examine the time-series behavior of the commodity futures index and compare its performance to that of a diversified index of US equities. This comparison highlights the distinct return dynamics and volatility profiles of futures-based investments relative to other asset classes. We also

[1]For a detailed description of the database, see Qiao and Rouwenhorst (2026).

compare our collateralized commodity index with the cumulative inflation rate to understand real returns over time.

The main findings are that over the past 155 years:

- Commodity futures have earned a risk premium over the riskless rate of 5.5%.
- Commodity futures have outperformed US stocks in two of every five years.
- The return to commodity futures has exceeded an index of US inflation by more than 6% per year.

Finally, we highlight the distinction between futures and spot returns through a decomposition of futures excess returns into spot returns and the roll yield.

In the next section, we define the excess return and collateralized return to commodity futures. Readers who are familiar with these concepts can skip to the section on data and index construction without loss of continuity.

Definition of Collateralized Commodity Futures Returns

When evaluating the investment performance of commodities, it is important to draw a distinction between investing in commodity futures versus the underlying physical commodities. A futures contract is a standardized agreement to buy or sell some physical good or financial asset (the "underlying") at a prespecified time in the future. The futures price itself is not the cost of entering into a futures contract but, rather, an agreed-on reference from which gains and losses are tallied.

At the initiation of a futures contract, no cash changes hands between the buyer and the seller because the futures price is set such that the value of the contract is zero at origination. As the futures price changes, futures buyers and sellers may be required to post collateral to alleviate counterparty risk, but the collateral remains theirs, can be placed in interest-bearing securities (commonly Treasury bills), and is therefore not a "cost" to the investor.

In contrast to futures, a spot transaction to buy or sell physical commodities does require a transfer of cash to open the position. A spot transaction is therefore a fully funded investment, similar to buying or selling stocks without a margin loan.

The return dynamics differ too. An investor in physical markets benefits from an increase in the (spot) price of the commodity but incurs the cost of "carrying" the commodity. The cost of carry includes storage fees, insurance costs, and loss associated with spoilage. In an efficient market, the futures prices will embed market expectations about future spot price movements, so a long futures investor will benefit from *unexpected* spot price increases. *Expected* spot price changes, however, are not a source of returns for a futures investor. We will discuss the difference between futures returns and spot returns in more detail later.

Let F_t^T denote the futures price at time t of a contract that matures at time T. The futures excess return from time t to time $t+1$, $\mathrm{ER}_{t,t+1}^{F,T}$, is calculated as follows:

$$\mathrm{ER}_{t,t+1}^{F,T} = \frac{F_{t+1}^T}{F_t^T} - 1. \tag{13.1}$$

$ER_{t,t+1}^{F,T}$ is an excess return because no cash changes hands when a futures position is initiated. To facilitate a comparison of a futures excess return to funded investments, such as stocks or physical commodities, we assume that the "funding" for the futures position is invested in a riskless investment. This is also how in practice "fully collateralized" commodity indices are constructed—as a holding of T-bills supporting a position in futures.

The total return of a fully collateralized futures position from time t to time $t+1$, $TR_{t,t+1}^{F,T}$, is given by

$$TR_{t,t+1}^{F,T} = ER_{t,t+1}^{F,T} + r_t, \tag{13.2}$$

where r_t is the one-period riskless rate. Because the collateral is invested in the riskless asset, the risk of the collateralized futures position is identical to that of the excess return. Therefore, the excess return on the collateralized futures position has the interpretation of the commodity futures risk premium (over the riskless asset).

A common economic explanation for the presence of a risk premium in commodity futures is to compensate the long side of the contract for absorbing the excess demand for short hedging of price risk in the underlying physical markets. First hypothesized by Keynes (1930), what is commonly known as the theory of normal backwardation has been extensively explored in the academic literature.[2]

Data and Index Construction

In this section, we cover the sources of our data and explain how we constructed our index.

Data Sources

Despite the long history of commodity futures trading, few comprehensive databases of historical price records exist. One of the most popular commercial datasets, offered by the Commodity Research Bureau (now Barchart), goes back to 1959. Dow Jones published a commodity index in 1933, but it was primarily used to track spot prices (Bhardwaj, Janardanan, and Rouwenhorst 2021). Two recent efforts to collect historical data (Levine, Ooi, Richardson, and Sasseville 2018; Geczy and Samanov 2019) covered very few contracts prior to 1950.

The data used in this chapter are drawn from a hand-collected dataset of 230 contracts going back to 1871, when futures trading commenced in the United States. This comprehensive dataset combines prices from prominent newspapers with exchange handbooks. A unique and important aspect of the database is the extensive coverage of contracts that have ceased trading over time. Qiao and Rouwenhorst (2024) show that poor investor performance is negatively correlated with contract survival. Hence, it is important to include nonsurviving contracts when evaluating the investment performance of commodity futures.

We complement our futures data with other datasets used in subsequent analysis and comparison. For the riskless rate, we use the 3-Month Treasury Bill Secondary Market Rate from FRED (Federal Reserve Economic Data) from 1934 to 2025, the Ibbotson Associates 30-Day Treasury Bill Total Returns from 1926 to 1934, and values obtained from Siegel (1992) prior to 1926.

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[2]See the reviews by Gray and Rutledge (1971) and Rouwenhorst and Tang (2012).

We use the all-cap composite portfolio from Ibbotson Equity Indices™ to represent the performance of the aggregate US stock market, kindly provided by Roger Ibbotson and described elsewhere in this volume. Because the Ibbotson Indices™ do not start until 1926, we use the market-capitalization weighted portfolio of all stocks from the Cowles Foundation from 1871 through 1925.

Finally, inflation data are obtained from the Federal Reserve Bank of St. Louis. From 1913 to 2025, we use the monthly series Consumer Price Index for All Urban Consumers: All Items in U.S. City Average, not seasonally adjusted (CPIAUCNS). From 1871 to 1912, inflation figures are calculated from Robert Shiller's CPI data used in his book *Irrational Exuberance* (Shiller 2000).

Index Construction

The construction of an index of commodity futures returns requires a number of choices regarding the tenor (time to maturity) of the contract and the roll schedule:

- Contract maturity: At the end of month t, the index tracks for each commodity the nearest-to-maturity contract that does not mature in month $t + 1$. This approach ensures that the index is invested in what is typically the "front" contract, which is typically the most liquid portion of the futures curve.
- Commodity weighting: Especially in the early days of futures trading, similar commodities are traded on multiple exchanges. For example, wheat was traded in Buffalo as well as Chicago, and Chicago offered multiple turkey contracts. For the purpose of index calculation, "similar" contracts on the same underlying commodities on the same exchange are treated (averaged) as one, but commodities that trade on different exchanges are always treated as separate commodities.
- Commodities receive equal index weights, and the index is rebalanced monthly.

In a given month, the index total return is defined as follows, where $TR^{F,T}_{i,t,t+1}$ is the total return of commodity i and N_t is the number of commodities in month t:

$$TR^{EW}_{t,t+1} = \sum_{i=1}^{N_t} \frac{TR^{F,T}_{i,t,t+1}}{N_t}. \tag{13.3}$$

Annual Index Returns

Exhibit 13.1 shows annual total returns for the collateralized equally weighted (EW) commodity futures index. A time series of annual total returns can be constructed from the data labels in the four panels. The advantage of having a bar plot along with specific values combines the ease of visual inspection of return sizes and dynamics with the precision of exact figures for each calendar year.

In its early history, toward the end of the nineteenth century, the index performed poorly because of a string of negative returns, despite experiencing one of the largest single-year returns in its 155-year history (54.2% in 1879). This period was marked by large increases in cultivated farmland and technological improvements (such as railways and tractors) in a largely deflationary environment that saw a steady decrease in consumer prices.

A remarkable string of positive annual total returns followed this period, from 1897 to 1919. The period between World War I and World War II was marked by large total returns of either sign, indicating heightened uncertainty in the resources markets. A more tranquil phase followed World War II, with many years exhibiting returns of relatively small magnitude, mostly positive, between 1950 and 1970.

The 1970s were again a turbulent decade, with several events putting inflationary pressure on commodity prices, such as the energy crisis of 1973 and the "Great Grain Robbery" in 1972, which saw the Soviet Union purchase massive amounts of grain from the United States at subsidized prices, subsequently causing global prices to soar. A period of mostly positive returns spans 1987 to 2010, although consecutive positive years are interrupted by a few negative ones, such as 2008. No clear pattern emerges from the most recent 15 years of history.

To provide a sense of the breadth of the index and the ebb and flow of commodity contracts over time, Exhibit 13.1 tracks the number of index constituents in each year at the bottom of each panel. During the first decade, the index consisted of fewer than 20 commodities,

Exhibit 13.1. Annual Total Returns of Equally Weighted Commodity Futures Index, 1871–2025

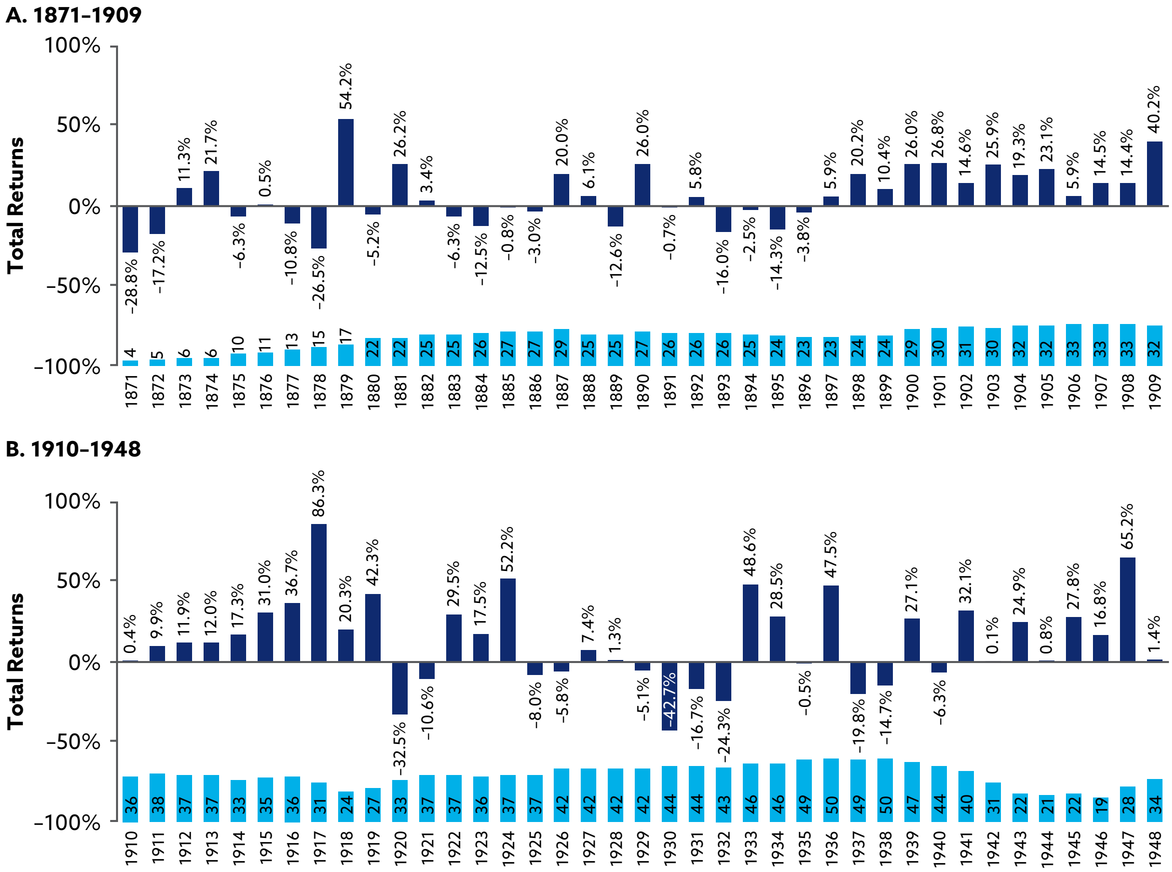
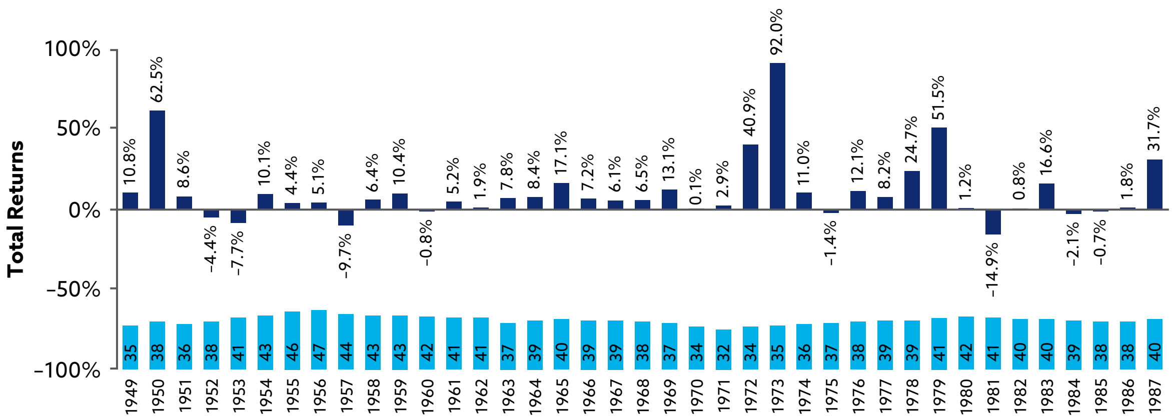
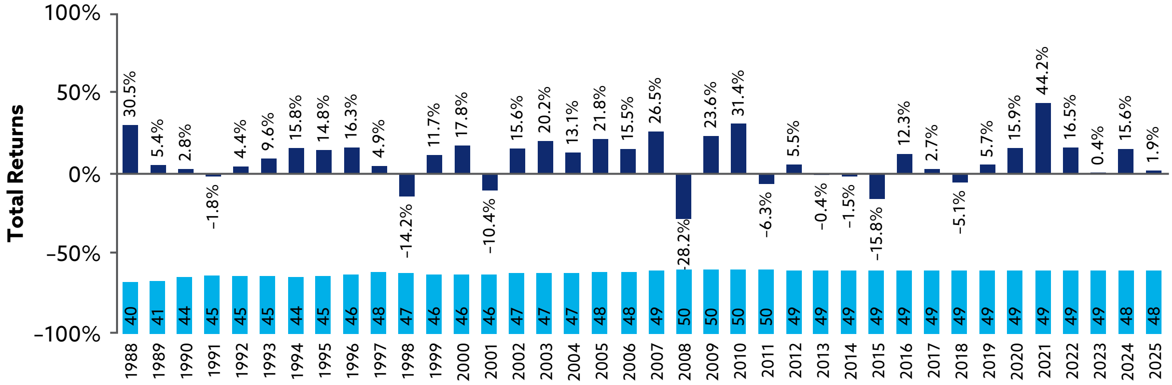


Exhibit 13.1. Annual Total Returns of Equally Weighted Commodity Futures Index, 1871–2025 (*continued*)

C. 1949–1987



D. 1988–2025



Source: SummerHaven Investment Management.

Notes: The exhibit provides annual total returns of the equally weighted commodity futures index. The number of index constituents in each year appears at the bottom of each panel.

reflecting the gradual expansion of commodity futures markets in the United States. By the turn of the twentieth century, the index covered about 30 distinct commodity futures, growing to 50 by the early twenty-first century. The two world wars were periods of index contraction because of trading suspensions and market closures.

Commodity Futures vs. Equities

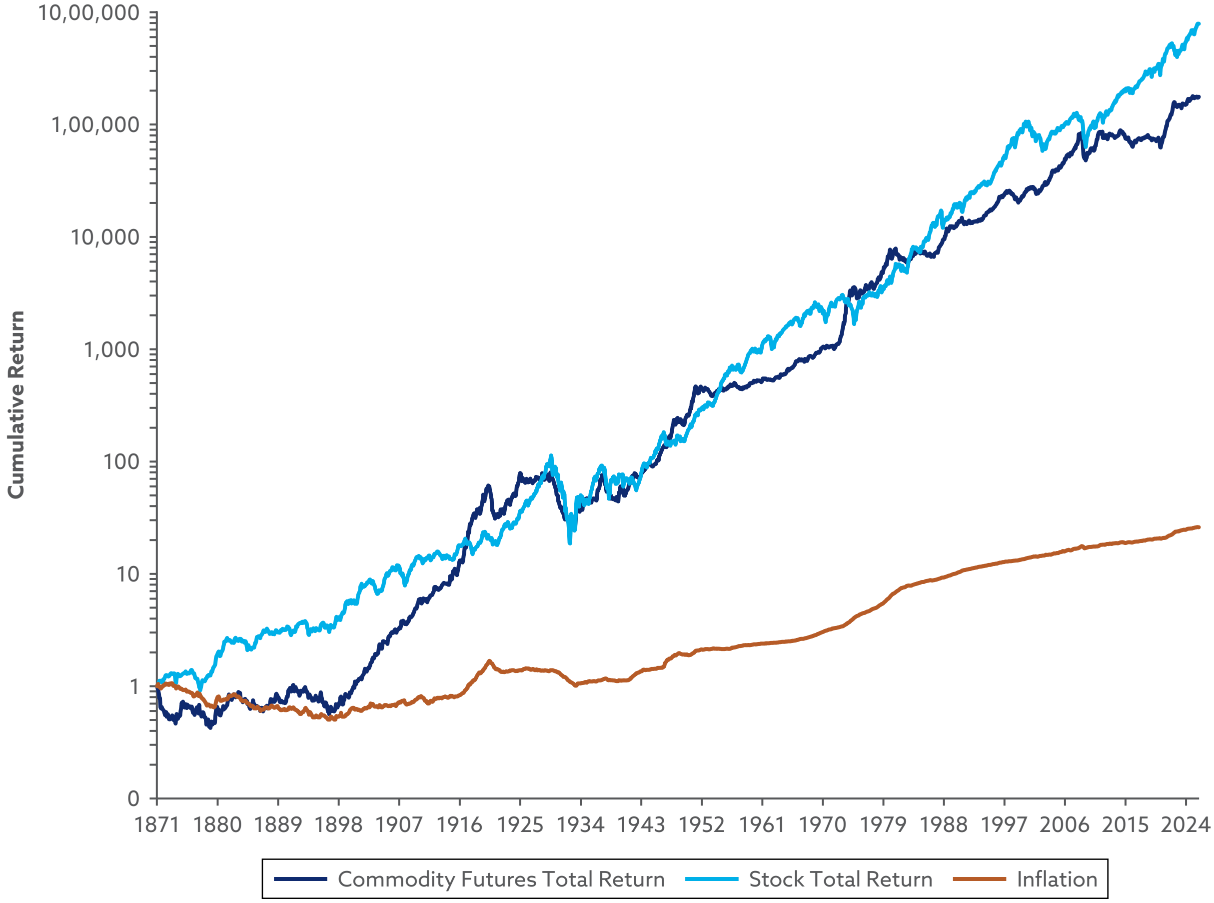
In this section, we compare the performance of commodities and equities since 1871.

Cumulative Performance

Exhibit 13.2 illustrates the cumulative total returns of commodities and stocks over 155 years versus cumulative inflation, plotted on a logarithmic scale to visualize changes in average returns over time. Three observations stand out:

1. A long position in commodity futures has historically earned a positive risk premium that is similar in magnitude to the equity risk premium, as evidenced by the similar average slope of the two indexes on a log scale.
2. Returns to commodity futures and equities have historically exceeded inflation by a wide margin.
3. The commodity risk premium and the equity risk premium have historically accrued in different periods, as evidenced by the divergence and subsequent convergence of the two performance lines.

Exhibit 13.2. Commodity and Stock Cumulative Total Returns and Inflation, January 1871–December 2025



Source: SummerHaven Investment Management, Federal Reserve Bank of St. Louis, Ibbotson Equity Indices™.

The first observation is evident from comparing the futures and equity lines in Exhibit 13.2. Anyone skeptical about the presence of a historical risk premium for commodities would have to explain why the two lines have tracked each other closely over a 155-year period. For others, the presence of a historical risk premium can provide direct evidence of an important requirement for qualification as an asset class.

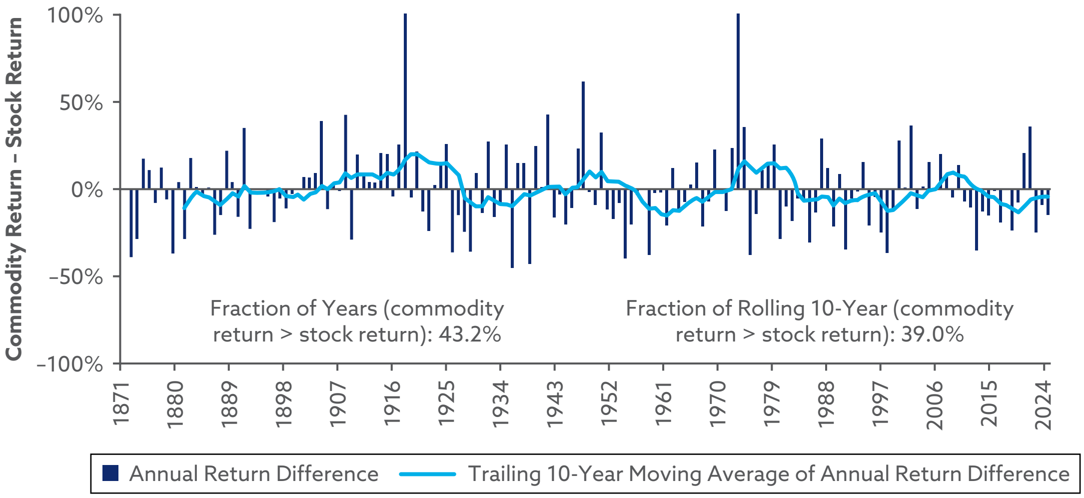
As Qiao and Rouwenhorst (2026) show, the index risk premium stems in large part from risk premiums embedded in the pricing of the *individual* index constituents. These authors showed that the majority of the 230 futures contracts that make up the index have earned a positive average excess return over their lifetimes. In this respect, commodity futures fit well with Sharpe's (1992) notion of an asset class. The second observation is self-evident from the discrepancy between the cumulative returns to commodity futures and equities, on one hand, and cumulative inflation, on the other.

Differential Performance and Diversification

The third observation is more clearly illustrated in **Exhibit 13.3**, which plots the annual difference between the return to stocks and the return to commodity futures over the past 155 years. A positive bar indicates a year where commodity futures outperformed equities, while a negative bar indicates underperformance of commodities relative to equities. The solid line tracks the 10-year trailing return difference of commodities over stocks. Two observations stand out:

- There is great variability in the annual return difference between commodities and stocks.
- Commodities have outperformed equities in two out of every five years historically. Similarly, in two out of every five historical 10-year periods, commodities outperformed equities.

Exhibit 13.3. Difference in Annual Returns Between Commodities and Stocks, January 1871—December 2025



Source: SummerHaven Investment Management, Ibbotson Equity Indices™.

The first observation suggests that commodity futures and equities have distinct fundamental risk drivers. If they had significant common drivers, we would expect to observe high comovement of returns and little variation in the return difference between the two indices. But we do not. In other words, commodities as a whole have a high "tracking error" relative to equities, marked by idiosyncratic movement in the respective asset classes. The second observation points to the potential diversification benefits of commodity futures. A portfolio that allocates to commodities and equities, rather than just equities, benefits from improved performance in the 40% of years that equities underperform commodities.

A Decomposition of Commodity Futures Returns

In this section, we discuss how the collateralized futures return differs from the spot return. The spot return, $R^{S}_{t,t+1}$, is defined as follows:

$$R^{S}_{t,t+1} = \frac{S_{t+1}}{S_t} - 1, \tag{13.4}$$

where S is the spot price of the commodity. The standard way to describe the link between the spot return (Equation 13.4) and the excess futures return (Equation 13.1) when rolling futures forward is through the approximate expression

$$\mathrm{ER}^{F,T}_{t,t+1} = R^{S}_{t,t+1} + \text{Roll Yield}_{t,t+1}. \tag{13.5}$$

"Rolling futures forward" refers to closing out the front contract and opening a comparable position in the next-closest-to-maturity contract. The roll yield, also known as "carry," is the slope of the futures curve between the two contracts.[3] When the futures curve slopes downward, the roll yield will be positive; this condition is called *backwardation*. When the futures curve slopes upward (called *contango*), the roll yield will be negative.

The theory of storage (Kaldor 1939; Working 1949) can be used to decompose the roll yield into (1) the benefits of holding the spot commodity, called the convenience yield (y), and (2) the cost of carrying physical inventories, which is the sum of the forgone interest (r) and direct storage costs (u):

$$\text{Roll Yield}_{t,t+1} = y_{t,t+1} - (r_t + u_t). \tag{13.6}$$

Note that Equation 13.5 links the futures excess return (excluding collateral) with the spot return, which is a funded investment. To facilitate a more meaningful comparison, we follow Levine et al. (2018) and combine Equations 13.5 and 13.6 to express the difference between the futures and spot in excess return form:

$$\mathrm{ER}^{F,T}_{t,t+1} - (R^{S}_{t,t+1} - r_t) = (y_{t,t+1} - u_t), \tag{13.7}$$

where $(y - u)$ is referred to as the "interest-adjusted carry."

The intuition for the difference in Equation 13.7 is that the convenience yield (net of storage) is a benefit embedded in the spot price of the physical commodity related to its use as an input in

[3]For an in-depth discussion on why the roll yield should not be interpreted as a cash flow to a futures investor, see, for example, Bessembinder (2018). Also see Gorton, Hayashi, and Rouwenhorst (2013); Erb and Harvey (2016); Koijen, Moskowitz, Pedersen, and Vrugt (2018); and Levine et al. (2018).

the productive process. It accrues to the futures investor as the futures price converges to the spot prices at the maturity of a futures contract.

As pointed out earlier, Keynes' theory of normal backwardation predicts that the first term on the left-hand side of Equation 13.7 is positive. By contrast, neither Keynes nor the theory of storage makes a direct prediction about the overall sign of the futures excess return. Whether the convenience yield has historically exceeded storage costs is an empirical matter, which we explore next.

The historical evolution of the components of Equations 13.5 and 13.7 for the equally weighted index is illustrated in **Exhibit 13.4**, which shows the following:

- The futures excess return has historically lagged the spot *total* return due to the cumulative effect of negative carry over the past 155 years (Panel A).
- The futures excess return has historically exceeded the spot price *excess* return (positive interest-adjusted carry; Panel B).

Exhibit 13.4. Decomposition of Futures Excess Returns, January 1871–December 2025

A. Spot Total Returns and Carry

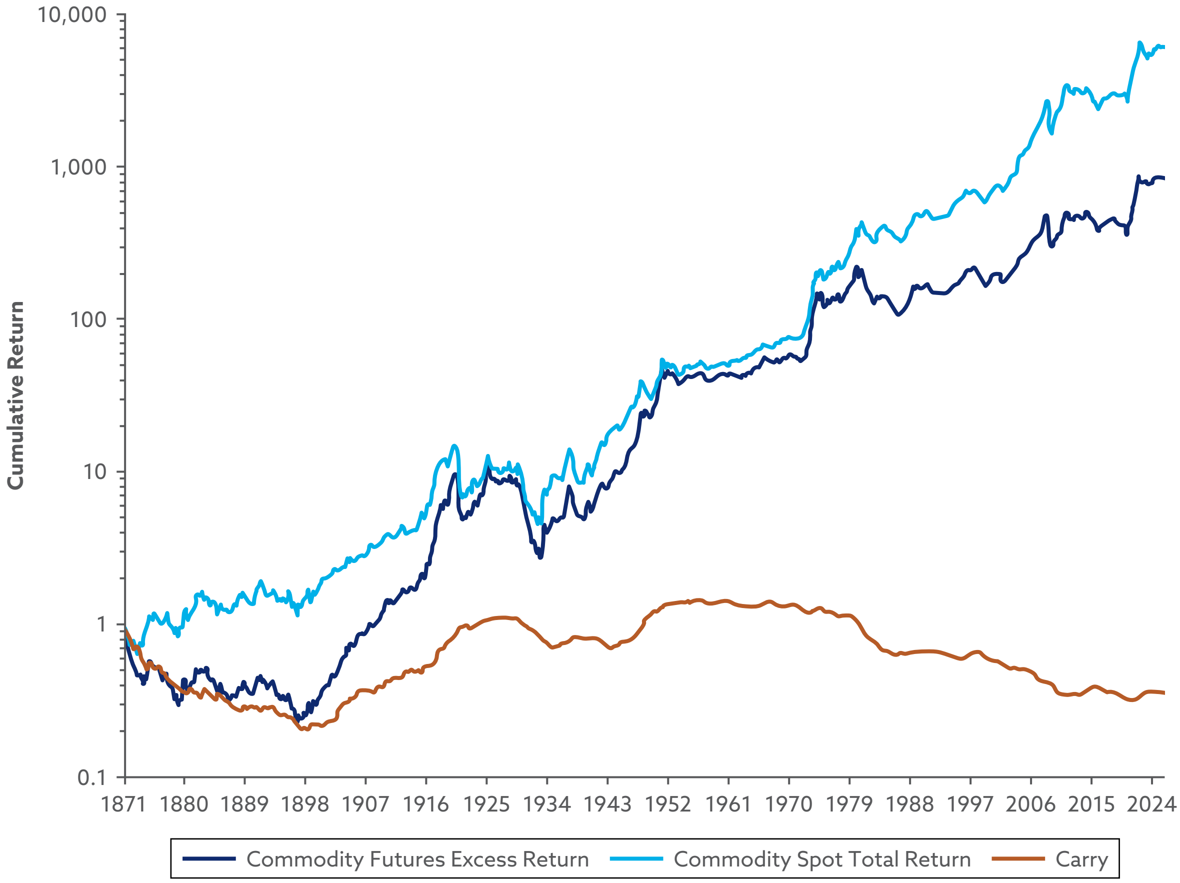
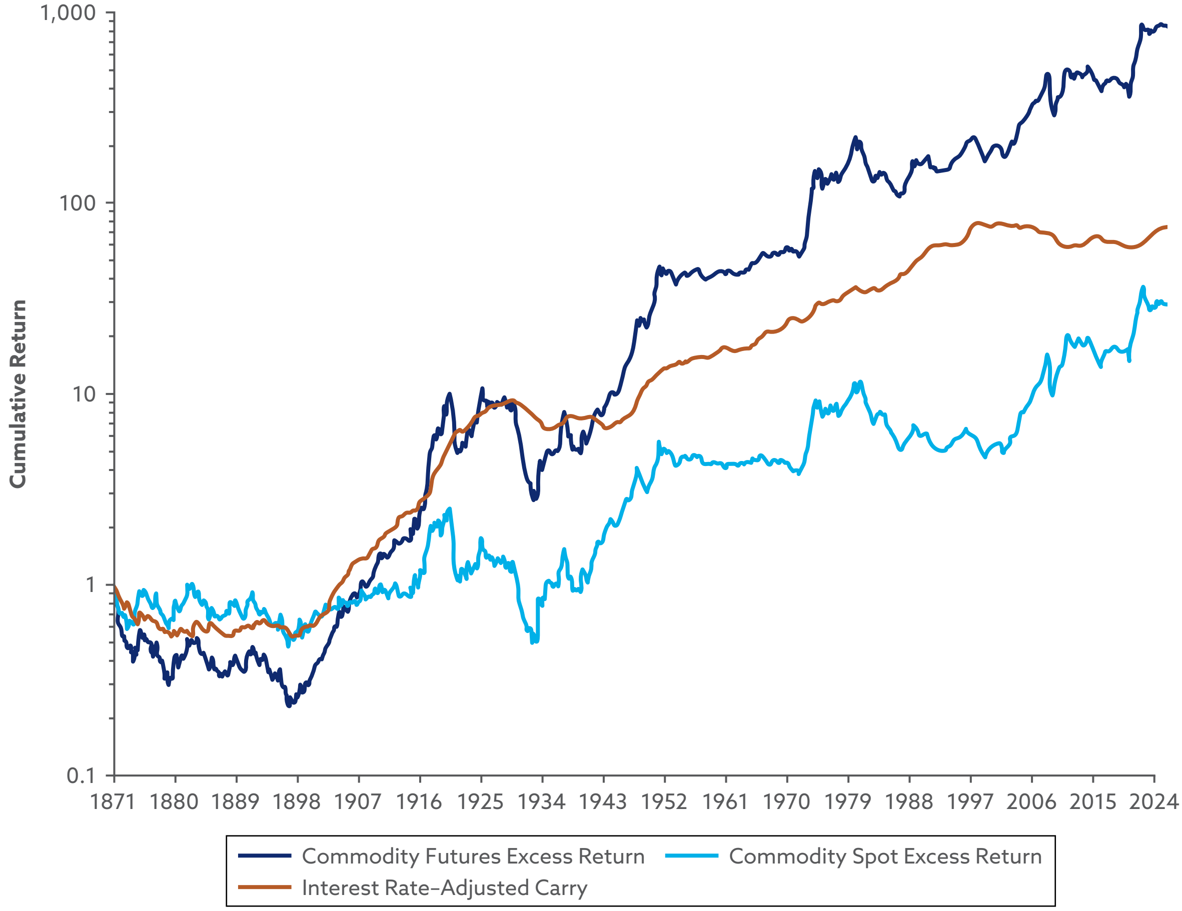


Exhibit 13.4. Decomposition of Futures Excess Returns, January 1871–December 2025 (*continued*)

B. Spot Excess Returns and Interest Rate-Adjusted Carry



Source: SummerHaven Investment Management.

The first observation empirically underscores the important fact that a negative roll yield does not preclude investors from earning a positive risk premium. The second observation implies that when collateral returns are included, futures returns have historically exceeded spot price returns. This is the case even before taking into account storage costs, which would be necessary for calculating the return to carrying physical inventories.

Summary of Asset Class Performance

We quantitatively summarize our results in **Exhibit 13.5**, which provides average returns, volatility, and Sharpe ratios of collateralized commodity futures, stocks, Treasury bills, and inflation over the 1871–2025 period. Panel A shows that the EW commodity futures index has earned a risk premium of 5.5%, with annualized volatility of 14.3% and a Sharpe ratio of 0.38.

Exhibit 13.5. Summary Statistics for Commodity Futures, Commodity Spot, and Stock Indices; the Riskless Rate; and Inflation, January 1871–December 2025

	Arithmetic Mean TR (%)	Geometric Mean TR (%)	Arithmetic Mean ER (%)	Geometric Mean ER (%)	Volatility (%)	Sharpe Ratio
A. Full Sample, 1871–2025						
Commodity futures index	8.9	8.2	5.5	4.5	14.3	0.38
Commodity spot index	6.7	5.8	3.2	2.2	14.3	0.22
Stock index	10.1	9.2	6.6	5.5	16.2	0.41
Riskless rate	3.5	3.5	—	—	0.7	—
Inflation	2.2	2.1	—	—	3.5	—
B. 1871–1922						
Commodity futures index	8.9	7.8	5.1	3.9	16.4	0.31
Commodity spot index	5.5	4.2	1.8	0.4	16.4	0.11
Stock index	7.0	6.5	3.2	2.6	11.3	0.29
Riskless rate	3.7	3.8	—	—	0.2	—
Inflation	0.7	0.6	—	—	5.5	—
C. 1923–1974						
Commodity futures index	9.3	8.7	6.9	6.1	14.4	0.48
Commodity spot index	7.1	6.2	4.7	3.7	14.4	0.33
Stock index	10.2	8.5	7.8	5.9	20.3	0.38
Riskless rate	2.4	2.4	—	—	0.6	—
Inflation	2.2	2.2	—	—	2.2	—
D. 1975–2025						
Commodity futures index	8.6	8.2	4.3	3.6	11.6	0.37
Commodity spot index	7.4	6.9	3.1	2.4	11.8	0.26
Stock index	13.2	12.6	8.9	7.9	15.5	0.57
Riskless rate	4.3	4.4	—	—	1.0	—
Inflation	3.6	3.7	—	—	1.3	—

Sources: SummerHaven Investment Management, Federal Reserve Bank of St. Louis, Ibbotson Equity Indices™.

Note: Total return (TR) and excess return (ER) are expressed as percentages per year.

For comparison, the stock index has a risk premium of 6.6% and a volatility of 16.2%, which results in a Sharpe ratio of 0.41. The commodity spot index has the same volatility as the commodity futures index but a markedly lower Sharpe ratio (0.22). The risk-adjusted returns are similar for the commodity futures index and the stock index, and these indices' risk-adjusted performance exceed that of the commodity spot index.

To examine Sharpe's (1992) requirement that an asset class "provides comparable risk and return characteristics over time," we split the 155 years of the sample into three periods of similar length (roughly 50 years each). The basic observations from the full sample statistics continue to hold for the subsamples: nearly identical volatility for commodity futures and spot returns, similar risk-adjusted returns for commodity futures and stocks, and a substantially lower risk-adjusted return for the commodity spot index.

Some sample-specific variation remains across the various time periods. In the first subperiod, 1871–1922, commodity spot returns show little appreciation, recording a near-zero geometric mean. In contrast, commodity futures in this period earn a risk premium of 5.1%, nearly 2 percentage points higher than stocks. From 1923 to 1974, commodity futures have a lower volatility than stocks but exhibit a higher Sharpe ratio (0.48 versus 0.38). The most recent subperiod saw the highest return and Sharpe ratio for equities.

Perhaps the most striking aspect of Exhibit 13.5 is the consistency of the 50-year commodity futures performance. Fifty-year averages of geometric total returns for commodity futures fall in a narrow range of 7.8%–8.7%, versus 6.5%–12.6% for stocks. Similarly, for commodity futures, the range of Sharpe ratios (0.31–0.48) is close to the full sample mean of 0.38, with less variability relative to the Sharpe ratio range for stocks (0.29–0.57) versus the full sample mean of 0.41.

Conclusion

Long-term returns provide critical input to inform investors about the properties of an asset class, especially when the underlying asset class constituents are volatile. This chapter presents a 155-year history of commodity futures markets. Using a unique hand-collected dataset, we presented annual returns and cumulative returns to an index of commodity futures and compared its performance with the aggregate stock market, inflation, and spot returns. Like stocks, commodity futures have a positive risk premium. Returns to commodity futures deviate from stocks in ways that provide periodic outperformance, likely resulting from different fundamental drivers of return. Although the index's performance is volatile over shorter investment horizons, the index shows consistent performance over long horizons—a critical requirement for any asset class.

Key Takeaways

- *Positive risk premium:* Commodity futures earned a risk premium of about 5.5% annually, comparable to the equity risk premium, with a Sharpe ratio of 0.38.
- *Diversification benefit:* Commodities outperformed US stocks in approximately 40% of years and 40% of rolling 10-year periods. This performance offers meaningful diversification benefits for investors with heavy equity exposure.
- *Outperformance versus spot and inflation:* The distinct performance of futures and spot indices highlights that futures returns are not driven solely by spot price changes.

- *Role of carry:* Futures excess returns exceeded spot excess returns because of a persistent positive interest rate–adjusted carry, reinforcing the notion that futures returns include a risk premium beyond mere spot price exposure.
- Commodity futures have historically delivered a stable long-term risk premium, diversification relative to equities, and performance not merely tied to spot price movements, supporting their role as a distinct asset class in strategic portfolios.

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CHAPTER 14. THE JAPANESE MARKET, 1952–2025

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Introduction: The Long-Run Perspective in Japan

A long view of capital market history in Japan, illustrated by the 74-year period (1952–2025) examined in this chapter, uncovers the basic relationships between risk and return among the various asset classes and between nominal and real (inflation-adjusted) returns in Japan. The goal of this study is to provide a period long enough to include almost all the major types of events that investors have experienced and may experience in the future. Such events include economic growth and decline, bull and bear markets, inflation and deflation, and other, less dramatic events that affect asset returns.

For Japan as for the rest of the world, one can make inferences about the future by studying the past. Although the actual events that occurred during 1952–2025 will not be repeated, the event types from that period can be expected to recur. From the early 1950s through the late 1980s, Japan experienced one of the most remarkable episodes of economic expansion in modern history. Rapid industrialization, technological upgrades, and export-led growth contributed to a prolonged equity bull market and substantial increases in national wealth. By the late 1980s, elevated asset valuations in both real estate and equities reflected strong growth expectations, although they also gave rise to imbalances that would later unwind. The subsequent period, particularly the 1990s and early 2000s, was marked by a prolonged adjustment in asset markets and subdued returns. Nevertheless, from around 2012 onward, Japanese equity markets exhibited a sustained recovery, supported by accommodative monetary policy, corporate governance reforms, enhanced capital efficiency, and a steady improvement in corporate earnings, thereby indicating a renewed phase of positive market dynamics.

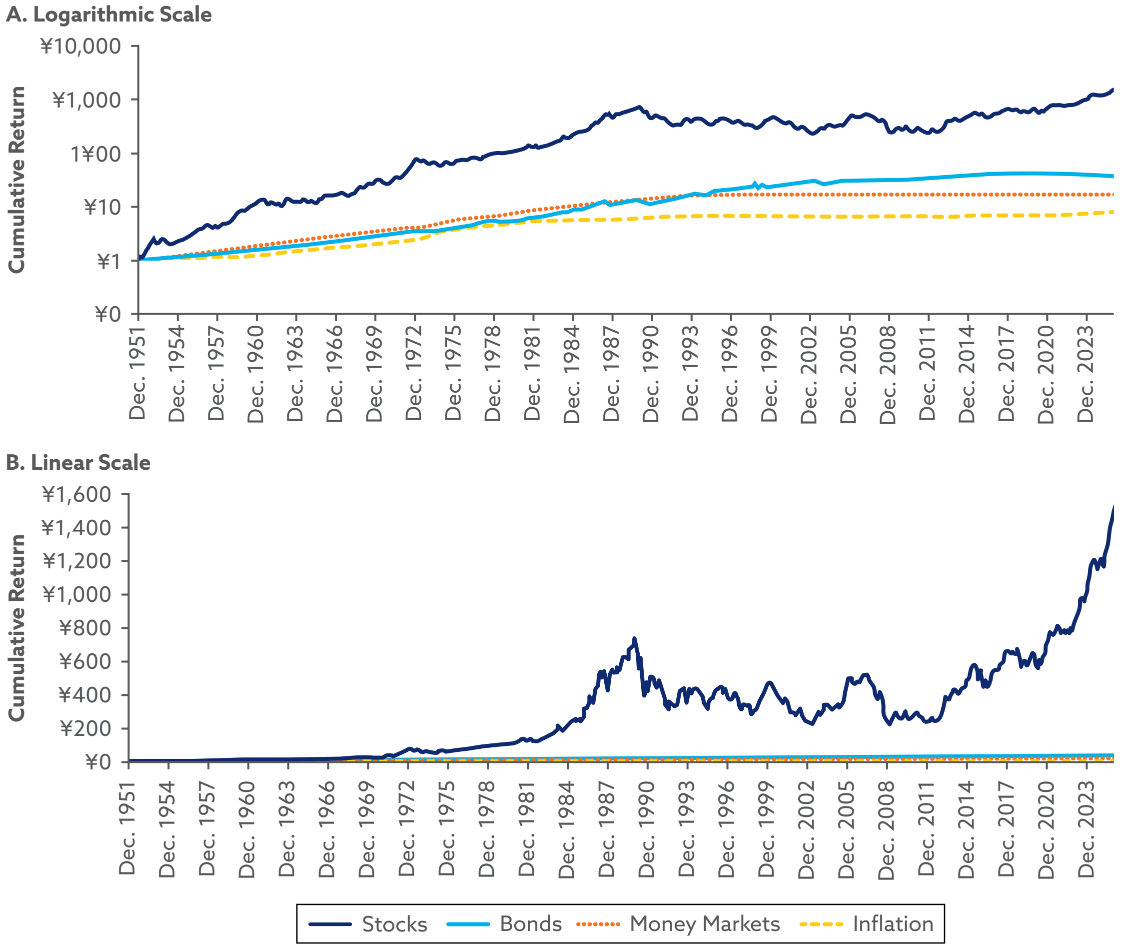
These experiences suggest that although the timing and specific triggers of market movements are difficult to predict, the underlying types of events tend to recur. As such, historical capital market data offer a valuable empirical foundation for forming expectations about future risk and return.

Historical Returns on Stocks, Bonds, Money Markets, and Inflation in Japan

Exhibit 14.1 depicts the growth of ¥1 invested in Japanese stocks, Japanese long-term government bonds, Japanese money markets, and a hypothetical asset returning the inflation rate over the period from the end of 1951 to the end of 2025.[1] All results assume reinvestment

[1] "Money markets" in Japan are the equivalent of short-term Treasury bills, sometimes called "cash" in an asset allocation context, in the United States.

Exhibit 14.1. Wealth Indices of an Investment of ¥1 in Japanese Stocks, Bonds, Money Markets, and Inflation, 1952–2025



Sources: Ibbotson Associates Japan™, Inc. (IAJ). Used with permission. All rights reserved. Underlying data sources are as follows: (1) Japanese stocks: Tokyo Stock Exchange First Section (TSE1) total return; (2) Japanese bonds: IAJ Japan Long-Term Government total return; (3) Japanese money markets: IAJ Japan Money Market total return; (4) Japanese inflation: IAJ Japan Inflation. Further details are provided in the Data Sources section.

of dividends and bond coupons and ignore taxes. Transaction costs are not included. Each cumulative index value is initialized at ¥1 at year-end 1951. The graph vividly illustrates that Japanese stocks were the big winners over the 74-year period. An investment of ¥1 in Japanese stocks at the end of 1951 would have grown to ¥1,520 by year-end 2025, while ¥1 invested at the end of 1951 in Japanese long-term government bonds would have turned into ¥37 by the end of 2025. Note that all returns and other data in this chapter are in Japanese yen except in the section “Japanese Stocks vs. US Stocks in US Dollars,” which discusses Japanese asset returns converted to US dollars.

Some notable details on the indices are as follows.

- *Japanese stocks:* An index of TSE1 total returns initialized on 31 December 1951 at ¥1.00 closed 2025 at ¥1,519.6, which represents a compound annual growth rate of 10.4%. The inflation-adjusted TSE1 total return index closed 2025 at a level of ¥193.3.
- *Japanese bonds:* The Ibbotson Associates Japan Long-Term Government Total Return index, constructed with an approximate 10-year maturity and initialized on 31 December 1951 at ¥1.00, closed 2025 at ¥37.1, representing a compound annual growth rate of 5.0%. Based on the capital appreciation component alone, the index closed at ¥1.70, resulting in a 0.7% compound annual capital gain over the period 1952–2025. This result indicates that the majority of the positive historical returns on long-term government bonds resulted from income returns.
- *Japanese money markets:* An investment of ¥1.00 in the Ibbotson Associates Japan Money Market Total Return index at the end of 1951 was worth ¥17.4 by year-end 2025, representing a compound annual growth rate of 3.9%. This asset tended to track inflation; therefore, the average annual inflation-adjusted return on Japanese money markets, representing the real riskless rate of return, was only 1.1% compounded annually over the 74-year period.
- *Japanese inflation:* The compound annual Japanese inflation rate over 1952–2025 was 2.8%. The Japanese inflation index, initiated at ¥1.00 at year-end 1951, grew to ¥7.90 by year-end 2025.

Japanese Long- and Short-Term Interest Rates

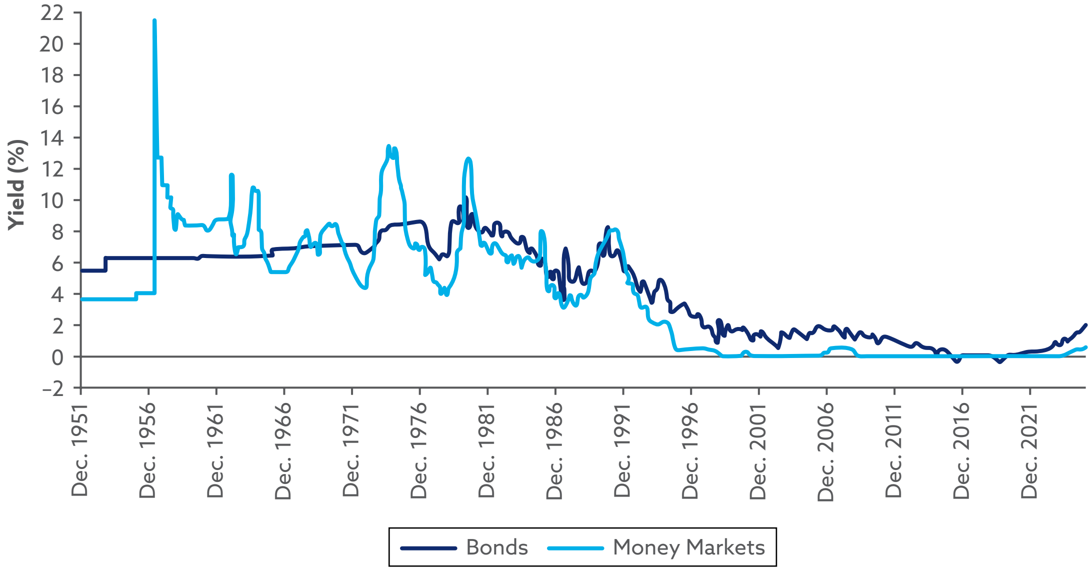
Exhibit 14.2 depicts the evolution of Japanese long- and short-term interest rates over the period studied. They have followed a pronounced secular decline over the entire 74-year period from the end of 1951 to the end of 2025.

Setting aside an extraordinary short-term rate peak around 1956, the trajectory shows an initial peak in both rates in the 1970s and early 1980s, coinciding with global inflationary periods. Following the collapse of the Japanese stock market bubble in the early 1990s, both yields fell sharply, initiating a prolonged ultra-low interest rate environment. Short-term rates, which are more sensitive to monetary policy shifts and business cycles than long-term rates are, have been particularly volatile but have largely hovered near zero since the late 1990s. This finding reflects Japan's persistent deflationary conditions and the Bank of Japan's long-standing accommodative stance. This historical trend in the term structure of interest rates mirrors the profound shifts in Japan's economic landscape from high growth to decades of low growth and deflation.

Summary Statistics of Total Returns

Exhibit 14.3 presents summary statistics (geometric mean, arithmetic mean, and standard deviation) of the annual total returns on each asset class over the entire 1952–2025 period. The data presented in this exhibit are described in the Data Sources section.

Exhibit 14.2. Yields-to-Maturity of Japanese Long-Term Bonds and Money Markets, 1952–2025



Sources: Ibbotson Associates Japan, Inc. (IAJ). Used with permission. All rights reserved. Underlying data sources are as follows: (1) bonds: IAJ Japan Long-Term Government Yld; (2) money markets: IAJ Japan Money Market Yld.

Exhibit 14.3. Summary Statistics of Annual Returns on Principal Japanese Asset Classes, in Japanese Yen, 1952–2025

	Geometric Average (%)	Arithmetic Average (%)	Standard Deviation (%)
Stocks	10.4	12.1	19.9
Bonds	5.0	5.1	4.7
Money Markets	3.9	3.9	1.1
Inflation	2.8	2.9	2.4

Source: See source notes to Exhibit 14.1.

Exhibit 14.3 summarizes the risk–return trade-off inherent in investing; that is, the potential return of an asset generally increases with the asset's risk. The compound annual return shown in the "Geometric Average" column is the rate of return that—if it had been earned each year—equates the investment's ending value with its beginning value; it assumes the reinvestment of all income. The numbers in the "Arithmetic Average" column represent the simple, or arithmetic, average of the individual annual returns over the past 74 years. The standard deviation, shown in the last column, is used to measure the risk of an investment.

Risk vs. Return of Principal Japanese Asset Classes

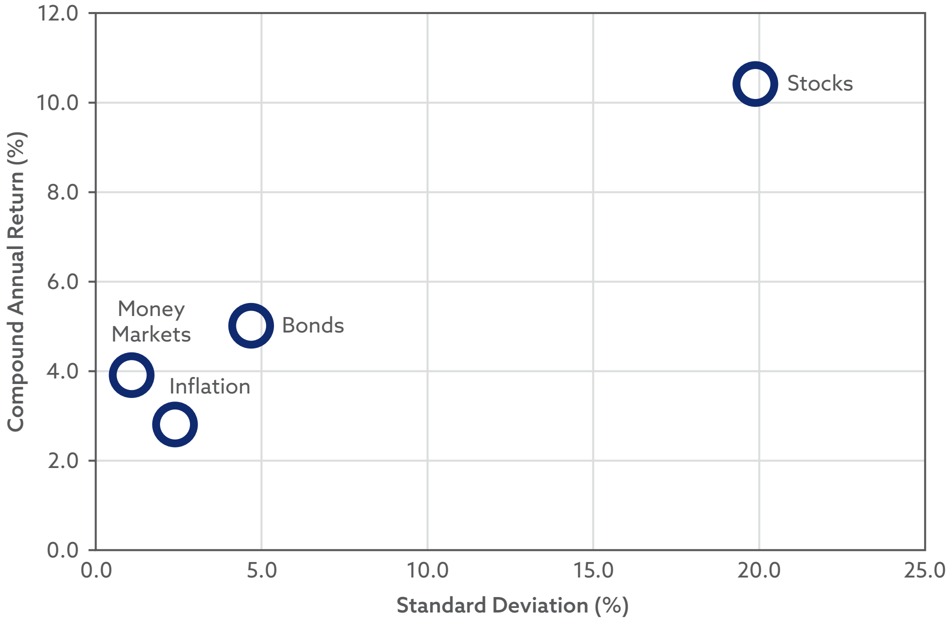
Exhibit 14.4 illustrates the relationship between the risk and return of three Japanese basic asset classes, along with inflation, over the past 74 years. Risk (standard deviation) is plotted on the *x*-axis, and compound annual return is plotted on the *y*-axis. As expected in a well-functioning market, the asset classes exhibiting higher risk had higher returns over the period studied.

Japanese stocks had the highest risk of the asset classes shown. Their high volatility was rewarded with high returns. At the low-risk end of the spectrum are Japanese bonds and money markets. These investments fluctuated much less than stocks did but provided lower returns as well.

Volatility of Stock and Bond Returns

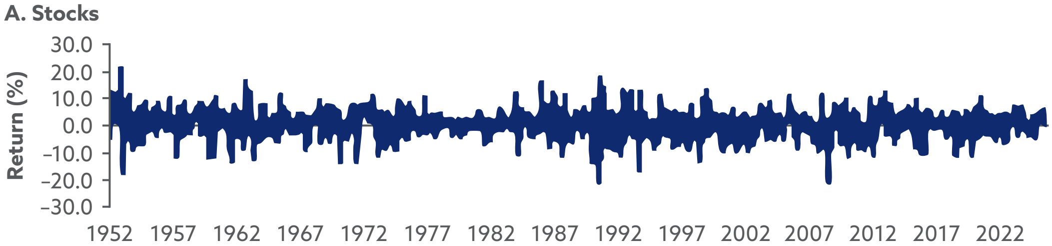
The volatility of Japanese stocks and bonds is shown in **Exhibit 14.5**. The volatility of the stock market has been nearly constant, with a minor decrease in the last decade. Before 1977, however, Japanese bonds were not traded on the market, so there was almost no visible price fluctuation. After 1977, bank deals for bonds began and prices began to fluctuate, in some cases dramatically. After 2000, Japanese bond volatility decreased due to the low interest rate policy.

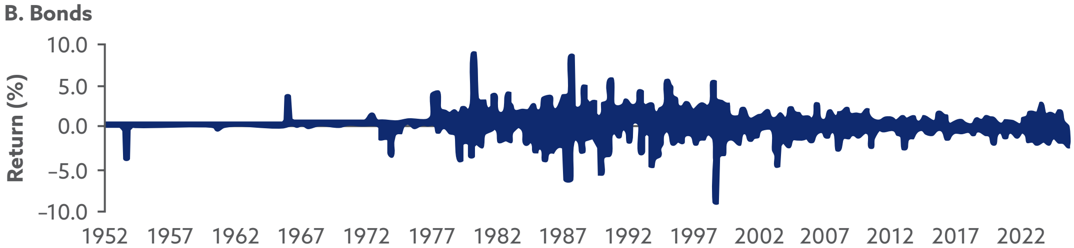
Exhibit 14.4. Risk and Return of Annual Total Returns on Principal Japanese Asset Classes, in Japanese Yen, 1952–2025



Source: See source notes to Exhibit 14.1.

Exhibit 14.5. Volatility of Japanese Stock and Bond Returns (Monthly Returns in Japanese Yen), 1952–2025





Source: See source notes to Exhibit 14.1.

One relationship has remained constant: Japanese stocks have been more volatile than bonds on a month-to-month basis. Over the long term, however, stock investors have been rewarded for assuming this greater volatility.

Cross-Correlations of Monthly Returns

As illustrated in Panel A of **Exhibit 14.6**, the period from 1977 to 2025 featured a high correlation between money market returns and inflation but a low correlation between money market returns and long-term bond returns. In contrast, the more recent 20-year period, from 2006 to 2025, exhibited a different set of relationships, as shown in Panel B of Exhibit 14.6. Over this time frame, stock returns were negatively correlated with both long-term bond returns and money market returns. Furthermore, long-term bond returns have also shown a negative correlation with inflation during this period.

Correlation Fluctuations

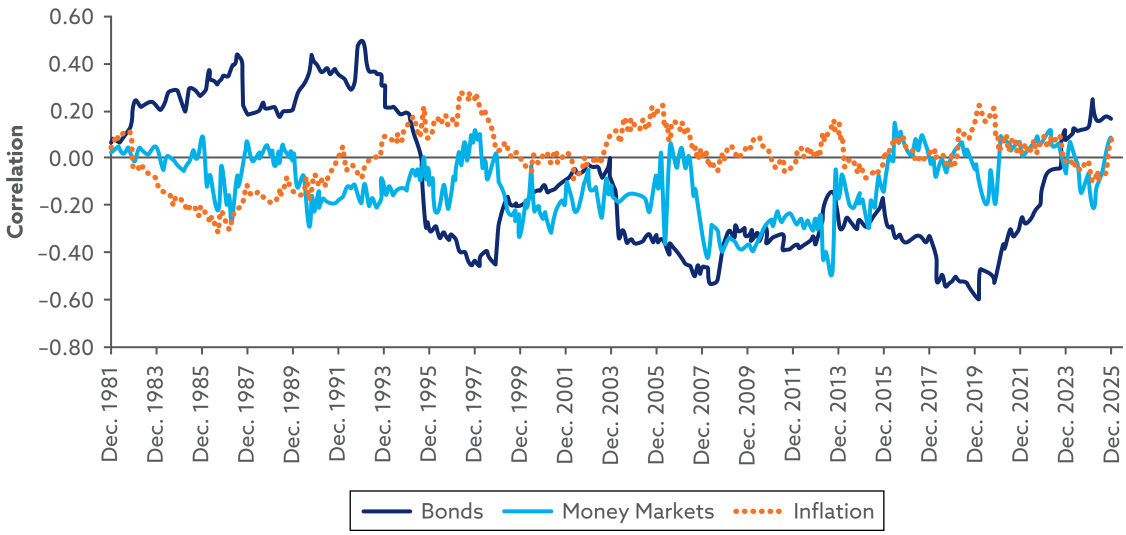
Exhibit 14.7 shows the rolling 60-month correlation between Japanese stocks and other assets. The correlations fluctuate in response to changes in the macroeconomic environment and business conditions. From the mid-1990s through the 2020s, when the economy was sluggish and monetary easing policies continued, stocks had a negative correlation with long-term bonds. As signs of economic recovery emerged, however, the correlation recently became positive.

Exhibit 14.6. Cross-Correlations of Monthly Returns on Principal Japanese Asset Classes, in Japanese Yen, 1977–2025 and 2006–2025

	Stocks	Bonds	Money Markets	Inflation
A. 1977–2025				
Stocks	1.00	−0.01	0.02	0.02
Bonds	−0.01	1.00	0.16	0.00
Money Markets	0.02	0.16	1.00	0.23
Inflation	0.02	0.00	0.23	1.00
B. 2006–2025				
Stocks	1.00	−0.24	−0.14	0.06
Bonds	−0.24	1.00	0.02	−0.06
Money Markets	−0.14	0.02	1.00	0.05
Inflation	0.06	−0.06	0.05	1.00

Source: See source notes to Exhibit 14.1.

Exhibit 14.7. Rolling 60-Month Correlations Between Japanese Stocks and Other Japanese Assets, in Japanese Yen, 1982–2025



Source: See source notes to Exhibit 14.1.

Firm Size and Return

I formed decile portfolios of the Japanese stock market sorted by capitalization size. Summary statistics of annual returns of the 10 deciles over 1978–2025 are presented in **Exhibit 14.8**. The risk and return of the 10 deciles over the same period are plotted in **Exhibit 14.9**. Note that the average return tends to increase as one moves from the largest decile to the smallest. On average, small companies have higher returns than large ones. The total risk, or standard deviation of annual returns, also increases with decreasing firm size.

Investors are compensated for taking on this additional risk by the higher returns provided by small companies. Note, however, that this risk–return relationship applies only over the long term. The increased risk faced by investors in small stocks is quite real. The long-term expected return for any asset class is quite different from short-term expected returns, and investors in small-cap stocks should expect losses and periods of underperformance.

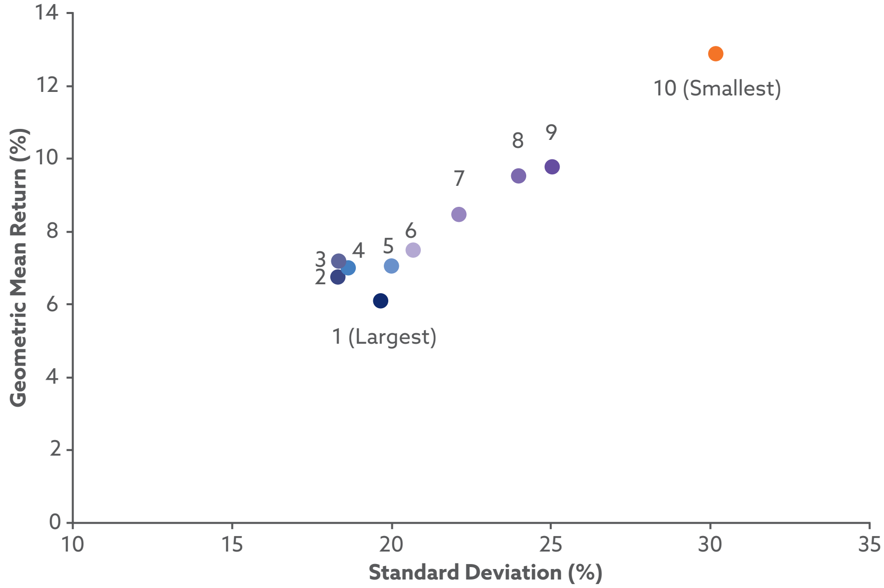
Exhibit 14.10 depicts the growth of ¥1 invested in each of these capitalization strata and the entire TSE1.

Exhibit 14.8. Summary Statistics of Returns on Japanese Size-Decile Portfolios and the Overall Japanese Stock Market, in Japanese Yen, 1978–2025

Decile	Geometric Mean (%)	Arithmetic Mean (%)	Standard Deviation (%)
1 (Largest)	6.1	7.9	19.6
2	6.8	8.3	18.3
3	7.2	8.7	18.3
4	7.0	8.6	18.6
5	7.1	8.9	20.0
6	7.5	9.4	20.7
7	8.5	10.7	22.1
8	9.6	12.0	24.0
9	9.8	12.5	25.0
10 (Smallest)	12.9	16.6	30.2
Mid Cap	7.1	8.7	8.7
Low Cap	8.3	10.4	10.4
Micro Cap	11.0	14.0	14.0
TSE1	6.3	8.0	18.7

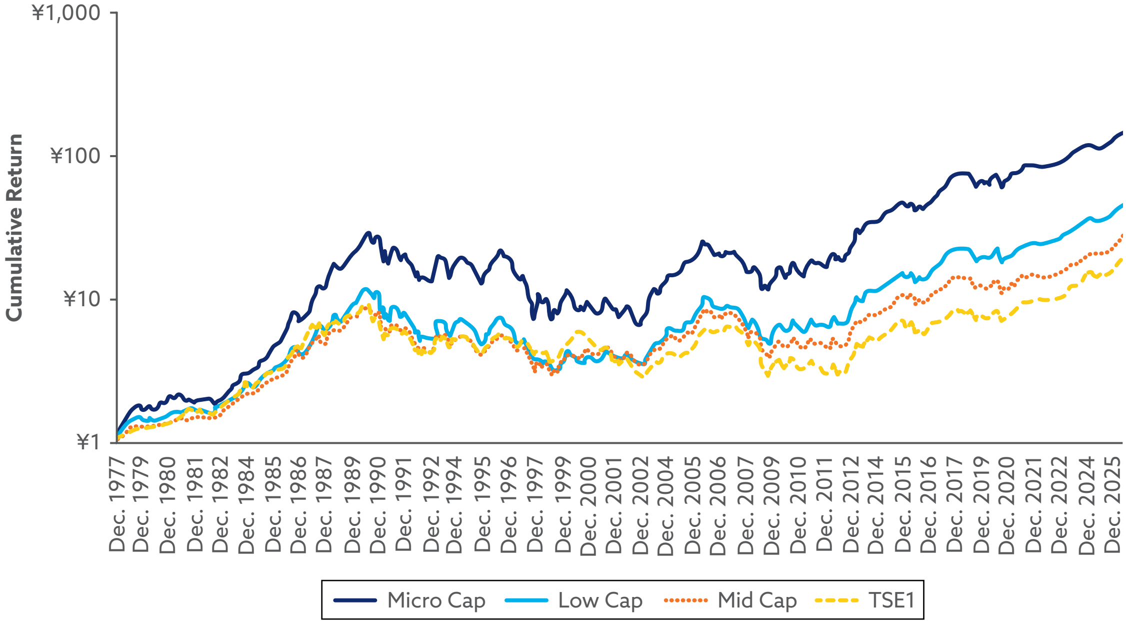
Sources: Ibbotson Associates Japan, Inc. (IAJ). Used with permission. All rights reserved. Decile 1–10: IAJ's Japanese Size-Decile Portfolios; Mid Cap: Deciles 3–5; Low Cap: Deciles 6–8; Micro Cap: Deciles 9–10; TSE1: TSE1 total return. Further details are provided in the Data Sources section.

Exhibit 14.9. Risk and Return of Japanese Size-Decile Portfolios, in Japanese Yen, 1978–2025



Source: See source notes for Exhibit 14.8.

Exhibit 14.10. Size-Decile Portfolios of the TSE1: Cumulative Return Indices in Japanese Yen, 1978–2025



Source: See source notes for Exhibit 14.8.

Decade-by-Decade Analysis of Japanese Asset Returns

Exhibit 14.11 presents a detailed, decade-by-decade analysis of the performance of the principal Japanese asset classes, plus inflation, from the 1950s to the 2020s. The postwar high-growth period (1950s–1960s) was distinguished by a government-directed financial system and a low interest rate policy that catalyzed explosive stock market growth and infrastructure investment.

In the 1970s, the Japanese economy shifted from a heavy-industry-centered model to a more energy-efficient, high-value-added, and technology-intensive industrial structure in response to oil crises and other global shocks. During this period, high inflation was followed by a process of disinflation, which led the Bank of Japan (BOJ) to place greater emphasis on price stability and to adopt a more disciplined approach to monetary policy.

In the 1980s, following the yen's appreciation after the Plaza Accord, the BOJ implemented monetary easing. This policy is widely regarded as one of the factors contributing to the subsequent asset price bubble. At the same time, because consumer prices remained relatively stable, rising asset prices were not a central focus of monetary policy.

Exhibit 14.11. Summary Statistics of Returns on Principal Japanese Asset Classes and Average Interest Rate by Decade, in Japanese Yen, in Percent, 1952–2025

	Stocks		Bonds		Money Markets		Inflation		Avg. Interest Rate	
	Compound Annual Return	Std. Dev.	Compound Annual Return	Std. Dev.	Compound Annual Return	Std. Dev.	Compound Annual Return	Std. Dev.	Long Term	Short Term
1952–1959	29.9	27.4	5.3	1.5	6.2	1.2	2.1	3.4	6.2	6.0
1960–1969	14.5	19.5	6.5	1.1	7.8	0.4	5.5	2.9	6.6	7.6
1970–1979	12.8	17.8	6.5	3.4	7.5	0.8	8.9	3.5	7.6	7.3
1980–1989	21.6	17.7	8.8	8.0	6.3	0.7	2.3	2.0	6.7	6.1
1990–1999	–4.2	22.3	7.3	7.8	2.7	0.8	1.1	1.5	3.9	2.7
2000–2009	–5.1	17.3	2.6	3.8	0.1	0.0	–0.2	1.0	1.4	0.1
2010–2019	8.9	18.3	2.4	2.3	0.0	0.0	0.6	1.1	0.5	0.0
2020–2025	14.8	15.0	–1.6	3.0	0.1	0.1	2.1	1.1	0.5	0.1
1952–2025	10.4	19.9	5.0	4.7	3.9	1.1	2.8	2.4	4.3	3.9

Source: See source notes for Exhibit 14.1.

The bursting of this bubble in the 1990s and 2000s was associated with a prolonged period of economic stagnation and deflation, known as the Lost Decades. During this era, the BOJ introduced unconventional monetary policies, such as the zero interest rate policy and quantitative easing, the efficacy of which sparked academic debate, with scholars questioning whether the economy was in a liquidity trap or facing deep-seated structural problems.[2]

The 2010s were defined by "Abenomics," the set of economic policies associated with Japanese Prime Minister Shinzo Abe, who served from 2006 to 2007 and again from 2012 to 2020. Abenomics featured large-scale quantitative and qualitative monetary easing (QQE) in an attempt to escape deflation, leading to a resurgence in the stock market and moderate inflation. However, structural headwinds from demographic changes persisted. The 2020s marked a fundamental turning point, with the BOJ finally beginning to exit its ultra-loose monetary policy. This normalization was made possible as persistent inflation, driven by external factors, provided the necessary conditions for unwinding unconventional policies.

A brief synopsis of each period follows.

- 1952–1959: Japan's postwar reconstruction and rapid industrialization drove extraordinary equity market performance, supported by high productivity growth and export expansion. Long-term government bonds offered modest but stable returns, while money market rates reflected gradual financial liberalization. Inflation was low, indicating a relatively stable macroeconomic environment.
- 1960–1969: The high-growth era saw equities continue to perform strongly, albeit at a more moderate pace than in the 1950s. Bond and money market returns improved, reflecting both economic expansion and financial deepening. Inflation began to pick up, partly in response to increased domestic demand and wage growth.
- 1970–1979: The oil shocks of 1973 and 1979 caused severe inflationary pressure, yet equities and fixed income still posted positive nominal returns. Money market yields stayed relatively high, reflecting tighter monetary conditions and inflation. Inflation reached its highest sustained levels of the postwar period.
- 1980–1989: The 1980s saw the asset price bubble form in the latter half of the decade, fueled by financial deregulation and aggressive monetary easing. Equities surged, long-term bonds benefited from declining inflation, and money market rates moderated. Inflation remained subdued.
- 1990–1999: Following the bursting of the bubble, equities entered a prolonged bear market. Bonds performed relatively well as yields fell in response to economic stagnation, while money market returns dropped sharply. Inflation was minimal, edging toward deflation.
- 2000–2009: A second "lost decade" took shape in the 2000s, with equities declining further amid banking crises and slow growth. Bond returns moderated, money market yields approached zero, and inflation was effectively absent.
- 2010–2019: Abenomics boosted equity sentiment in the latter half of the decade, but the overall pace of growth was moderate. Bond returns were low, reflecting the prolonged

[2] A liquidity trap occurs when economic stimulus through the lowering of interest rates becomes ineffective on the margin as interest rates approach zero.

low/zero interest rate policy, while money market rates stayed near zero. Inflation remained below the BOJ's 2% target.

- 2020–2025: Despite the COVID-19 shock, equities rebounded strongly, aided by fiscal stimulus and global liquidity. Bond returns turned negative amid rising global yields, while money market rates stayed at zero. Inflation picked up modestly but remained well below international peaks.

The History of US Dollar/Japanese Yen Exchange Rates

Exhibit 14.12 depicts the US dollar/Japanese yen (USD/JPY) exchange rate over the period from the end of 1965 to the end of 2025. This exchange rate was fixed at ¥360 per dollar prior to 1970.[3] The evolution of the dollar–yen exchange rate over the past 60 years reflects broader shifts in the global monetary order and the structural maturation of the Japanese economy. This period can be divided into three phases.

Exhibit 14.12. The History of the USD/JPY Exchange Rate, December 1965–December 2025

Sources: The exchange rates are "Tokyo interbank USD/JPY Spot Rate at 17:00 in JST, End of Month, Tokyo Market," obtained from Bank of Japan from 1973 onward, while earlier observations were constructed using historical Federal Reserve H.10 and central-bank exchange-rate data standardized through Morningstar's US dollar–based conversion framework.

Notes: In this context, USD/JPY exchange rates are quoted as the number of Japanese yen per US dollar. Thus, a decrease in the rate denotes an appreciation of the Japanese yen and a depreciation of the dollar; conversely, an increase in the rate denotes a depreciation of the Japanese yen and an appreciation of the dollar.

[3] In this chapter, the dollar–yen exchange rate (the number of yen per dollar) will be referred to as "dollar–yen" or USD/JPY, following the conventions of the currency market. For example, an exchange rate of $1 = ¥150 is expressed as USD/JPY = 150.

Phase 1: The End of Fixed Rates and the Move to Market Prices (Early 1970s)

In the early 1970s, the Bretton Woods system—functioning as a gold–dollar standard that had fixed the Japanese yen at 360 per US dollar since 1949—reached its limit and collapsed. The collapse was caused by the large "twin deficits" (budget and trade deficits) that the United States ran to fund the Vietnam War while simultaneously expanding domestic social programs. This heavy deficit spending caused high inflation and made investors doubt whether the United States had enough gold to back the dollar, a problem known as the "Triffin dilemma" in reference to Belgian-American economist Robert Triffin.

In August 1971, President Richard Nixon unilaterally suspended the dollar's convertibility into gold—an event called the "Nixon shock"—which triggered an immediate and sharp decline in the dollar–yen exchange rate. Although the December 1971 Smithsonian Agreement tried to save the fixed-rate system by resetting the rate at ¥308 per dollar, the rate continued to drift lower despite the agreement. Market pressure to sell the dollar remained too strong, and by February 1973, Japan and other major nations completely gave up on fixed rates. The dollar value of the yen finally began to be determined by supply and demand in the open market.

Phase 2: The Long Era of a Strong Japanese Yen (1970s–2011)

For nearly 40 years following the move to floating rates, the Japanese yen was defined by a long-term strengthening trend against the US dollar. The primary driver was the massive trade surplus created by Japan's powerful manufacturing sector, particularly in cars and electronics, which led to a constant market demand for the currency. This trade imbalance led to the Plaza Accord in 1985, where the G5 group of advanced economies agreed to implement coordinated interventions aimed at correcting the overvalued US dollar. Within just one year of this agreement, the dollar–yen exchange rate tumbled from 240 to 150, representing a rapid surge in the Japanese yen's value.

Reflecting not just trade but other factors, the Japanese yen became a global "safe haven" because of Japan's low inflation and its status as the world's largest creditor. During global crises, such as the 2008 financial crash, and Japanese crises, such as the 2011 Fukushima earthquake, the yen would spike as investors closed out "yen carry trades" (borrowing in yen at low interest rates to invest elsewhere at high rates) and bought back yen to reduce risk. This trend peaked in 2011, when the dollar–yen rate reached its record low of 75 (a record high for the Japanese yen). This circumstance forced many Japanese companies to move their factories overseas to remain competitive.

Phase 3: The Era of a Strong US Dollar and a Weak Japanese Yen (2012–Present)

The landscape shifted dramatically in late 2012 with the start of Abenomics. To end decades of falling prices (deflation), the BOJ launched an unprecedented monetary easing program known as quantitative and qualitative monetary easing. This policy flooded the market with liquidity, intentionally driving down the yen to boost exports and stock prices. The situation intensified after 2020, when the US Federal Reserve began raising interest rates aggressively to fight inflation while the BOJ kept its rates at zero or negative. This interest rate differential made the

Japanese yen the world's cheapest funding currency, encouraging a massive wave of yen carry trades in which investors sold the yen to buy the US dollar.

By 2024, the dollar–yen exchange rate hit a 34-year high of 160, marking a historic decline in the yen's value against the dollar. Today, structural changes—such as Japan's growing "digital deficit" and the fact that many Japanese companies now keep their profits abroad—continue to limit the natural demand for the Japanese yen, keeping the currency at historic lows.

Japanese Stocks vs. US Stocks in US Dollars

This section compares the performance of Japanese stocks with that of US stocks from a US dollar perspective, incorporating the impact of dollar–yen exchange rate fluctuations. **Exhibit 14.13** illustrates the cumulative performance of a $1 investment in both markets starting at the end of December 1951. **Exhibit 14.14** shows the geometric mean return and annualized standard deviation for each specific period. Because the dollar–yen exchange rate and Japanese stocks exhibited varied behaviors over this time frame, the analysis is segmented into three distinct phases to examine performance under different market regimes.

The exchange rates used to convert Japanese stocks from yen to dollars are "Tokyo interbank USD/JPY Spot Rate at 17:00 in JST, End of Month, Tokyo Market," obtained from the BOJ from

Exhibit 14.13. Wealth Indices of Investments in Japanese Stocks and US Stocks, in US Dollars, 1952–2025

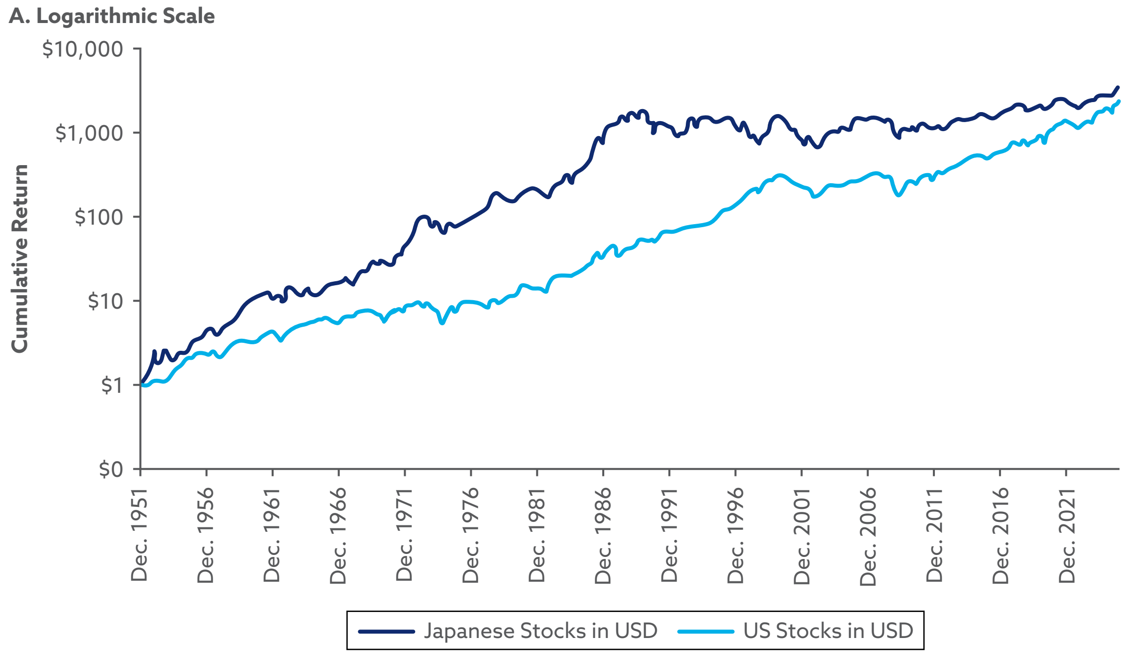
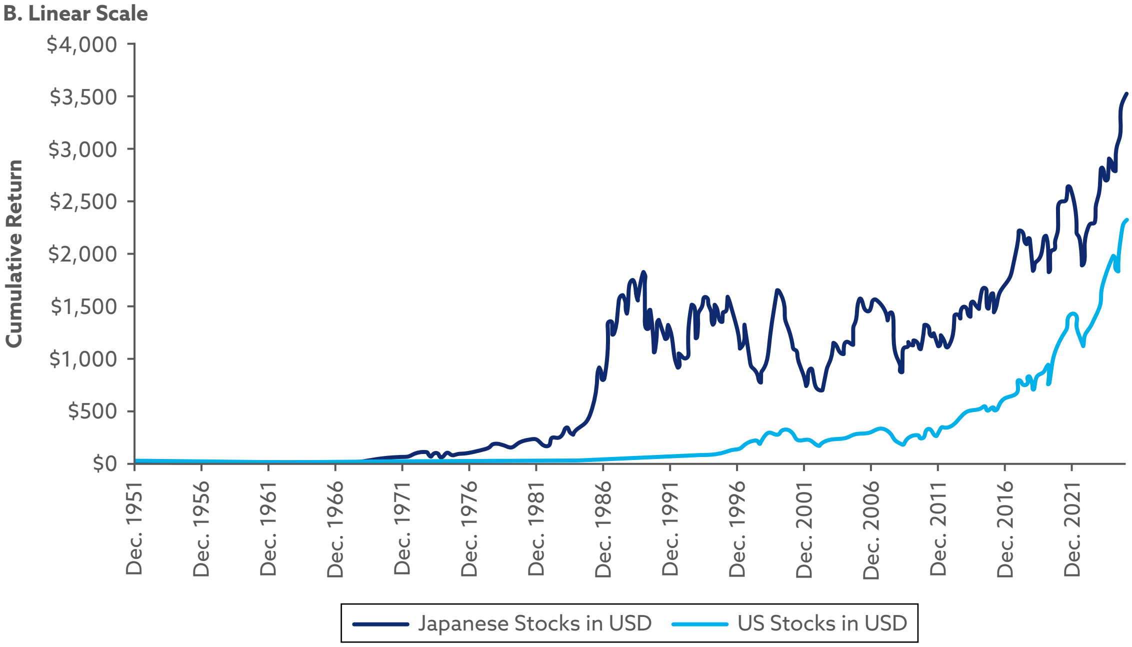


Exhibit 14.13. Wealth Indices of Investments in Japanese Stocks and US Stocks, in US Dollars, 1952–2025 (*continued*)



Sources: Japanese stocks: TSE1 total return; US stocks: Large Cap Total Return provided by CRSP.

Exhibit 14.14. Summary Statistics of Japanese Stocks and US Stocks in US Dollars (%), 1952–2025

	Japanese Stocks in US Dollars			US Stocks in US Dollars			Correlation of Monthly Returns
	Compound Annual Return (1)	Std. Dev. (2)	(1)/(2)	Compound Annual Return (3)	Std. Dev. (4)	(3)/(4)	
1952–2025	11.7	22.0	0.53	11.0	16.1	0.68	0.32
1952–1989	21.9	23.6	0.92	11.1	15.8	0.70	0.18
1990–2011	–2.3	22.3	–0.10	8.1	16.5	0.49	0.39
2012–2025	8.7	14.7	0.59	15.6	16.2	0.96	0.72

Sources: Japanese stocks: TSE1 total return; US stocks: large-cap total return provided by CRSP.

1973 onward. Earlier observations were constructed using historical Federal Reserve H.10 and central-bank exchange-rate data standardized through Morningstar's US dollar–based conversion framework.

Overview: 1952–2025

Over the 74-year span from 1952 to 2025, Japanese stocks delivered a compound annualized (geometric mean) return of 11.7%, with a standard deviation of 22.0%, in US dollar terms. During the same period, US stocks generated a geometric mean return of 11.0%, with a standard deviation of 16.1%. Although the compound annual return of Japanese stocks slightly exceeded that of US stocks, the significantly higher volatility in the Japanese market resulted in a lower risk-adjusted return compared with US equities.

Phase 1 (1952–1989): High Growth and Yen Appreciation—The "Double Tailwind"

During this era, Japan experienced unprecedented economic growth, ranging from the postwar miracle to the "Shōwa bubble."[4] This growth, combined with the yen's strengthening against the dollar, created a "double tailwind" for US dollar–based investors. As a result, Japanese stocks substantially outperformed US stocks during this period.

Phase 2 (1990–2011): Market Slump and Yen Appreciation

Following the collapse of the bubble economy, Japanese equities struggled in response to a prolonged economic downturn triggered by the nonperforming loan crisis. However, the continued appreciation of the yen provided a crucial buffer for US dollar investors.

Despite the currency support, the absolute decline in stock prices led to a negative compound annual return for Japan, with US equities showing superior relative performance.

Phase 3 (2012–2025): Market Rally and Yen Depreciation

Driven by the ultra-loose monetary policy of Abenomics, the yen shifted toward a significant depreciation. This shift boosted the earnings of Japanese exporters, propelling the domestic stock market to record highs by the end of 2025. Conversely, the weak yen acted as a major headwind for dollar-based returns.

Although Japanese stocks rallied in local terms, the substantial depreciation of the yen (foreign exchange headwinds) meant that the US dollar–denominated returns of Japanese stocks lagged far behind the returns of their US counterparts.

[4] The Shōwa era (1926–1989) is a period in Japanese history characterized by the reign of Emperor Hirohito (Emperor Shōwa). The "Shōwa bubble" refers to Japan's asset price bubble of the late 1980s (roughly 1986–1991), driven by loose monetary conditions and resulting in subsequent financial and economic stagnation.

Key Takeaways

- *Equities beat bonds.* Over the 74-year period from 1952 to 2025, Japanese stocks were the big winners. A ¥1 investment in 1951 grew to ¥1,520 by year-end 2025, representing a compound annual geometric mean return of 10.4%.
- *Risk was rewarded with a higher return.* The Japanese market demonstrated a clear risk–return trade-off where returns increased with an asset's risk. Although stocks exhibited the highest volatility, they provided greater rewards than both bonds (5.0% compound return) and money markets (3.9% compound return).
- *For bonds, income returns dominated capital gains.* The large majority of historical returns on long-term government bonds were driven by income returns (coupons) rather than capital appreciation. Japanese bonds saw a mere 0.7% capital gain, compounded annually, over the entire period.
- *Interest rates declined.* Japanese long- and short-term rates have followed a pronounced secular decline since the early 1980s. Following the collapse of the market bubble in the 1990s, Japan entered a prolonged ultra-low interest rate environment, reflecting persistent deflationary conditions.
- *Correlations fluctuated significantly over time.* Stock returns were negatively correlated with bonds during Japan's era of ultra-accommodative monetary policy (from the mid-1990s until March 2024), but the correlation has recently turned positive as the economy recovered and monetary policy began to normalize.
- *Small caps beat large caps.* Investors were compensated for the higher standard deviation of small companies with higher realized returns, although they had to endure periods of significant underperformance, sometimes lasting many years.
- *Historical returns are representative of what can happen.* Although specific historical events, such as the 1987 crash or the 1990s bear market, are unique, the event types tend to recur. Examining these past returns remains highly informative for making inferences about future market behavior.

Data Sources

Primary Data Source

Ibbotson Associates Japan, Inc. Stocks, Bonds, Money Market, and Inflation Japan (SBMI-J) Series (1952–2025).

Specific Asset Class Indices

Japanese stocks: Tokyo Stock Exchange First Section (TSE1) Total Return Index.

Subperiod 1952–1989: Japan Securities Research Institute, "Stock Investment Return" (TSE1).

Subperiod 1989–2025: JPX Research Institute, Inc., TOPIX Total Return Index.

Japanese bonds: IA Japan LT Government Total Return Index (approx. 10-year maturity).

Data derived from: Ministry of Finance (Financial Bureau); Bond Underwriters Association; Japan Securities Dealers Association.

Japanese money markets: IA Japan Money Market Total Return Index.

Data derived from: Bank of Japan, "Collateralized/Uncollateralized Overnight Call Rate."

Japanese inflation: IA Japan Inflation Index.

Data derived from: Ministry of Internal Affairs and Communications (Statistics Bureau), Consumer Price Index (Nationwide, General).

Japanese size-decile portfolios: IA Japan Size-Decile Portfolio Series (TSE1/TOPIX Universe).

USD/JPY exchange rate: Tokyo interbank USD/JPY Spot Rate at 17:00 in JST, End of Month, Tokyo Market; historical Federal Reserve H.10 and central-bank exchange-rate data standardized through Morningstar's US dollar–based conversion framework.

Data derived from: Bank of Japan; Morningstar, Inc.

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CHAPTER 15. THE CHINESE MARKET, 2005–2025

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To fully understand the risk and return characteristics of financial assets, investors and researchers must examine long-term historical return series because asset returns—particularly those of equity investments—exhibit extreme short-term volatility. Only through the analysis of long-term historical data can we uncover the fundamental underlying logic of risk and return and, in turn, use these insights to inform sound long-term investment decisions.

This chapter, based on the *SBBI® China Investment Yearbook*, documents the historical returns of major Chinese asset classes from year-end 2004 to year-end 2025 (Chen and YouZhiYouXing forthcoming 2026). Its purpose extends far beyond mere archival record keeping; it aims to explain, analyze, and distill actionable insights for investors. As Niccolò Machiavelli wrote, "Whoever wishes to foresee the future must consult the past." This sentiment is echoed by Theodore Roosevelt, who observed, "The more you know about the past, the better prepared you are for the future."

The original Ibbotson and Sinquefield dataset was first compiled in the United States in 1976. This work represented the first rigorous, systematic statistical analysis of long-term historical risks and returns across major US asset classes. Upon its publication, the dataset garnered widespread attention from academics and finance practitioners worldwide because of its transformative implications for understanding financial market mechanics, asset class behavior, and the development of long-term investment strategies. Under its previous names, CFA Institute Research Foundation published updates in the form of research monographs by the two authors in 1977, 1979, 1982, and 1989.[1] Ibbotson Associates and successor firms continued to publish annual updates until recently.

This chapter applies the Ibbotson and Sinquefield approach to China, the fastest-growing large economy in the world during the period this study covers (2005–2025). Although that is a short period compared with the capital market histories of many other countries, it is one during which China experienced massive economic growth and achieved an increasing degree of maturity in its capital markets.

Compiling the SBBI® China dataset on which this chapter is based has been a longstanding personal and professional aspiration. I first encountered the original Ibbotson and Sinquefield data while writing my doctoral dissertation in the 1990s and later had the privilege of collaborating with those authors, as well as other leading financial practitioners, for more than 20 years, beginning in 1997. Through this framework, I gained invaluable insights into the fundamental underlying logic of financial asset pricing, and I had the opportunity to promote its application to serve a diverse range of institutional and individual investors globally.

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[1]At the time of the first three updates, the organization's name was Financial Analysts Research Foundation. The name in 1989 was Research Foundation of the Institute for Chartered Financial Analysts, and Dow Jones-Irwin co-published this update. See Ibbotson and Sinquefield (1977, 1979, 1982, 1989).

Since 2020, I have increasingly recognized the critical importance of compiling and analyzing a rigorous historical returns dataset along these lines for the Chinese market—primarily to determine whether the financial market laws and logic observed in mature overseas markets hold true in China's unique market environment.

The return histories presented in this study help reveal the fundamental relationships among various asset classes and between risk and return, including both nominal returns and real (inflation-adjusted) returns. By studying the long-term historical record, one encounters most of the major types of market events that investors have experienced in the past and are likely to encounter in the future. These include geopolitical tensions, economic expansion and recession, bull and bear markets, inflation and deflation, and other less dramatic events that affect asset returns.

The primary goal of this chapter is to help investors understand contemporary Chinese financial markets through the lens of financial history. I aim to do the following:

- Document historical market returns to demonstrate the long-term equilibrium relationship between risk and return in China's capital markets.
- Reveal the structural relationships between the returns of various asset classes, including the drivers of inflation, real interest rates, risk premiums, and other return components.
- Encourage a deeper, data-driven understanding of China's economic and financial markets through empirical data and visualizations.
- Assist readers in answering fundamental, practical questions about the functioning of China's financial markets.

Major Asset Classes and Asset Class Indices in China

The asset classes included in this chapter not only highlight the structural differences across segments of China's financial market but also adhere strictly to the Ibbotson and Sinquefield classification framework, in order to ensure comparability with global historical data. I segment the Chinese equity market into large-cap and small-cap stocks. The fixed-income market is differentiated along two core dimensions: Riskless government bonds are categorized by time horizon, or maturity (represented here by long-term and short-term government bonds), and long-term corporate credit bonds are compared with long-term government bonds to isolate and quantify the default risk premium.

Exhibit 15.1 describes the six major asset classes analyzed in this study and identifies their representative market indices.

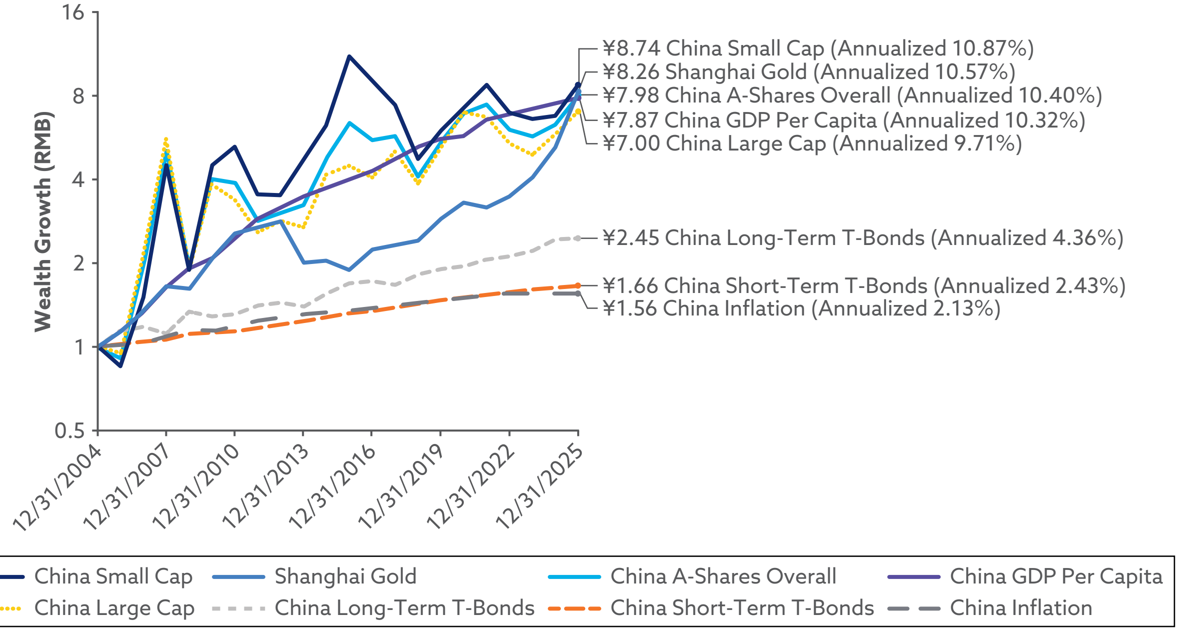
Exhibits 15.2 and **15.3** show cumulative wealth indices of these asset classes, with the latter showing details on the fixed-income asset classes. All returns are total returns (including reinvestment of dividend or interest income). All data in this chapter are in Chinese renminbi (RMB) except where noted.

Exhibit 15.4 presents summary statistics for these asset classes and depicts the distribution of their annual returns over the sample period. Over 2005–2025, higher-risk assets produced higher returns, with Chinese small-cap stocks producing the highest returns and experiencing the highest volatility. Lower-risk assets, such as investment-grade bonds, have return distributions tightly clustered around the series mean. The return distribution for short-term

Exhibit 15.1. Chinese Asset Classes

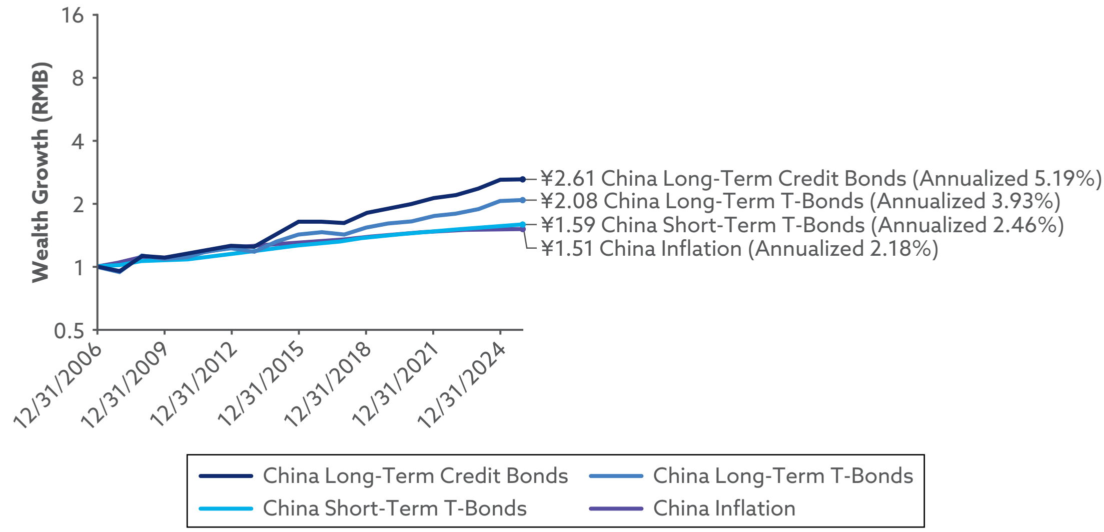
Chinese Asset Class	Representative Index (代表指数)	Index Ticker (指数代码)	Source (数据来源)	Note (备注)
Inflation	Chinese CPI		China National Statistics Bureau 国家统计局官网	
Chinese short-term government bonds	China Bond 0–1 Year Government Bond Index 中债 0–1 年国债指数	CBA14101.CS	China Central Depository & Clearing Co., Ltd. (www.ccdc.com.cn/en/) 中央国债登记结算有限责任公司官网	Returns in 2005 and 2006 are estimated using 6-month government bond yields for each month. 2005、2006 两年以 6 月期国债收益预估得到
Chinese long-term government bonds	China Bond 7–10 Year Government Bond Index 中债 7–10 年国债指数	CBA06501.CS	Same as above	Returns in 2005 and 2006 are estimated using 7-year government bond yields for each month. 2005、2006 两年以 7 年期国债收益预估得到
Chinese long-term corporate bonds	China Bond Investment Grade 7–10 Year Bond Index 中债-高信用等级新财富(7–10年)指数	CBA04751.CS	Same as above	Without data from 2005 and 2006 缺少 2005、2006 年的数据
Chinese stocks (all market)	CSI All Share Index 中证全指	000985.SH	Wind Terminal	
Chinese large-cap stocks	CSI 300 Index 沪深 300	000300.SH	Wind Terminal	2005 dividend of index is estimated using the underlying dividend data for each stock. 2005 年的分红数据根据成分股分红数据估算得到
Chinese small-cap stocks	CSI 1000 Index 中证 1000	000852.SH	Wind Terminal	

Exhibit 15.2. The China Market: Cumulative Indices of Total Returns on Stocks, Bonds, Bills, and Gold, and Inflation Index, 2005–2025



Sources: See sources listed in Exhibit 15.1.

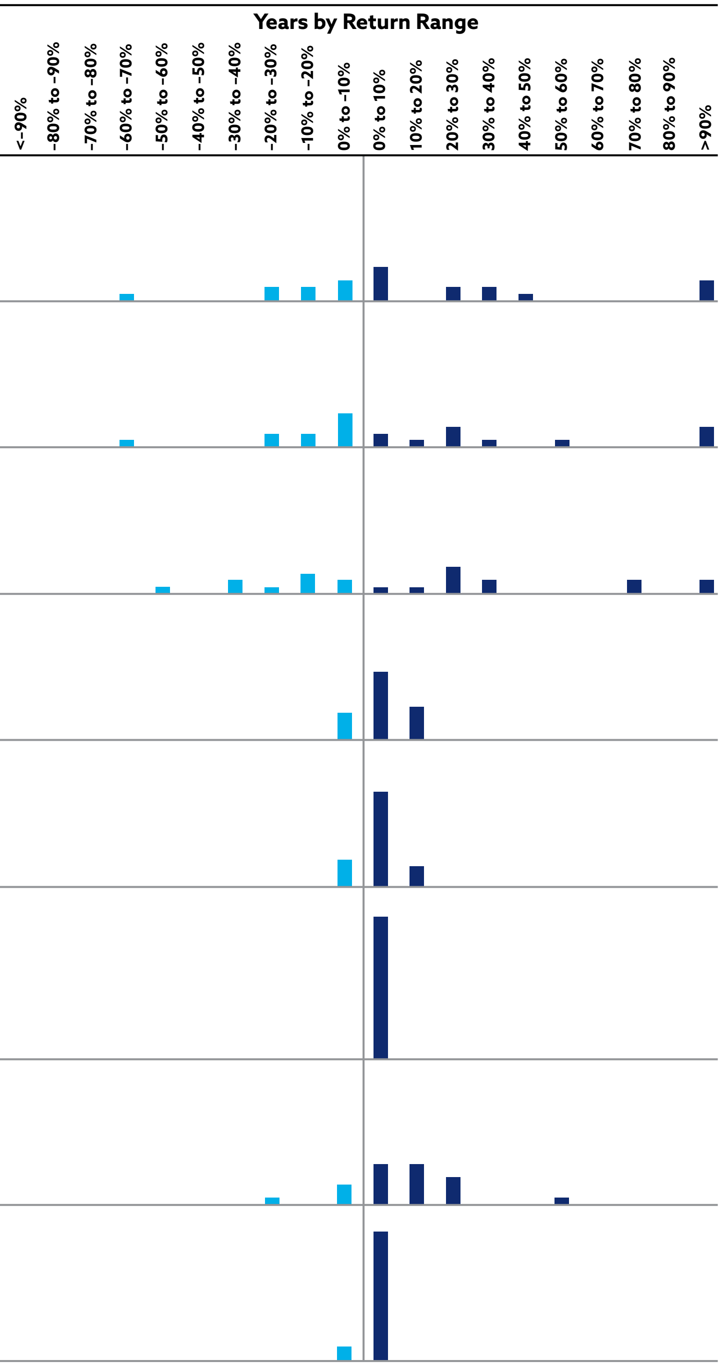
Exhibit 15.3. Chinese Long-Term Corporate Credit, Long-Term Government, and Short-Term Government Bonds, 2007–2025



Sources: See sources listed in Exhibit 15.1.

Exhibit 15.4. Summary Statistics and Distributions of Returns on Principal Chinese Asset Classes, 2005–2025 (2007–2025 for Long-Term Credit Bonds)

Asset Type	Annualized Returns	Annualized Volatility
China A-Shares Overall	+10.40%	54.10%
Large-Cap Stocks	+9.71%	53.44%
Small-Cap Stocks	+10.87%	60.93%
Long-Term Credit Bonds	+5.19%	6.18%
Long-Term T-Bonds	+4.36%	6.16%
Short-Term T-Bonds	+2.43%	0.88%
Shanghai Gold	+10.57%	17.32%
Inflation	+2.13%	1.69%



Sources: See sources listed in Exhibit 15.1.

government bonds lies entirely to the right of the zero-return line. In other words, these bonds never delivered a negative annual return over the sample period.

Exhibit 15.5 presents year-by-year returns in renminbi on each of the asset classes, plus gold (also quoted in renminbi) and Chinese inflation rates.

Exhibit 15.5. Year-by-Year Total Returns on Principal Chinese Asset Classes, 2005–2025

Year	Chinese Small-Cap Stocks (%)	Chinese Stocks (all cap) (%)	Chinese Large-Cap Stocks (%)	Chinese Long-Term Corporate Bonds (%)	Chinese Long-Term Government Bonds (%)	Chinese Short-Term Government Bonds (%)	Gold (%)	Inflation (%)
2005	−14.99	−9.43	−5.25		14.23	2.46	13.10	1.80
2006	76.73	115.38	125.23		3.10	1.80	19.31	1.51
2007	203.10	172.40	163.28	−4.46	−5.26	1.99	22.40	4.80
2008	−59.19	−63.77	−65.61	17.91	19.64	4.39	−2.25	5.90
2009	140.44	108.10	98.58	−1.64	−3.31	1.15	28.25	−0.71
2010	17.64	−2.99	−11.58	4.06	1.64	0.95	23.44	3.29
2011	−32.78	−27.32	−24.05	4.07	7.06	3.35	5.96	5.39
2012	−0.77	6.24	9.80	5.08	2.67	2.65	4.60	2.60
2013	32.50	7.10	−5.33	−1.24	−3.54	2.53	−29.31	2.60
2014	35.26	48.41	55.85	14.85	11.43	3.93	1.75	2.00
2015	76.59	33.78	7.22	13.96	9.03	3.00	−7.37	1.40
2016	−19.69	−13.31	−9.26	0.70	1.86	2.08	18.42	2.00
2017	−16.89	3.68	24.25	−1.77	−2.94	2.76	3.45	1.59
2018	−36.28	−28.79	−23.64	11.62	8.67	3.57	4.25	2.10
2019	26.98	33.41	39.19	5.98	4.40	2.75	19.75	2.90
2020	20.45	26.87	29.89	4.40	2.52	2.00	14.44	2.49
2021	21.61	7.70	−3.52	6.76	5.76	2.46	−4.14	0.90
2022	−20.77	−18.93	−19.84	3.24	3.00	1.94	9.80	2.01
2023	−5.28	−5.34	−9.14	7.74	4.80	2.09	16.83	0.20
2024	2.79	9.98	18.24	10.22	9.38	2.00	28.19	0.20
2025	29.02	27.03	20.98	0.30	0.89	1.23	58.57	0.00

Source: See Exhibit 15.1.

Components of Total Return: Interest, Dividends, and Capital Gains

For all asset classes analyzed in this study, annual total return is decomposed into three components: capital gain return, income return (dividends for equities, coupon interest for fixed income), and return from the reinvestment of income. **Exhibit 15.6** shows the decomposition. For equities, capital appreciation accounts for the majority (70%–90%) of total annualized returns but exhibits extreme year-to-year volatility. In contrast, dividend income and the return from dividend reinvestment are far less volatile but constitute a smaller portion of total annual returns. In other words, capital gain returns are less stable and inherently riskier in the short term, whereas equity dividend income offers greater stability and certainty for investors.

For fixed-income investments, the vast majority of total returns are derived from coupon income and the reinvestment of that income, with capital gains accounting for a small fraction of total returns—and typically turning negative during periods of rising interest rates. This behavior is consistent with the core structural characteristics of fixed-income assets observed in mature global markets.

Exhibit 15.6. Capital Gain and Income Returns on Principal Chinese Asset Classes, 2005–2025

Asset Class	Compound Annual Return	Capital Gain	Income Return
Chinese stocks (all cap)	10.40%	8.84%	1.43%
Chinese large-cap stocks	9.71%	7.57%	1.99%
Chinese small-cap stocks	10.87%	10.14%	0.77%
Chinese long-term corporate bonds	5.19%	0.51%	4.65%
Chinese long-term government bonds	4.36%	0.89%	3.43%
Chinese short-term government bonds	2.43%	–0.35%	2.79%

Source: Chen and YouZhiYouXing (forthcoming 2026).

The Chinese Capital Market from 2005 to 2025

The 2005–2025 period represents one of the most transformative eras in the history of China's capital markets. What began as a relatively small, retail-dominated, policy-driven market evolved into the world's second-largest equity market and bond market by capitalization, with substantial improvements in institutional structure, openness, regulatory governance, and investor sophistication. This backdrop is essential to interpreting the return patterns, volatility, and risk premiums documented in this chapter.

The period opened with a foundational institutional breakthrough: the launch of the split-share structure reform in 2005, which resolved a longstanding structural flaw whereby two-thirds of listed shares—mostly state-owned and legal-person shares—were nontradable. By requiring nontradable shareholders to pay consideration to tradable shareholders, the reform unified shareholder incentives, improved price discovery, and laid the groundwork for a genuine market-oriented valuation system. This reform coincided with strong economic growth, rapid industrialization, and rising corporate profitability, fueling a historic bull market that peaked in 2007 before collapsing amid the global financial crisis in 2008. These extreme swings help explain the exceptionally high volatility observed in Chinese equity returns over the full sample.

In the decade that followed, China's capital markets underwent layered institutional development. Key milestones include the launch of the China Growth and Enterprise Market in 2009 to support innovative small and medium-sized enterprises, the introduction of margin trading and short selling in 2010, and the rollout of cross-border connectivity mechanisms, starting with Shanghai-Hong Kong Stock Connect in 2014 and followed by Shenzhen-Hong Kong Stock Connect in 2016. These channels gradually opened A-shares to global capital, culminating in the inclusion of Chinese domestic equities in major international indices, such as those compiled by MSCI, FTSE Russell, and S&P Dow Jones Indices, marking a decisive shift toward institutionalization and global integration.

The market also experienced repeated cycles of boom, bust, and regulatory tightening. The highly leveraged rally of 2014–2015 and subsequent sharp correction underscored persistent risks from retail-dominated trading, speculative sentiment, and procyclical liquidity conditions. These episodes reinforced why Chinese equities exhibit much higher annual volatility than mature markets, even as long-term returns remained competitive.

From 2019 to 2025, the market entered a new era of high-quality development driven by the registration-based initial public offering reform. Beginning with the launch of the SSE STAR Market (Shanghai Stock Exchange Science and Technology Innovation Board) in 2019, the reform shifted from a government approval system to a disclosure-based, market-driven registration system, which was fully implemented across all exchanges by 2023. Parallel reforms strengthened delisting mechanisms, improved investor protection, and enhanced oversight of accounting and disclosure quality. Meanwhile, the investor base matured: Institutional holdings rose; passive investment products, such as exchange-traded funds, expanded rapidly; and market behavior gradually became more driven by fundamentals, earnings quality, and long-term cash flows rather than short-term policy sentiment or speculative flows.

By 2025, China's equity market featured 5,000 listed firms, with a total market capitalization of USD15 trillion. It had become far more liquid, regulated, and globally connected than at the start of our sample. Nevertheless, it retained distinctive characteristics: strong sensitivity to macro policy, liquidity cycles, and regulatory shifts; a mix of state-owned enterprises and dynamic private firms; and ongoing structural transition toward higher-value-added growth. These unique features shaped the return, volatility, correlation, and risk premium patterns observed across asset classes during 2005–2025 and provide essential context for the empirical analysis in this chapter.

Parallel to the equity market, China's bond market also experienced extraordinary expansion and institutional maturation over 2005–2025, growing from a relatively narrow funding channel into the world's second-largest bond market, with total outstanding volume exceeding USD25 trillion by 2025. The period saw steady development in market structure, with the emergence of a comprehensive ecosystem encompassing Treasury bonds, policy bank bonds, local government bonds, financial bonds, and corporate credit bonds, supported by robust interbank and exchange trading platforms. Regulatory frameworks were gradually unified, issuance mechanisms became more market-driven, and investor bases expanded to include commercial banks, insurance companies, asset managers, and global institutional investors.

The opening of the Chinese markets to non-Chinese investors accelerated notably after 2015, with the launch of Bond Connect in 2017 and the inclusion of Chinese government bonds in major global bond indices starting in 2020, drawing substantial international participation and enhancing price discovery and liquidity. Throughout the period, fixed-income assets exhibited far more stable return patterns and lower volatility than equities, providing investors with a reliable, low-risk alternative and forming an essential pillar for asset allocation and risk management in China's capital markets.

Supply-Side Equity Return Decomposition

Following the Ibbotson and Chen (2003) supply-side return decomposition framework documented in Chapter 9, this section takes the total returns of the China total A-share market index over 2005–2025 and decomposes them into their supply-side components: inflation, real earnings growth, price-to-earnings ratio (P/E) changes, dividend yield, and dividend payout ratio. In this way, the Ibbotson–Chen Dividend Model is implemented.

The results show that over 2005–2025, the geometric mean (compound annual) total return of China's A-share market was 10.40%, of which real earnings per share (EPS) growth was the dominant factor, at 7.11% per year. The P/E showed a slight long-term contraction of –0.50% per year, the average dividend yield was 1.43% per year, and the dividend payout ratio showed a slight downward movement of –0.30% per year. **Exhibit 15.7** shows the decomposition results, and **Exhibit 15.8** provides a graphic depiction.

Exhibit 15.9 illustrates the fact that the growth rates of earnings, dividends, and stock market prices in China have consistently moved together over time.

The annualized growth rate of real EPS of A-shares was 7.11%, representing the majority of equity returns. The P/E contracted slightly over the long term (–0.50% per year), indicating that the long-term returns of A-shares have solid fundamental support, are not driven by valuation changes, conform to supply-side pricing logic, and are consistent with the conclusions of Ibbotson and Chen (2003).

Exhibit 15.7. Historical Supply-Side Return Decomposition, 2005–2025

Building Blocks		Capital Gain and Income	
Component	**Compound Annual Return**	**Component**	**Compound Annual Return**
Equity risk premium	5.67%	Income	1.43%
Riskless rate	2.18%	Real capital gain	6.57%
Inflation	2.13%	Inflation	2.13%
Reinvestment	0.13%	Reinvestment	0.13%
Earnings		**Dividends**	
Component	**Compound Annual Return**	**Component**	**Compound Annual Return**
Income	1.43%	Income	1.43%
Growth in P/E	–0.50%	Growth in P/E	–0.50%
Growth in real EPS	7.11%	Growth in real dividends	6.79%
Inflation	2.13%	– Growth in payout ratio	–0.30%
Reinvestment	0.13%	Inflation	2.13%
		Reinvestment	0.13%

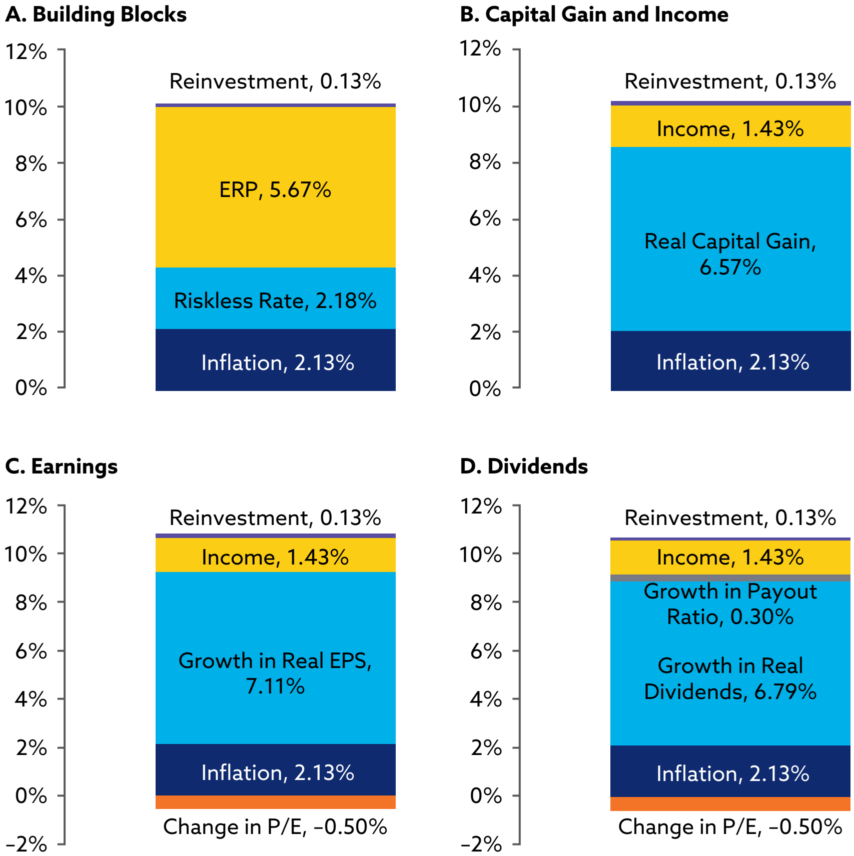
Source: Chen and YouZhiYouXing (forthcoming 2026).

The geometric mean of the long-term equity risk premium of A-shares over government bonds is 5.67%, indicating that holding A-share equity assets over the long term can produce a reasonable return for the amount of risk taken and supporting a substantial allocation to equities for institutional investors and individual investors. Under the new listing policies, the dividend distribution mechanism has been gradually improved. The average dividend yield and payout ratio have risen in recent years and are expected to continue to rise.

Risk Premiums

Risk and return are closely related over long investment horizons. This fundamental relationship exists because investors demand higher expected returns for asset classes with greater underlying risk exposures. The differences in expected or realized returns across asset classes, which compensate investors for bearing incremental risk, are called risk premiums. By examining the historical return differentials between asset classes bearing different amounts of risk, we can calculate the realized or historical risk premiums in China's capital markets over the 21-year sample period.

Exhibit 15.8. Graphic Historical Supply-Side Return Decomposition, 2005–2025



Source: Chen and YouZhiYouXing (forthcoming 2026).

Exhibit 15.10 compares the realized risk premiums in China over 2005–2025 with the much longer-term realized risk premiums in the US market over 1926–2025, calculated using the same methods.

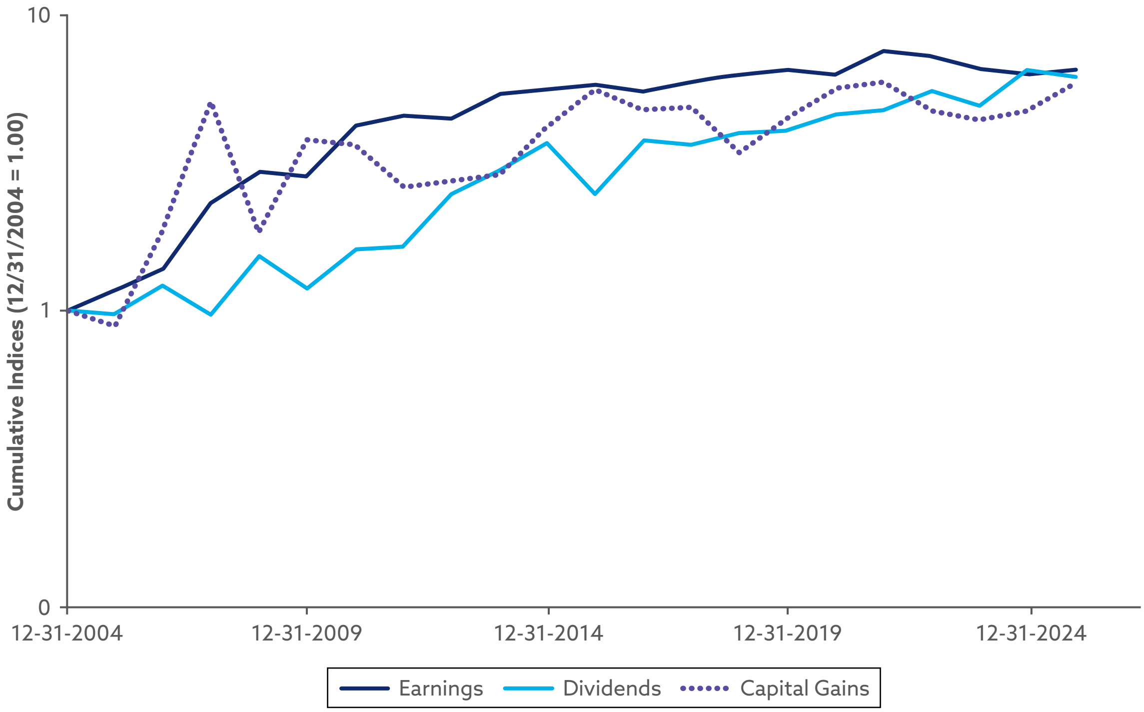
Exhibit 15.11 decomposes the total returns over 2005–2025 on the various Chinese asset classes in this study into risk premiums, the real riskless rate, and the inflation rate using the "building block" analysis described in Chapter 4.

Exhibit 15.12 performs the same analysis for the comparable US asset classes, using data over 1926–2025.

Regarding the Chinese market, I find the following:

- Investing in short-term government bonds incurred no credit risk and no significant horizon (maturity) risk. This instrument delivered a compound annual riskless rate of 2.43%, roughly on par with the inflation rate over the sample period.

Exhibit 15.9. Growth of Earnings, Dividends, and Capital Gains in China, 2005–2025



Source: Chen and YouZhiYouXing (forthcoming 2026).

Note: Growth of RMB1 invested in hypothetical assets returning the growth rate of stock prices ("capital gains"), earnings, and dividends.

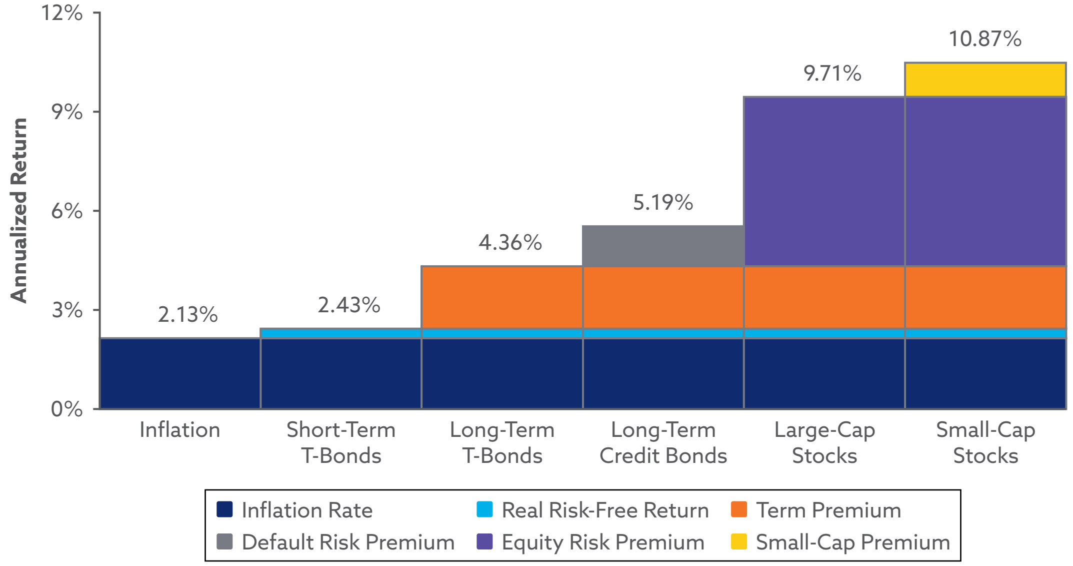
- Compared with short-term government bonds, long-term government bonds have a longer maturity and expose investors to more uncertain risk factors and thus generated an annualized term premium of 1.88%.
- Compared with long-term government bonds, long-term credit (corporate) bonds require investors to bear corporate default risk, with the possibility of partial (or even total) loss of

Exhibit 15.10. Historical Risk Premiums in China and the United States

	Inflation	Real Riskless Rate	Bond Horizon (Term) Premium	Credit Risk Premium	Equity Risk Premium (Large Cap)	Small-Cap Premium
China, 2005–2025	2.13%	0.29%	1.88%	1.21%	5.13%	1.06%
US, 1926–2025	2.94%	0.31%	1.57%	0.76%	5.35%	0.36%

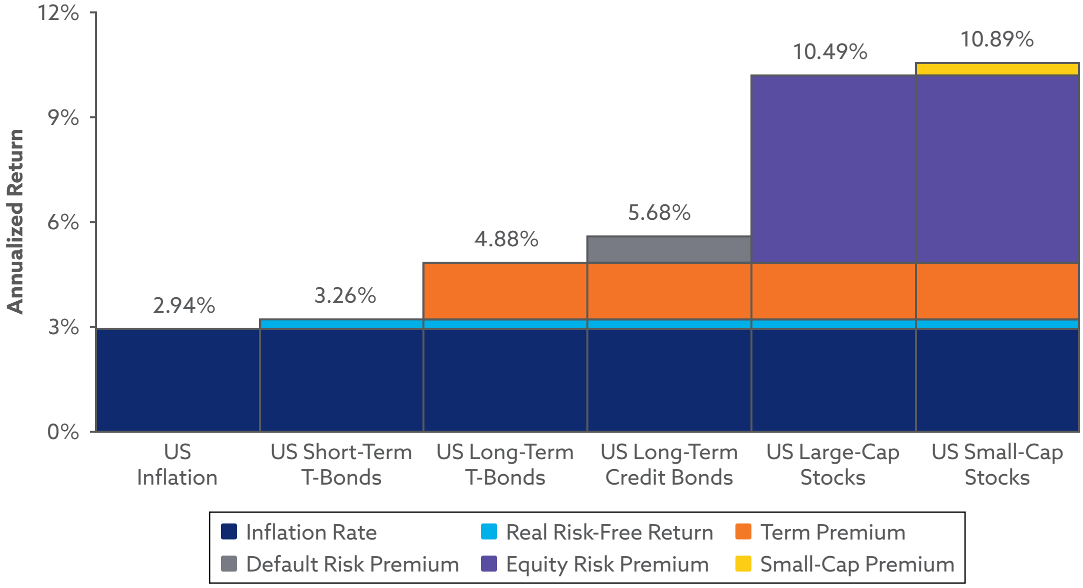
Source: Chen and YouZhiYouXing (forthcoming 2026).

Exhibit 15.11. Building Blocks of Chinese Capital Market Returns, 2005–2025 (2007–2025 for Long-Term Credit Bonds)



Source: Chen and YouZhiYouXing (forthcoming 2026).

Exhibit 15.12. Building Blocks of US Capital Market Returns, 1926–2025



Source: Chen and YouZhiYouXing (forthcoming 2026).

principal in the event of issuer default. These bonds therefore delivered an annualized credit risk premium of 1.21%.

- Bonds represent a contractual debt obligation, whereas stocks represent an ownership stake in a business, making these two types of investment have different risk and return characteristics. Compared with long-term government bonds, investing in A-share large-cap stocks requires investors to bear significantly higher systematic and idiosyncratic risk. As a result, stocks earned an annualized equity risk premium of 5.13% over the period studied.
- Compared with large-cap stocks, small-cap stocks carry higher operational risk, lower secondary market liquidity, and higher transaction costs. Investors in small-cap stocks were compensated for bearing these incremental risks with an annualized small-cap size premium of 1.06%.

I also compare risk premiums earned in China and the United States and find that despite the relatively short history of China's capital market and the material differences in national conditions, regulatory policies, and economic development between the two countries, the realized risk premiums for Chinese and US asset markets have been strikingly similar. This observation confirms that the underlying logic of financial markets is consistent across borders: Risk and return are inextricably linked, and over the long term, higher risk requires higher return compensation. This fundamental law has been empirically verified in both the Chinese and US markets, fully demonstrating the powerful force of the market's "invisible hand" in the allocation of capital and resources.

Conclusion

Over the long term, equities delivered the strongest absolute and risk-adjusted performance of all the major asset classes in China. Over the 21-year sample period (2005–2025), Chinese broad-market (all cap) equities achieved a compound annual total return of 10.40%, compared with 4.36% for Chinese long-term government bonds and 2.43% for Chinese short-term government bonds (cash equivalents). These findings mean that equity investments generated an average annual excess return (equity risk premium) of approximately 5% for investors over the 21-year period.

Small-cap stocks outperformed large-cap stocks over the period studied, with a compound annual total return of 10.87%, versus 9.71% for large-cap stocks, consistent with the size premium observed in global markets. Long-term investment-grade corporate bonds returned 5.19% per year, outperforming government bonds of the same duration (4.36%); this performance reflects the credit risk premium for bearing corporate default risk. Although I do not present multi-asset-class performance in this chapter, such analysis reveals that diversified strategic allocation across equities and other asset classes significantly improved portfolio risk-adjusted return profiles for Chinese investors over the sample period.

This study represents the first comprehensive analysis of asset class risk and return characteristics in China using the rigorous, globally recognized methodology pioneered by Ibbotson and Sinquefield (1976). It is important to note that the major findings from this 21-year historical return analysis align closely with the findings from longer-term studies of the US market and other global markets: Equities consistently outperform bonds, cash equivalents, and inflation over the long term, and these premium returns come with correspondingly higher levels of risk. This research contributes to our understanding of the market dynamics and long-term performance characteristics of China's stock and bond markets and provides a foundational empirical dataset for future academic and industry research.

Key Takeaways

- The core findings, based on 21 years of data on the principal Chinese asset classes, align closely with those of more mature international markets. The results verify that despite China being a developing market with unique national conditions, the underlying logic of financial markets and investor behavior remains largely consistent with global norms.
- Overall, Chinese A-shares (including both large- and small-cap stocks) produced a compound annual return of 10.4% over 2005–2025, with very high volatility (a standard deviation of annual returns of 54.1%). Small caps beat large caps at a compound rate of 1.1% per year.
- Chinese fixed-income asset classes, as expected, provided much lower returns—for example, long-term government bonds with a compound return of 4.4% over the same period. Inflation proceeded at a modest 2.1% annual rate. Across all the Chinese asset classes studied, higher-risk assets produced higher returns in a monotonic fashion.
- This dataset provides an empirical foundation for further academic and industry research on China's capital markets, asset pricing, and strategic asset allocation. Most importantly, the dataset equips investors with essential, quantitative knowledge for a better understanding of China's market and the risk–return characteristics of its major asset classes, enabling more rational, disciplined long-term investment decisions.

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CHAPTER 16. GLOBAL MARKETS IN PREVIOUS CENTURIES

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Between 1601, when shares of the Vereenigde Oost-Indische Compagnie (VOC, or Dutch East India Company) started trading in Amsterdam, and July 1914, when almost every stock market in the world closed because of World War I, financial markets became essential to running the modern economy. In 1601, only one stock traded regularly on the Amsterdam stock exchange, but by 1914, thousands of stocks and bonds traded on dozens of exchanges throughout the world.

Global stock market capitalization was less than 1% of global GDP in 1800, but by 1900, it was 36%. By 1914, stocks and bonds worth billions of dollars were traded on a daily basis. Financial markets transformed the world during the nineteenth century and enabled railroads, telecommunications, energy, and other industries to create the modern economy.

Four Financial Revolutions

Four separate financial revolutions transformed the global economy. The first began in 1171, when Venice imposed forced loans on its citizens to fund its war with Byzantium. These loans were eventually converted into *prestiti* bonds, which were bought and sold in Venice until the 1500s. The first known trade fair occurred in France in 1127, the first currency transfer occurred in 1156, shares in the *Société des Moulins de Bazacle* were traded in the 1250s (Le Bris, Goetzmann, and Pouget 2018), and the first gold coins since antiquity were issued in Italy in 1252 (Kindleberger 1984, p. 23). Between 1150 and 1600, exchanges sprung up throughout Europe, although they existed primarily to trade commodities and currencies, not stocks and bonds.

The second revolution occurred in the late 1500s, when England created trading companies that were given monopolies in different parts of the world. Thousands of companies would follow in the centuries to come (Scott 1912). The first corporation was the Muscovy Company, which was chartered in 1555 and had a monopoly on trade between Russia and England. It still exists today as a charity working in Russia. The four East India companies were founded in England (1601), the Netherlands (1602), France (1604), and Denmark (1616). Each of these countries created corporations that had monopoly trading rights in southern and eastern Asia and were able to raise large amounts of capital to fund their operations.

Editor's note: Much of the text in this chapter comes from a recent CFA Institute Research Foundation monograph (Taylor 2026b).

Shares in Dutch East India Company stock began trading in Amsterdam in 1602, and shares in the Dutch West India Company began trading in 1623.[1] Shares traded in coffee shops in London in the 1690s, and by 1720, trading in over a dozen companies occurred regularly in Amsterdam, London, and Paris. Because of the wars of the 1700s, the amount of outstanding government debt grew more rapidly during the eighteenth century than the capitalization of stock markets grew.

The third revolution occurred after the Napoleonic Wars ended in 1815. The number of corporations and stock markets expanded, leading to stock and bond trading in every major market in the world. Gradually, countries across Europe began trading shares on domestic markets, including France (1801), the Netherlands (1814), Austria (1817), Belgium (1832), Germany (1834), Switzerland (1851), Italy (1856), Russia (1865), and Sweden (1870). Shares traded domestically in India (1850), Hong Kong (1865), China (1869), Singapore (1872), and Japan (1878). Countries that had shares listed in London, such as Canada (1822), Australia (1825), and South Africa (1835), began trading shares domestically as well.

The fourth revolution occurred in the 1980s. The economic problems of the 1970s led Ronald Reagan, Margaret Thatcher, and other world leaders to emphasize global free trade and privatization in the economy, bringing about an explosion in the size of stock markets. Between 1981 and 1999, global stock market capitalization as a percentage of GDP rose from 22% to 109%. Stock markets continue to play an important role in the global economy. Today, stock markets exist in more than 100 countries, and their market capitalization exceeds global GDP.

The Growth of Financial Markets

Financial markets developed rapidly during the 1600s and 1700s. In the 1600s, nations began to issue debt securities that were held by domestic citizens. The issuance of shares by the English East India Company in 1601, the VOC in 1602, the French East India Company in 1604, and the Danish East India Company in 1616 initiated a new period of investment in financial markets.

The Amsterdam Stock Exchange was founded in 1602, when VOC stock started trading. Although a number of corporations were established in England in the 1500s and 1600s, the number of shares that were issued by each company was limited, and there was very little trading in their shares (Michie 2006, pp. 25–31; van Dillen, Poitras, and Majithia 2006). The only company for which regular data on share values in the 1600s exist is the Dutch East India Company.

Before 1689, share trading primarily occurred in Amsterdam, but when William of Orange replaced James II as the King of England in 1689, initiating the "Glorious Revolution," he brought with him knowledge of Dutch finance. Consequently, in the 1690s, English share trading increased dramatically. Shares in more than a dozen companies were traded in the coffee houses in London in the 1690s, and share trading grew by leaps and bounds for the next 30 years. In 1689, there were 15 major joint-stock companies in London, with a total capitalization of almost £1 million. By 1695, there were more than 150 companies, with more than £4 million in capital. The Bank of England alone raised £1.2 million in capital in 1694. The Bank of Scotland was established in 1695.

It was not until the 1690s that data on the prices of stocks and bonds became regularly available. As already mentioned, trading occurred in coffee shops, and the *Course of the*

[1] "West India," in this case, refers to islands in the Caribbean (the West Indies), plus a broader area that includes large parts of the New World.

Exchange published the price of foreign currencies, coins, commodities, stocks, and annuities twice a week beginning in 1698 using trades from Jonathan's Coffee House.

The Nine Years' War was fought between 1689 and 1697, and the War of the Spanish Succession took place between 1701 and 1714. These two wars dramatically increased the debt of both Britain and France. British government debt grew from less than £1 million in 1688 to more than £50 million by 1720, equal to about 60% of British GDP. The British and French governments wanted a way to unload their debt.[2] Both countries used debt–equity swaps and encouraged their citizens to trade their government debt for shares in the *Compagnie des Indes* in Paris and the South Sea Company in London. Prices of the two securities skyrocketed, creating the Mississippi Bubble of 1719 and the South Sea Bubble of 1720.

Share prices for the *Compagnie des Indes* in Paris rose from 300 livres in 1718 to 10,000 livres in 1719, and South Sea shares rose from £100 to £1,000 in 1720. But these share prices eventually collapsed. The first stock market bubbles drew in thousands of people, including Sir Isaac Newton, who was Master of the Royal Mint at the time and nevertheless lost a fortune (Neal 1990).

After the bubbles of 1719–1720 and the losses that investors incurred, interest in stocks remained low for the rest of the century. Interest in government bonds grew, however, as British government debt increased to more than £400 million by the end of the eighteenth century, with Britain funding its wars with debt paying 3%–4%. The value of outstanding shares declined while the amount of outstanding government bonds grew.

England introduced the 3% bond in 1729 and consolidated its debts in 1752, creating the "consol," which was a perpetuity—a bond without a maturity date. The consol continued to trade for the next 260 years and was the most traded bond in the world until World War I. France issued similar bonds in 1746, and in the late 1800s, most European governments issued perpetuities to cover their debts. There was little difference between the returns of stocks and bonds during the 1700s. Both were traded for their yield, not their capital gains.

The Century of Peace and Economic Growth

The period between 1689 and 1815 was one of increasing government debt, leaving little capital for investment in individual companies. For a long time after the collapse of the stock market bubbles in 1720, investors were wary of individual stocks. A century later, however—between 1815 and 1914, a period of peace—government debt declined and investment in corporations grew dramatically. In 1789, there were only a handful of companies whose shares traded publicly, but by 1914, thousands of companies were listed on dozens of stock exchanges around the world.

The French Revolution led to the dissolution and bankruptcy of French and Dutch corporations and to default on the government debts of every country that participated in the Napoleonic Wars except for the United Kingdom. In the United States, Alexander Hamilton reorganized the debts of the central and state governments in 1792. Dutch and French debt was reorganized, with bondholders receiving new bonds worth one-third of their face value. Interest payments on Swedish, Russian, and Spanish debt were suspended during the wars, although these payments later resumed. Britain suspended its link to gold in 1797, only to restore it in 1821.

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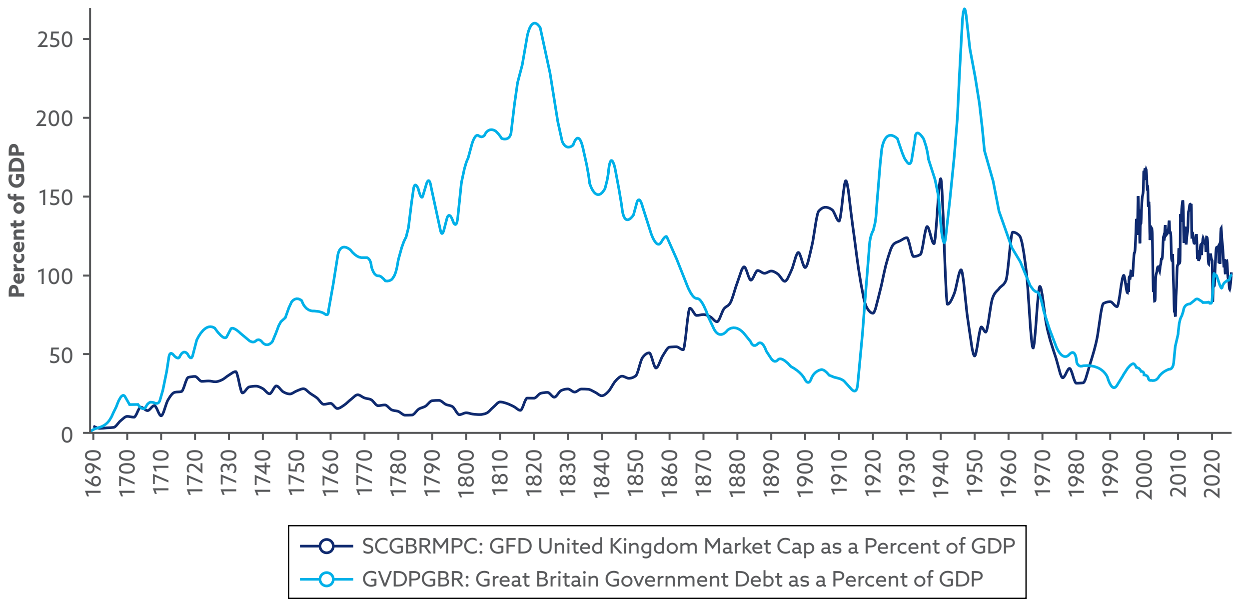
[2] See Balen (2004) and Carswell (1960) on the South Sea Bubble, as well as Buchan (2018).

Before 1789, national monopolies represented the majority of stock market capitalization. After the Napoleonic Wars ended, capital flowed out of bonds and into dozens of new industries. Canal mania struck England in the 1790s, when Parliament approved 44 canals to be built in the Midlands between 1791 and 1794. The price of many canal stocks doubled and quadrupled in the early 1790s before the bubble burst in November 1792 and the price of most canal stocks returned to their par value, £100 (de Salis 1904).

In 1815, the Treaty of Vienna brought peace to Europe, and between 1825 and 1845, railroads provided immense growth to European economies. Railroads quickly became the largest industry traded on stock exchanges in Europe. The collapse of railroad shares after 1845, however, led to the most severe global bear market of the 1800s.

With peace prevailing and governments no longer issuing bonds to fund wars, capital was reallocated from government bonds to corporate bonds and equities. Between 1815 and 1914, stock market capitalization grew relative to both government debt and GDP. Although British government debt shrank from 182% of GDP in 1815 to 29% in 1914, British stock market capitalization grew from 17% to 122% of GDP. By 1914, every developed country in Europe had exchanges that traded stocks and bonds. Commitment to the gold standard provided fixed exchange rates between countries, enabling financial assets to be freely traded across borders. The rise and fall of government debt in Britain in the 1700s and 1800s and the increase in stock market capitalization in the 1800s are illustrated in **Exhibit 16.1**.

Exhibit 16.1. UK Equity Capitalization and Government Debt as a Percentage of UK GDP, 1689–2025



Source: Finaeon, Inc.

Growth of the Stock Market in the Early 1800s

Before 1790, there was rarely activity in more than a dozen stocks in London. Beginning in 1805, however, the number of stocks trading on the London Stock Exchange exploded, reaching 100 in 1814, 200 in 1824, and 300 in 1832. During the 1840s, railroads were built in every major European country, using both domestic and foreign capital. The transatlantic cable connected Europe and North America in 1866, the transcontinental railroad in the United States connected the Atlantic and the Pacific in 1869, and the Suez Canal opened in 1869, making it easier, cheaper, and quicker to send goods and information around the world.

Railroads and telecommunications transformed the world between 1850 and 1900. New industries were born, and their benefits quickly spread around the world. Canals and turnpikes, railroads, utilities, iron and steel, chemicals, the telegraph and telephone, cinema, bicycles, sewing machines, automobiles, and dozens of other industries came into existence, completely transforming the global economy.

Whereas Europe's railroads connected existing cities to improve transportation, the United States spent the next few decades building the country by using the railroads to link the Atlantic and Pacific coasts and establish new cities along the railroad routes. By 1850, newspapers in England, France, Germany, Austria, the Netherlands, Belgium, the United States, and other countries were listing stock market prices from their own and other countries on a daily basis. The greatest beneficiaries of these cash flows were the railroads, which by mid-century had become the largest sector in the stock market.[3]

The continental Revolutions of 1848 led to sharp declines in stock and bond prices throughout Europe and brought about the worst bear market of the nineteenth century. The combination of the collapse of the Railroad Bubble in 1845 and the Revolutions of 1848 sent stock markets to the lowest levels they would reach for the rest of the century. Gold was discovered in California in 1849 and in Australia in 1851, leading to a reflation of the global economy and recovery from the Revolutions of 1848.

Financial Markets Before World War I

The United States stock market grew steadily after the Civil War. Paris sought to challenge London's domination of global capital markets but fell short. The institution of the gold standard after 1870 led to a steady deflation over the next 20 years. Prussia unified the German lands and used the French indemnity from 1870 to adopt the gold standard between 1871 and 1873. In the United States, the "Crime of 1873" demonetized silver and de facto moved the United States onto the gold standard in 1878. The Latin Monetary Union in southern Europe and the Scandinavian Monetary Union in the north helped provide a common currency to their member countries.

The Panic of 1873 affected the United States, England, France, Germany, and Austria. The crash of the Berlin Stock Exchange in November 1872 and the Vienna Stock Exchange in May 1873 led to the Long Depression, which lasted until 1879. The period from 1873 to 1896 was a period of mild deflation and falling bond yields, whereas the period from 1896 to 1914 was one of mild inflation and rising bond yields.

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[3] See Odlyzko (2010). For Germany, see Michaelis (1854, 1859, and 1863).

Stocks and bonds in the 1880s and 1890s provided some of the highest returns to investors until the 1980s and 1990s. By 1881, the market capitalization of the London Stock Exchange was greater than the United Kingdom's GDP, the first time this had happened anywhere in the world. Although bear markets occurred in every country in the world between 1873 and 1914, they were not coordinated, with bull markets in one country offsetting bear markets in others. So, there was no global bear market during the last half of the nineteenth century.

One of the best ways to understand financial markets before World War I is to read the newspapers that printed quotes of securities. Quotes were taken from either local exchanges or stockbrokers seeking publicity. Newspapers provided prices not only from local exchanges but also from the four primary exchanges as well. Interest in the stock market became so widespread that *The Times*, *Financial Times*, *Figaro*, *Allgemeine Zeitung*, and newspapers in other countries regularly printed the prices of stocks and bonds from the world's major markets. The majority of the quotations were for government bonds, but stocks became more prominent over time. Dow, Jones & Co. began calculating its averages in 1885, and *The Banker's Magazine* in the United Kingdom started to calculate stock market indices in 1887.

In the United States, the primary exchange was in New York City, with Boston, Philadelphia, and Chicago providing secondary exchanges. The primary exchange in Germany was in Berlin, with Frankfurt, Munich, and others trading shares as well. The primary exchange in France was in Paris, with exchanges in Lyon, Lille, Marseille, and Bordeaux. The situation was similar in Asia: India had exchanges in Bombay and Calcutta; Japan had exchanges in Tokyo and Osaka; and China had Shanghai and Hong Kong. In addition, Australia had exchanges in Sydney and Melbourne. Each of these exchanges might trade more than 100 securities. The nineteenth century was truly an era of free capital markets.

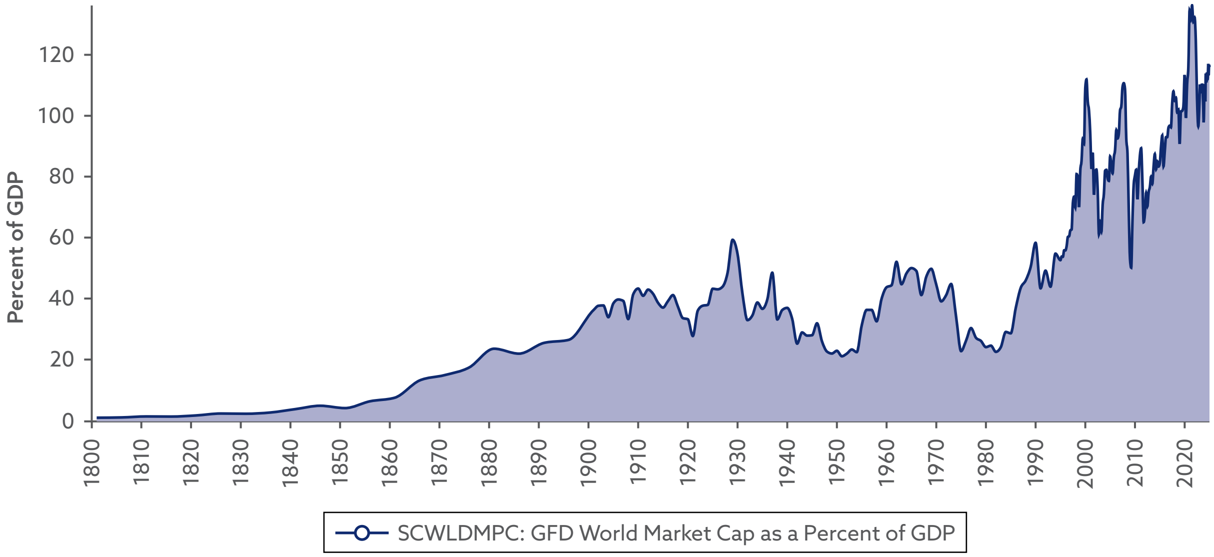
Share markets grew dramatically after 1815. It is probably no coincidence that the economic historian Angus Maddison points to 1820 as the time when the world escaped the low rates of growth that had prevailed between 1 AD and 1820 and saw the beginning of two centuries of unprecedented economic growth (Maddison 2007, p. 380).

World War I Changed the World

World War I changed financial markets forever. Before July 1914, Europe had integrated exchanges on which thousands of stocks and bonds were traded in every country in Europe. Investors in London and other cities readily bought American railroad bonds, Russian securities, South African gold shares, and government bonds from dozens of countries. With the declaration of war by Austria-Hungary on Serbia on 28 July 1914, fears of mass selling of securities and the repatriation of funds forced the closure of exchanges across the world.

For the next 70 years, governments regulated financial markets extensively, controlling the opening and closing of exchanges, the listing of stocks and bonds, the rights of international investors to invest in domestic markets, the flow of funds across borders, the link to gold, links to another currency, or the floating of currencies. Before July 1914, governments tried to minimize the regulation of financial markets. After July 1914, everything was subject to regulation. As illustrated in **Exhibit 16.2**, global market capitalization grew steadily until 1914 and then stagnated as a share of GDP for the next 70 years.

Exhibit 16.2. World Stock Market Capitalization as a Share of GDP, 1800–2025



Source: Finaeon, Inc.

After World War I, the United Kingdom no longer had the financial ability to lead global financial markets the way it had done before 1914, and the United States was reluctant to take on the responsibility of directing international political, economic, and financial markets. World War I forced nations to float their currencies and restrict international cash flows. The dislocations that followed World War I led to a severe global recession. The victors in World War I recovered, and their stock markets soared during the 1920s, while the losers collapsed into political chaos, recession, and hyperinflation.

The recovery from World War I led to the Roaring Twenties. Stock markets peaked in 1929. Economies in Europe and the United States collapsed into the Great Depression between 1929 and 1932 because governments were unable to provide the leadership needed to rescue the global economy. With little trust in foreign trade and international agreements, nations fell back on domestic production. Germany began preparing for World War II, which engulfed Europe between 1939 and 1945.

The world enjoyed a remarkable recovery and expansion in the 1950s and 1960s, referred to as the *Wirtschaftswunder* (economic miracle) in Germany and *les trentes glorieux* (30 glorious years) in France. By the 1970s, however, stagflation had set in, with low growth and high inflation replacing the high growth and low inflation that occurred in the 1950s and 1960s. The oil price increased tenfold. Economists and the public lost their faith in the government's ability to successfully regulate the economy.

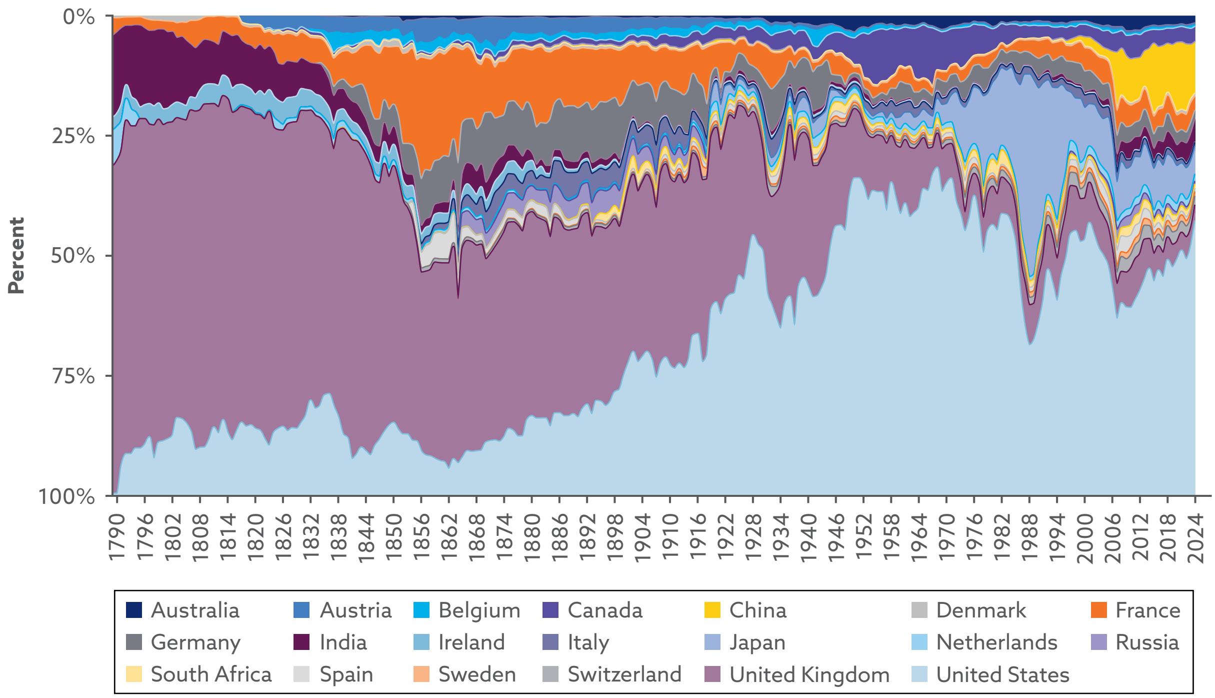
Milton Friedman and others recommended that governments choose markets over regulation. Ronald Reagan and Margaret Thatcher promoted markets, and in the 1980s, the world moved from Keynesian attempts to regulate the business cycle to a world of floating exchange rates, privatization, globalization, and freer markets. Communist governments collapsed, and by the 1990s, almost every country was using stock exchanges to allocate capital, pursuing freer markets and economic growth.

Distribution of Stock Markets

Financial markets can be divided into three groups before World War I. London was the largest, representing more than half of global market capitalization. Paris, Berlin, and New York provided important secondary markets for both domestic and foreign securities. The remaining countries provided access to capital for local investors, but foreign securities primarily traded on one of the four primary exchanges.

Exhibit 16.3 illustrates the global distribution of market capitalization between 1789 and 2024. The United Kingdom represented more than 50% of global market capitalization throughout the nineteenth century. London was the center of global capital markets. Hundreds of corporations throughout the British Empire and South America raised more capital in London than they did on their domestic markets. Government and corporate bonds from almost every country in the world traded in London.

Exhibit 16.3. Distribution of Global Market Capitalization by National Market, 1789 to Mid-2024



Source: Finaeon, Inc.

In 1789, the London Stock Exchange (on which securities from the United Kingdom, India, and Ireland were listed) represented almost 90% of global market capitalization. In 1850, the United Kingdom, including Ireland, represented 57% of global market cap, the United States 15%, India 10%, and the rest of the world about 18%. Diversification continued during the nineteenth century, and by 1914, the United Kingdom represented about 38% of global market cap, the United States 28%, Germany and France each about 8%, and the remaining 20% scattered around the rest of the world.

The United States' share of global market cap increased steadily from 7% in 1860 to 66% in 1950. In 2025, the United States represented more than 60% of the investible global market cap. Japan exceeded the United States' market cap briefly in the late 1980s, peaking in 1989, but today, Japan's market cap is one-tenth that of the United States. Developed markets outside the United States represent about 27% of global market cap, and emerging markets represent 11%. Exhibit 16.3 shows changes in the distribution of global market cap between 1789 and 2024.

Long-Term Return Data

What were the returns to stocks, bonds, and bills before World War I? I have collected data from almost every country for which data on stocks, bonds, and bills exist prior to World War I to track changes in the prices of these assets over time.[4]

Global returns to stocks, bonds, and bills were calculated in British pounds between 1700 and 1789 and in US dollars between 1789 and 2025. These returns are summarized in **Exhibit 16.4** using data from Finaeon's Global Index of Developed Stock Markets. Calculations use British bonds and bills from 1700 to 1789 and US bonds and bills from 1789 to 2025.[5] Over time, the average annual real return to stocks has increased and the average real annual return to bonds and bills has declined. Consequently, the retrospective or realized equity risk premium (ERP) has increased.

The returns in Exhibit 16.4 show how different the twentieth century was from the nineteenth century. During the nineteenth century, there was very little government interference in capital markets and returns to bonds were not significantly different from returns to stocks.

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[4] I used a multiplicity of data sources collected by Finaeon and used with permission. First, I found the broadest price and return index that is currently calculated for each country. Second, because many of these indices began recently, I identified indices that were calculated in real time before the current indices existed, chain-linking the indices together. Because many of the historical indices are price-only indices, I collected dividend and share outstanding information for each country. Third, data were collected on individual stock prices, corporate actions, dividend payments, shares outstanding, and dividend yields so indices could be calculated where none currently existed.

Data were collected from newspapers published in each country. In the United States, for example, these included *The New York Times*, *The Commercial and Financial Chronicle*, and the *Bank and Quotation Record*. For the United Kingdom, newspapers included *Course of the Exchange, The Investor's Monthly Manual*, and *The Times*. Information on corporate actions and shares outstanding also came from, among other sources, the manuals published by Moody's and Standard & Poor's in the United States and *The Stock Exchange Official Yearbook* in the United Kingdom. Similar resources were found for each country analyzed.

In addition to price and total return indices for each country, I calculated sector indices, stock and bond market capitalization, and economic indicators. Finally, I calculated world and regional indices. For more information on the sources for each country, see Taylor (2026a, 2026b).

[5] The Developed World Index includes the United States, Canada, the United Kingdom, the Netherlands, Belgium, France, Spain, Sweden, Italy, Germany, Austria-Hungary, Ireland, Denmark, Australia, New Zealand, and Japan.

Exhibit 16.4. Real Annual Returns on Global Stocks, Bonds, and Bills; the Equity Risk Premium; and Inflation Rates, 1700–2025 (Returns in British Pounds to 1789, US Dollars Between 1789 and 2025)

Period	Real Annual Total Return (%)			Risk Premiums (%)		Inflation Rate (%)
	Stocks	Bonds	Bills	Bond ERP	Bill ERP	
1700–1789	4.92	4.33	3.74	0.56	1.18	0.01
1789–1914	5.31	3.47	3.04	1.94	2.27	0.62
1914–2025	6.37	0.72	0.32	5.61	6.08	3.17

Source: Finaeon, Inc.

Financial markets were allowed to evolve on their own, and there was a prejudice against government intervention.

The Federal Reserve was established in the United States in 1913, and World War I began in 1914. Between 1914 and 1981, governments intervened heavily in capital markets. Governments allowed inflation to increase, and financial repression drove down the real return on fixed income, even to negative levels. Fixed-income investor returns were clearly impacted by government intervention in the economy after 1914.

Over time, significant changes in political, economic, and financial environments have driven the economy. Between 1815 and 1914, Europe transformed from a continent riven by war to an integrated financial market where capital moved freely between countries and new industries and corporations were born on a regular basis. By 1914, the global economy was integrated, and capital and goods flowed freely between countries. No one could imagine that a war would disrupt the progress made during the previous 100 years, but it did. The century of peace between 1815 and 1914 evolved into the twentieth century of war.

I provide three exhibits that present the evolution of real returns to stocks, bonds, and bills between 1789 and 2025. **Exhibit 16.5** shows the returns from various starting dates (between 1789 and 1815) to 1914 in five countries. **Exhibit 16.6** covers 1848–1914, and **Exhibit 16.7** covers 1914–2025. All data have been converted to US dollars after inflation to facilitate comparisons between countries.

Although the start dates differ for each country's data, at least 100 years of data are provided for each. Returns are similar for stocks and bonds, although they are lower for the United Kingdom than for the other countries, especially for bonds because the consol was the safest and most traded security in the world. Stocks outperformed bonds, which outperformed bills. Inflation was almost nonexistent in the 1800s.

By starting in 1848, the coverage expands to a dozen countries. Returns between 1848 and 1914 were fairly consistent for all the countries. Markets in London and Paris offered

Exhibit 16.5. Annual Returns on Stocks, Bonds, and Bills in Real US Dollars; Risk Premiums; and Inflation Rates, Up to 1914 (All Data in Percent)

Country	Real Returns			Risk Premiums		Inflation	Start Date
	Stocks	Bonds	Bills	Bond ERP	Bill ERP		
France	5.30	5.08	3.25	0.21	1.99	0.48	1800
India	5.75	3.80	3.68	1.53	1.64	0.48	1789
Netherlands	6.61	4.39	2.84	2.13	3.67	−0.37	1815
United Kingdom	4.57	2.91	3.04	1.61	1.48	0.19	1789
United States	6.09	4.26	3.67	1.76	2.34	0.58	1791

Source: Finaeon, Inc.

Exhibit 16.6. Annual Returns on Stocks, Bonds, and Bills in Real US Dollars; Risk Premiums; and Inflation Rates, 1848–1914 (All Data in Percent)

Country	Real Returns			Risk Premiums		Inflation
	Stocks	Bonds	Bills	Bond ERP	Bill ERP	
Australia	8.45	3.56	1.51	4.87	6.84	0.00
Austria	4.46	4.75	2.93	−0.26	1.49	0.94
Belgium	4.80	2.98	2.03	1.76	2.72	1.59
Canada	4.77	3.23	2.60	1.49	2.12	0.13
Denmark	4.51	3.23	3.32	1.24	1.16	0.42
France	4.31	3.59	2.08	0.70	2.18	0.32
Germany	4.34	2.87	2.12	1.42	2.17	1.56
India	5.22	2.04	3.35	3.13	1.83	1.25
Ireland	4.89	1.59	2.06	3.25	2.78	0.04
Netherlands	6.31	3.12	2.05	3.09	4.17	−0.01
United Kingdom	4.30	1.57	2.06	2.68	2.20	0.04
United States	7.25	3.18	2.60	3.94	4.53	1.11

Source: Finaeon, Inc.

Exhibit 16.7. Annual Returns on Stocks, Bonds, and Bills in Real US Dollars; Risk Premiums; and Inflation Rates, 1914–2025 (All Data in Percent)

Country	Real Returns			Risk Premiums		Inflation
	Stocks	Bonds	Bills	Bond ERP	Bill ERP	
Australia	6.45	1.60	0.28	4.78	6.16	4.05
Austria	1.04	–1.45	–7.19	2.53	8.86	11.69
Belgium	2.93	0.81	–0.35	2.09	3.28	5.44
Canada	5.36	1.97	0.57	3.33	4.78	3.02
Denmark	5.90	3.23	2.35	2.59	3.47	4.05
Finland	5.84	–0.19	–1.20	6.03	7.12	5.39
France	3.06	–1.81	–6.88	4.96	6.17	7.46
Germany	3.61	–5.58	–21.63	9.73	32.2	28.45
India	3.85	–0.18	–0.56	4.42	4.82	5.34
Ireland	5.31	1.89	0.89	3.36	4.38	4.41
Italy	1.70	–2.01	–2.22	3.78	4.00	9.16
Japan	3.78	–1.54	–3.27	5.41	7.28	6.79
Netherlands	5.57	1.61	0.34	3.89	5.21	3.29
New Zealand	5.47	1.21	1.38	4.20	4.04	4.08
South Africa	5.63	0.46	–0.66	5.15	6.33	5.48
Spain	3.10	0.31	–0.55	2.78	3.66	5.76
Sweden	5.88	1.34	0.82	4.48	5.02	3.78
Switzerland	5.47	2.23	1.08	3.16	4.34	2.17
United Kingdom	5.37	0.77	0.28	4.56	5.07	4.25
United States	7.46	1.43	0.25	5.94	7.19	3.17

Source: Finaeon, Inc.

investors the opportunity to invest in multiple countries and multiple securities. Capital could be moved from securities in one country to another if returns were low in any one country. Returns on stocks in most countries were in the 4%–5% range because capital was free to flow between countries. Returns to fixed income were in the 2%–3% range, with returns in the United Kingdom being the lowest. Inflation was low in all of these countries during the century before World War I.

Providing data between 1914 and 2025 allows the coverage to be expanded to 20 countries. In contrast to Exhibit 16.6, covering 1848 to 1914, there is much greater variation in the returns between countries. Capital was unable to flow freely between countries between 1914 and the 1980s, causing a wide variation in returns because domestic economic policies had a large impact on returns. Fixed income provided negative returns in countries with high inflation (Austria, Germany, Italy, and Japan). Returns to fixed income were lower in every country in our sample between 1914 and 2025 compared with returns before World War I. Fixed-income investors paid the price of inflation and financial repression.

There was a large difference in returns to stocks. Countries that suffered less from the destruction of World War I and World War II (Australia, Canada, New Zealand, and the United States) had higher returns than countries that were more directly involved (Austria, France, Italy, and Japan). Of the 20 countries, the United States had the highest returns and Australia was second. Nine countries had annual returns in the 5% range, and five countries were in the 3% range. Austria and Italy provided the lowest returns, mainly because of their involvement in World War I and World War II. Consequently, the ERP has been higher since World War I than before. Economic policy clearly impacts returns to stocks, bonds, and bills.

Conclusion: 1914 Changed Everything

Before 1914, there was steady growth in financial markets. Every major country had markets that allowed stocks and bonds to freely trade on a daily basis. Capital flowed between different countries to find the best investments possible. Newspapers provided quotes from all the world's major markets for those who invested in multiple countries, and both stocks and bonds provided similar returns based on yield and risk. Stock market capitalization as a share of global GDP grew from 1% in 1800 to more than 40% in 1910. One can only wonder how much the world would have continued to grow if World War I had not begun. But the war intervened.

In 1984, global market capitalization as a share of GDP was lower than it was in 1914. Between 1914 and the early 1980s, inflation rates increased and, along with financial repression, dramatically reduced returns to fixed income. Countries that escaped the destruction of the world wars provided high returns to stocks, but countries that suffered from the destruction of the wars saw returns collapse. It was not until the 1980s that the world began returning to the globalization and free capital markets that existed before World War I.

Our understanding of the equity risk premium has come a long way since it was first studied in the 1960s, mainly because the accumulation of return data on stocks, bonds, and bills over the last four centuries has enabled us to understand how the realized ERP has changed over time. Economics and politics impact the returns to stocks, bonds, and bills. Policies that favor freer markets and lower inflation clearly benefit investors.

Key Takeaways

- In 1601, only one stock traded regularly on the Amsterdam stock exchange, but by 1914, thousands of stocks and bonds traded on dozens of stock exchanges throughout the world.
- Four financial revolutions transformed the global economy. The first began in 1171, when Venice imposed forced loans on its citizens to fund its war with Byzantium, creating a market for government bonds.
- The second revolution occurred in the late 1500s, when England created trading companies. The four East India companies were founded in England (1601), the Netherlands (1602), France (1604), and Denmark (1616). The period between 1689 and 1815 was one of increasing government debt, leaving little capital for investment in individual companies.
- The third revolution occurred after 1815, when the expansion in stock markets led to stock and bond trading in every major country.
- With peace prevailing, capital was reallocated from government bonds to corporate bonds and equities. British government debt shrank from 182% of GDP in 1815 to 29% in 1914; British stock market capitalization grew from 17% to 122% of GDP.
- Before July 1914, governments tried to minimize the regulation of financial markets. After July 1914, everything was subject to regulation. In 1984, global market capitalization as a share of GDP was lower than it was in 1914.
- The fourth revolution occurred in the 1980s, when global free trade and privatization in the economy brought about an explosion in the size of stock markets, which continues today.

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CHAPTER 17. REVIEW AND CRITIQUE OF GLOBAL INDICES

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In this chapter, we survey the growing body of evidence on the magnitude and consistency of historical returns across the major asset classes of stocks and bonds. We update and extend earlier work reported by us in Chambers, Dimson, Ilmanen, and Rintamäki (2024). Our focus is stocks, bonds, and inflation over the very long term. We refer the reader to our 2024 work for a critical appraisal of the returns from investing in real assets, notably commodities and real estate. Most financial research uses data extending back to the early years of the last century. In this chapter, we try to look even farther into the past.

There are two main benefits from taking a long-horizon perspective on asset returns (Chambers and Dimson 2016). The first is simply that it gives us more data. Using as much historical data as possible helps investors form better return expectations. Statistically, a longer sample period gives more reliable average return estimates thanks to the law of large numbers and the resultant smaller standard errors. Second, we can test the robustness of in-sample results with the out-of-sample evidence that distant historical data provide. This ability is especially useful given that accumulating out-of-sample evidence as we move forward is painfully slow in a situation where the in-sample period has been thoroughly data mined.

At the same time, two caveats are important to bear in mind when using long-run data. First, the longer the run of financial data, the more likely it is that regime shifts occur that complicate the interpretation of long-run average return estimates. Second, the quality of financial data deteriorates the farther we reach into the past. For example, when stocks and bonds are delisted, it can be impossible for scholars to discover whether the firm was acquired for value or whether it went bankrupt and investors lost all their money.

Pástor and Stambaugh (2001); Lettau, Ludvigson, and Wachter (2008); and others have sought to identify and predict regime shifts. Such shifts—particularly in the case of more gradual structural changes—are obscured by the evolution of the investment landscape (e.g., expanding

Editor's Note: Much of the text in this chapter is adapted from Chambers, Dimson, Ilmanen, and Rintamäki (2024).

asset universes, falling trading costs) and by the changing nature of the investor community (e.g., the shift from individual to institutional investors, enhanced investor protection).

Paying adequate attention to the quality of long-run historical data is often difficult. In this review, we highlight four common challenges in seeking to uphold data quality: easy-data bias, macro-consistency, replicability, and total return estimation. We also make suggestions for best practices when compiling, interpreting, and using such datasets. These long-run datasets enable us to address questions using broader and more extensive evidence than was possible until recently.

The rest of this study deals with three important research questions. First, we address one of the central issues in empirical asset pricing: whether stocks consistently beat bonds in the long run. Much of this evidence is based on studies of data series starting in 1900 or, notably, 1926 in the case of US stocks and bonds—the start date of the CRSP dataset and the Ibbotson and Sinquefield (1976 et seq.) dataset that is updated in this book.

The choice of start date matters. The evidence regarding average returns drawn from post-1900/1926 studies delivered the conventional wisdom that the long-run equity risk premium over bonds was substantially positive in the United States and in every other country with a long history. In returning to this question, however, we examine the pre-1900/1926 history of stock and bond returns, primarily in the United States and the United Kingdom. The evidence suggests that during that earlier time, the gap between the average returns on stocks and on bonds was low in the United Kingdom and seemingly negligible in the United States.

Second, we examine just how abnormally low bond yields were in the two opening decades of the twenty-first century. When viewing the yields of government bonds (or other bonds with little credit risk) in a much longer-run perspective, we conclude that the recent yield experience was indeed unprecedented.

The third question concerns corporate bonds and the credit risk premium. The reliable evidence regarding the extent of the excess returns or premiums attributable to credit risk is based on a relatively short history stretching back to the 1970s. We therefore ask whether long-horizon corporate bond data histories can provide insights on credit excess returns. In brief, the evidence is at best mixed because of estimation problems and a paucity of data.

We begin with a discussion of the challenges in handling long-run financial data. Next, we deal with each of our important research questions that can be addressed with historical data. We conclude with some potentially promising directions for future research.

Challenges of Long-Run Financial Data

Although we are proponents of the use of long-run datasets, it is important to exercise care when using such data. The danger of not understanding the limitations of long-horizon data increases the longer the history. For example, structural changes may occur in characteristics of the data, such as the number of stocks in the universe and the degree of sector diversification. Therefore, it is important for historical datasets to include as full a description as possible of the key characteristics of the underlying records and how they were processed.

Next, we briefly outline four common challenges when handling long-run historical data. They are various biases, macro-consistency, replicability, and total return estimation. We focus on stock indices, but similar issues arise in other asset classes.

Easy-Data, Survival, and Success Biases

Researchers can be misled into assuming that long-term historical financial series are as high quality as contemporary indices. Dimson, Marsh, and Staunton (2002) noted that severe data weakness can result from reliance on easy-to-collect data. Seemingly innocuous decisions, such as selecting a base date that follows a period of market trauma, can distort estimates of expected return. The authors highlighted the fact that in 2002, the standard publications on long-term stock market returns in the United Kingdom started at the end of 1918, in the Netherlands in 1947, in Germany in 1952, and in Japan in 1971. Each data start point occurred after a major decline, before a major advance, or both.

Dimson, Marsh, and Staunton (2002) also pointed to index compilers' inclusion of markets that had grown and omission of those that had been laggards. For the 16 standard sources they examined, one for each country, the equity returns over the varying periods covered in prior studies exceeded the returns over the full period starting in 1900 by an average of 3 percentage points per year. Easy-data bias alone gave rise to estimated long-run equity premiums that were almost double the unbiased estimate.

We need to be particularly vigilant about possible biases that could make a dataset unrepresentative of the true long-term market experience we are seeking to document—that is, shortcomings that add not only noise but also bias. Easy data may expose the researcher to a variety of selection biases in terms of both the securities included and the countries studied. One cause of this bias is that the financial returns of stocks or countries are correlated with decisions about asset inclusion or exclusion.

Survivorship bias may be illustrated through comparisons of equity market country returns. Brown, Goetzmann, and Ross (1995); Jorion and Goetzmann (1999); and Dimson, Marsh, and Staunton (2021) all stressed that the US equity market has been one of the best-performing stock markets over the long term, outpacing the rest of the world by 2%–3% per year. Not coincidentally, the United States has until recently been the primary focus of most academic research. Meanwhile, markets that lacked full capital market histories during the past century and lagged in performance comparisons—including Russia, China, Argentina, and Zimbabwe—have often been excluded from historical studies of global equity market performance. As a result, researchers may have reported an unrealistically favorable picture of long-run equity returns.

Of course, the fact that the United States and the United Kingdom are recognized as markets with relatively accessible historical data going back to the 1800s and 1900s also reflects success bias. Easy-data bias points in the same direction as success bias, which often means that historical samples begin after some difficult periods when asset valuations may have been low. Some studies omit observations that were outliers or were not investable. Sometimes, periods were chosen with the benefit of hindsight. The German hyperinflation of 1923 is one example; most studies of German capital markets leave out that period or begin with data collected after it ended. Such issues are hard enough to address with recent data; they may be unresolvable with nineteenth century data.

Macro-Consistency

Early indices were rarely weighted by the market value of each constituent. They were typically unweighted—computed on an equally weighted basis—or, alternatively, as with the Dow Jones

Industrial Average, weighted by the price of each constituent stock. Many other indices followed investment approaches that could not be replicated by investors, including the *Financial Times* 30 index, or FT 30 (a UK index launched in 1935), and the Value Line Index (a US index launched in 1961). Both of these indices are geometric and thus incapable of being replicated by investors or index fund managers.[1] A geometric index understates the performance of the asset class that it purports to follow.

Indices can be constructed in many ways. Most useful are indices that measure the investment performance of a portfolio that contains every security in the investment universe, with each one held in proportion to its outstanding value. Such market-capitalization-weighted indices are macro-consistent (Sharpe 2010), meaning that everyone could hold the index with no stocks left over. They reflect the fact that the average investor must hold the market portfolio (Cochrane 2011).

Therefore, when we use a historical index, we need to know how the index is defined. Does it represent a broad all-stock universe or a narrower subset? What has been included, which stocks have been omitted, and why? When there is a choice between broader and more focused coverage, we favor using an all-share index, which provides the broadest coverage in every country. Indices should wherever possible be capitalization weighted, not equally weighted, and index composition should reflect the experience of real-world investors. It is difficult to create stock market indices for early periods that satisfy these criteria.

Replicability

Stock market indices should be designed in such a way that, without any foresight about future performance, investors can replicate index composition with real money. We have already discussed index design and the importance of having a value-weighted arithmetic index rather than, say, an equal-weighted index. We now turn to the challenge of stocks that disappear from databases; such securities often have low returns toward the end of their lives. What should a financial historian do to estimate stock market performance when stocks are deleted?

The crudest (and wrong) approach is to exclude stocks that, with the benefit of hindsight, no longer exist. Doing so is equivalent to assuming the investor is clairvoyant—that she exits from a holding before a disaster occurs. When delistings occur, researchers may assign overly optimistic estimates of pre-delisting returns. Grossman (2002) showed a wide range of UK equity return estimates for the period 1870–1913, depending on the delisting return assumptions used. Shumway (1997) showed that because of delisting bias, estimates of the long-run US equity return and especially the small-cap premium were significantly overstated. Foreman-Peck and Hannah (2012) and Campbell, Grossman, and Turner (2021) reported that a standard equity index used in the United Kingdom had serious omissions that made the index inadequate (Gregory 2024, p. 5).

Even transitory or occasional omissions matter. Pioneers will frequently see their early work as financial archaeologists criticized and their foundational research subsequently improved on by later scholars. McQuarrie (2024, p. 14) compared his new index for US common stocks in

[1]A geometric index (not to be confused with the geometric mean of a time series of returns) is constructed by calculating the ratio of each stock's closing price to its previous closing price, multiplying all the ratios together, and raising that result to the reciprocal of the total number of stocks. Such a "paper" strategy cannot be replicated with real money.

the nineteenth century with earlier computations and reported that Siegel's (2014) omission of a major stock had a major impact on estimated returns. Omissions can also be numerous, and Zweig (2009) reported that Siegel omitted "97% of all the stocks that existed in the earliest years of the U.S. market." Graham and Zweig (2024, p. 86) observed that "more than 300 companies in various industries had been launched in the U.S. by 1801. Most ended up fading into oblivion, leaving no record of their hapless investors' losses. Yet the earliest of the data in *Stocks for the Long Run* tracks only seven bank stocks—all of which were selected because they did not go bust."

The large number of omissions from the index meant that it failed the test of macro-consistency. Moreover, unless an investor was clairvoyant—knowing which firms were destined to disappear—the investment strategy of the index could not have been replicated in real life.

Many real-world indices apply liquidity screens that take account of constituent information from before an index is rebalanced. Historical reconstructions can require a prospective constituent to have a minimum number of observations over the following year or to have other information for the year after rebalancing. In addition to rebalancing bias (e.g., Roll 1981; Lyon, Barber, and Tsai 1999), there may be a significant gap between estimated index returns and true buy-and-hold returns. We defer this concern to future research.

The expanded interest in research on long-term investment returns, supported by extensive digitization of historical data sources, has given rise to multiple approaches to creating and analyzing security price data. These include single-country studies, such as those mentioned previously for the United States and United Kingdom. More recent initiatives include the work of Annaert, Buelens, and Riva (2016), which covered more than two centuries of Brussels Stock Exchange history, and Hautcœur and Riva's (2018) comprehensive database on French stock markets since 1795.[2]

Total Return Estimation

The real return on a portfolio held over the long run is driven by the income it generates. The importance of income was recognized in the first careful studies of returns on the New York Stock Exchange by Fisher and Lorie (1964, 1968), who computed not only capital appreciation but also total returns including dividends. Ibbotson and Sinquefield (1976) also noted the importance of dividend income in their landmark study of US stock returns. As we go back in time, in general, asset price data are more easily obtained than dividend data, and so price-only return estimates tend to be more common than total return estimates. Accurate estimates of dividends are difficult to assemble, especially for early time periods and for markets with incomplete records.

Jorion and Goetzmann's (1999) analysis of investment returns from stock markets around the world was based on long-term capital appreciation indices in 39 countries. They noted that the inclusion of dividend income would elevate return estimates in both the United States and other countries. Moreover, small adjustments to estimated dividend yields have a sizable impact on long-term returns. Zweig (2009) highlighted inaccuracies in dividend estimates in Siegel's (1992) early data and the resulting bias in computed returns.

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[2]For additional information, refer to the Study Center for Companies and Exchanges at www.uantwerpen.be/scob and the Data for Financial History (DFIH) database at https://dfih.fr, respectively.

When we consider pre-1900 data, income return dominated price appreciation in the total real returns of stocks and bonds. However, income or payout data are harder to source than stock price data for that period. Collecting data on realized as opposed to contractual income payments becomes particularly challenging in the case of coupons on bonds. In the case of bond defaults, identifying recovery rates may not be possible. Plugging in contractual cash flows or interpolating data will overstate realized returns.[3]

We close this section with some remarks on best practice, in the spirit of Annaert et al. (2016) and Baltussen, van Vliet, and van Vliet (2023). Scholars should do the best they can with the available historical data, with all its inherent problems and shortcomings. At the same time, there should be a clear disclosure of data sources and design and measurement choices, and researchers should highlight challenges, potential biases, and interpolation or back-casting of data. Good practice involves robustness checks of reported results reflecting the various possible design choices. Finally, we should give full credit to previous researchers, especially those who have undertaken the painful effort to create and clean datasets and to make them available to others.

The Big Questions

With long and broad datasets, we can take a fresh look at many issues. The questions we discuss next represent those that we believe are of first-order importance to academics and practitioners alike and that have been directly addressed in the prior literature using data from the past century.

Equities: Was the Twentieth Century an Anomaly?

An abundance of evidence has shown that the total returns of equities have exceeded those of government bonds over various long-run periods since the beginning of the twentieth century—both in the United States (Ibbotson and Sinquefield 1976; Siegel 1994, 2022) and in the rest of the world (Jorion and Goetzmann 1999; Dimson, Marsh, and Staunton 2002, 2026). In this section, we address one of the central questions in empirical asset pricing: whether the evidence we have cited—that stocks consistently beat bonds over the long run—is robust.

As we noted previously, this evidence relies primarily on data series starting in 1900 or, in the case of the United States, 1926, when the University of Chicago's CRSP data starts. In this section, we first discuss the history of stock and bond returns before 1900/1926 and critically review these out-of-sample estimates of the equity risk premium before making comparisons with twentieth century estimates. As well as looking at the United States, we consider the United Kingdom—the home of the premier stock and government bond markets in the nineteenth century.

We will review the long-run evidence on the total returns achieved by stocks. The ideal measure of stock returns is the compound annual (geometric mean) total return, including price changes, dividends, and any other payouts to existing shareholders, for a market-capitalization-weighted universe of all listed stocks, adjusted for delistings and corporate actions.

[3]Apart from total versus price-only returns, nominal versus real returns, and arithmetic versus geometric means, many return measurement issues have received increasing research attention but are beyond the scope of this chapter. Bessembinder, Chen, Choi, and Wei (2025) summarized issues related to the measurement horizon, the rebalancing strategy, the reinvestment rate assumptions of interim cash flows, and the gap between investment and investor return.

Researchers have undertaken admirable detective work in searching physical and digital archives to gather data and construct estimates of nineteenth century stock returns. In the United States, the first pre-CRSP evidence on stock returns drew on the efforts of Smith and Cole (1935), Macaulay (1938), and Cowles (1938). These estimates were later used by Schwert (1990) and Siegel (1992), among others, as their pre-CRSP source and were subsequently modified by Goetzmann, Ibbotson, and Peng (2001). More recently, Baltussen, van Vliet, and van Vliet (2023) made a detailed and valuable contribution to our understanding of US stock returns from 1866 to 1926 based on a careful data collection exercise. McQuarrie (2024) made a similar heroic effort going back to 1800 for the United States (with much help from Sylla, Wilson, and Wright 2005).

Similarly, in the United Kingdom, considerable efforts have been made to extend stock return histories back to 1829 (Acheson, Hickson, Turner, and Ye 2009; Campbell et al. 2021) and to preceding periods (Campbell, Quinn, Turner, and Ye 2018). An even earlier equity series, from Golez and Koudijs (2018), can be used to extend the Campbell et al. (2021) indices back to 1800. Thomas and Dimsdale (2018) provided the corresponding bond returns and inflation rates, reflecting the adjustments proposed by Klovland (1994).

Exhibit 17.1 summarizes the annualized nominal returns of equities and bonds, the equity risk premium (over bonds), and the annualized real returns of equities over 1800–1899, 1900–1999,

Exhibit 17.1. Annualized Percentage Returns on US Stocks and Bonds Since 1800

Period	Siegel (2014)	McQuarrie (2024)	Taylor (2023)	DMS (2026) Extended	Siegel (2014)	McQuarrie (2024)	Taylor (2023)	DMS (2026) Extended
	US Equity Nominal Return				**US Bond Nominal Return**			
1800–1899	6.8	5.5	6.8	5.5	5.1	6.2	5.5	6.2
1900–1999	10.5	10.2	11.2	10.3	4.8	4.9	4.4	4.5
2000–2025	8.3	7.8	7.5	7.9	4.8	4.8	3.7	4.9
1800–2025	8.6	7.8	8.8	7.9	4.9	5.5	4.8	5.3
	US Equity–Bond Premium				**US Equity Real Return**			
1800–1899	1.6	−0.6	1.2	−0.6	7.2	5.9	6.7	5.9
1900–1999	5.5	5.1	6.5	5.5	7.3	7.0	7.8	7.0
2000–2025	3.4	2.8	3.7	2.9	5.6	5.1	4.8	5.2
1800–2025	3.5	2.3	3.8	2.5	7.1	6.3	6.9	6.3

Sources: McQuarrie (2024), including his estimates of Siegel (2014); Taylor (2023); Dimson, Marsh, and Staunton, or DMS (2026). The DMS extended series merges the McQuarrie (2024) data up to 1899 with DMS (2026) estimates for 1900–2025. For 1800–1801, we used Siegel (2014) data to extend McQuarrie (2024) data back to 1800. We used DMS (2026) data to extend the McQuarrie (2024), Siegel (2014), and Taylor (2023) series forward.

and 2000–2025. It covers the US returns reported by Siegel (2014) and later roughly reconstructed by McQuarrie (2024), accompanied by estimates from Taylor (2023) and Dimson, Marsh, and Staunton (2026). All the quoted figures are geometric means (compound returns) and are thus lower than arithmetic means (simple average returns), with the difference between the two kinds of means being larger for more volatile series.

The main message is that the US equity premium over (government) bonds, observed to be 5% or greater in the 1900s, was considerably higher than estimates for the 1800s, which range between +1.6% and −0.6%. The disagreement between these two figures results from differing estimates of equity and bond returns in roughly equal measure. First, Siegel (1992, 2014) overestimated equity returns, and (as noted previously) his estimate suffers from both survivorship bias and a crucial stock omission. Second, there are problems with Siegel's (1992, 2014) attempts to proxy risk-free bonds in the nineteenth century.

McQuarrie (2024) eschewed such a risk-free proxy in favor of the return on a bond index, drawing on a comprehensive dataset of municipal, federal, and corporate bond returns. This method will inevitably capture some credit premium in municipal and corporate bonds and will thus not produce a pure riskless return, partly explaining McQuarrie's (2024) higher bond return and lower equity premium in the early data.[4] Hence, the 1800–99 US equity premium over truly riskless bonds would probably not be a negative figure but most likely a small positive number, yet still a lot smaller than the premium for the 1900s. Given that national government bonds did not exist on any sort of consistent basis during the nineteenth century in the United States, we look next at evidence for the United Kingdom, where default-free government bonds *did* exist.

Exhibit 17.2 provides geometric mean returns for equities and bonds in nominal terms, equities in real terms, and the realized equity premium over bonds in the United Kingdom over 1800–1899, 1900–1999, 2000–2025, and the full 1800–2025 period.

The UK equity–bond premium for the 1800s is estimated to be near 1.5%. We consider the UK estimate for the nineteenth century a more reliable measure of the equity premium than the US estimate for the same period, given that the bond returns are based on obligations of the British government (so-called consols)—the prime credit available to investors throughout the 1800s. The 226-year estimate of the annualized UK equity–bond premium is around 3%, well below the twentieth century premium of 4%–5%.[5]

Recent empirical studies of equity and bond returns in the nineteenth century for Belgium and France—both were among the most important capital markets in the world at this time—also indicate a low premium compared with the twentieth century. Annualized nominal returns for Belgian equities and government bonds have been estimated to be 4.0% and 4.4%, respectively, over 1838–1900 (Van Mencxel, Annaert, and Deloof 2024, Table 5). This slightly negative equity–bond premium contrasts with a 3% premium for 1900–1999 (Dimson et al. 2026, Table 24). In France, annualized nominal returns over 1854–1914 for equities were estimated at 5.3%

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[4]All bond sources use long-dated government bonds since the 1920s, although with different maturities.

[5]There are fewer sources for short-term bill returns than long-term bond returns before 1900, so we do not include them in Exhibit 17.1 or Exhibit 17.2. Finaeon has estimated a 1.2% lower return for US bills than bonds in the 1800s, reflecting a healthy term premium (compared with a term premium of 0.7% in the 1900s and 2.3% in the 2000s). The term premium was lower in the United Kingdom: 0.2% in the 1800s, near 0% in the 1900s, and near 2% in the 2000s. Chen, Jiang, Lustig, Van Nieuwerburgh, and Xiaolan (2022) discussed the shifting location over several centuries of the world's dominant safe-haven asset supplier—from the Netherlands to the United Kingdom to the United States.

Exhibit 17.2. Annualized Percentage Returns on UK Stocks and Bonds Since 1800

Period	Taylor (2023)	DMS (2026)	DMS (2026) Extended	Taylor (2023)	DMS (2026)	DMS (2026) Extended
	UK Equity Nominal Return			UK Bond Nominal Return		
1800–1899	5.6	—	5.4	4.0	—	4.0
1900–1999	10.2	10.2	10.2	4.9	5.4	5.4
2000–2025	5.5	5.4	5.4	3.3	3.5	3.5
1800–2025	7.6	9.2	7.5	4.3	5.0	4.5
	UK Equity–Bond Premium			UK Equity Real Return		
1800–1899	1.5	—	1.4	5.8	—	5.4
1900–1999	5.0	4.6	4.6	6.0	6.1	6.1
2000–2025	2.1	1.9	1.9	2.0	2.8	2.8
1800–2025	3.1	4.0	2.9	5.4	5.4	5.5

Sources: Taylor (2023); DMS (2026); for equity returns, Golez and Koudijs (2018) over 1800–1829 and Campbell et al. (2021) over 1830–1899; for bond returns and inflation, Thomas and Dimsdale (2018) over 1800–1899. We used DMS (2026) data for the year 2025 to extend the Taylor (2023) series forward. Not to be reproduced without express written permission from the authors.

Note: All returns are annualized geometric means in local currency.

and for government bonds at 4.0%, implying an equity–bond premium of 1.3% (Le Bris and Hautcœur 2010, Table 10), compared with 4.3% for 1900–1999 (Dimson et al. 2026, Table 37). In short, the robust and substantially positive equity premium of the 1900s—almost universal across the countries in the Dimson et al. (2002, 2026) dataset—was much smaller and quite close to zero in the previous century.

A full discussion of the reasons for the lower equity returns in the nineteenth versus the twentieth century is beyond the scope of this chapter, but we will touch on them briefly. Mechanically, the lower return could reflect lower growth; indeed, the 1800s experienced lower growth in *per capita* income, lower productivity growth, and lower dividend growth relative to the 1900s. The payoff from the First Industrial Revolution (steam and the railroad) of the late eighteenth and early nineteenth centuries was modest compared with that of the Second Industrial Revolution (electricity, the internal combustion engine, and many other innovations) in the late nineteenth and early twentieth centuries and that of the Information Revolution (information and communication technology) starting in the late twentieth century.

A decomposition analysis of total equity returns supports such claims about the relatively poorer fundamentals of the 1800s. From a return source perspective, the components of total real equity returns are the dividend yield, the real growth in dividends per share, and the change in equity valuation. The decompositions for the United States and the United Kingdom in the 1800s and 1900s show that dividend yield is overwhelmingly the most important contributor to returns in both centuries.[6] The real growth in dividends and the upward trend in equity valuations of the twentieth century were nowhere as apparent in the earlier period.

From a rational asset pricing perspective, these growth arguments are beside the point. Instead, lower average equity premiums over a century suggest less risk in the 1800s than in the 1900s, which seems hard to justify, especially in the United States, given political instability and immature markets. That said, measured equity market volatility was lower, and bonds were hardly riskless in the 1800s (with their high real return raising the bar for stocks).

Moreover, realized average stock returns may not reflect expected returns even over a century-long history, especially if there was significant repricing. The twentieth century saw many improvements in corporate governance and disclosure necessary to induce outside equity ownership, as well as improved equity investability (via pooling and diversification) and higher investor risk tolerance. All these developments likely contributed to the generally rising valuations of equities and to stocks outpacing bonds over the century. Realized stock returns were boosted by falling required returns (rising valuation multiples) and thus likely exceeded the returns investors had been expecting.[7]

To summarize, the equity risk premium was exceptionally high in the twentieth century and low in the nineteenth century—especially in the United States. The reasons for these differences are worthy of further research. Both centuries may have been abnormal. Consistent with this conjecture, leading experts at a recent equity premium symposium estimated a prospective equity–bond premium of between 0% and 5% (Siegel and McCaffrey 2023, Appendix A). The best guidance on future premiums may be to use a number between one drawn from the lucky 1900s and one from the disappointing 1800s.

Bonds: How Abnormal Were the Recent Low Bond Yields?

Having looked at bond returns in the previous section, here we turn to bond yields with a long-run perspective. Certainly, bond yields in the past decade were as low as they had been since 1900 (reaching negative real yields in major bond markets and even negative nominal yields in Japan, Germany, and the United Kingdom).

Given that bond markets have existed for much longer than stock markets, what do the pre-1900 data tell us about just how unusually low real yields became? The longest data sources relating to loan or bond yields are by Homer and Sylla (2005) and Schmelzing (2020). The former dates back to ancient times and the latter to the early fourteenth century. However, interpreting these estimates of historical bond yields is problematic. Bond contracts in the nineteenth century incorporated many features that make estimating a consistent series of bond yields

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[6]Total equity return can be decomposed in increasingly granular ways. The most common decomposition is in the spirit of the dividend discount model, splitting the return into dividend yield (d/p), dividend-per-share growth, and valuation change, or $\Delta(p/d)$, components (e.g., Ilmanen 2022). Dimson et al. (2026, Table 12) presented this decomposition for 21 national markets over the 1900–2025 period. Kuvshinov and Zimmermann (2022) documented the declining role of dividend income in stock returns across centuries.

[7]The cyclically adjusted price-to-earnings ratio, or CAPE ratio, of US equities, based on 10-year averaging of inflation-adjusted earnings, rose from 18.5 at year-end 1899 to 44.2 at year-end 1999, contributing to roughly 1% annual repricing gains. Moreover, both average growth and average inflation likely surprised on the upside (see Exhibit 17.3).

very difficult. Beyond maturity and coupon, there are such complications as sinking funds and embedded options (mostly for the issuer's benefit), tax features, and even lotteries. Furthermore, bond ratings for either government or corporate bonds were not introduced until the 1900s, making credit risk virtually impossible to estimate before then.

Notwithstanding such challenges, Schmelzing (2020)—through his own efforts as well as those of others—assembled a global history of yields on loans or bonds since the early 1300s. We focus on GDP-weighted average yields across eight countries once each became available: Italy (1310), Great Britain (1310), Germany (1326), France (1387), Spain (1400), the Netherlands (1400), the United States (1786), and Japan (1870). Of the six European states, only France existed as a nation when the time series began, so the loans in the early sample were to local rulers, princes, or cities. As capital markets evolved, loans were replaced by tradable bonds, and for the past century, the dataset covers 10-year government bonds. Earlier, maturity and credit quality varied over time and across countries.

Exhibit 17.3 tracks the evolution of nominal and real (inflation-adjusted) bond yields, inflation, and real GDP growth. (The real GDP growth series is from the Maddison Project Database 2020 [Bolt and van Zanden 2020], discussed later.) The exhibit shows that nominal and real yields were in double digits in the Middle Ages but fell to approximately 5% near the First Industrial Revolution and, with episodic exceptions, ever lower thereafter.[8] Global inflation was mildly positive but near zero in most centuries before the 1900s. Century average inflation near zero did not mean stable inflation near zero, because there were oscillating waves of inflation and deflation, some of which were very large.

Exhibit 17.3. Nominal and Real Bond Yields, Inflation Rates, and Growth Rates, 1314–2018 (%)

Rate	1314–1399	1400–1499	1500–1599	1600–1699	1700–1799	1800–1899	1900–1999	2000–2018
Nominal rate	11.5	12.2	9.2	7.4	5.1	5.4	5.4	3.0
Real rate	10.4	11.5	7.1	6.8	4.2	4.9	1.0	1.3
Inflation rate	1.2	0.8	2.1	0.6	0.9	0.5	4.4	1.7
Real GDP growth per capita	0.4	0.1	0.2	0.2	0.2	0.9	2.2	1.1

Sources: Schmelzing (2020) and Bolt and van Zanden (2020). Not to be reproduced without express written permission from the authors.

Notes: All series are GDP-weighted averages across countries and arithmetic means across years of annualized rates from (up to) eight countries since data became available, in most cases before the birth of each nation. Nominal rate refers to loans or bonds, and real rate is the difference between the nominal rate and the seven-year centered average inflation rate. The last series, real GDP growth per capita, is from the Maddison Project Database 2020 (Bolt and van Zanden 2020) and where possible reflects the same GDP weights as the Schmelzing (2020) series.

[8] Looking back even farther, Homer and Sylla (2005) documented yields near 20% in Mesopotamia four or five millennia ago. A local trough occurred amid Pax Romana near AD 1, with perhaps 4% yields, before double-digit yields again became commonplace.

Schmelzing's (2020) data in Exhibit 17.3 reveal that despite fluctuating inflation rates, over century-long intervals there was little difference between nominal and real yields, both of which fell to the 3%–4% range by around 1900. The twentieth century saw more persistent price rises, however—in particular, the Great Inflation of the 1970s, which pushed nominal rates up to double digits, a level last seen in the 1500s except in wartime. The post-1982 Great Moderation witnessed global convergence in inflation rates toward 2%—back to the low long-term levels that characterized the pre-1900 economy.[9]

Even after inflation expectations stabilized at low levels in the 2000s, real yields and policy rates kept falling to negative territory. Eventually, even nominal yields in many European countries and Japan turned negative or reached record low levels in places where they remained positive (the United States and the United Kingdom). The global rise in inflation in 2021–2022 finally turned bond yields higher after a 40-year downtrend. The yield evidence in Exhibit 17.3 stretching back over centuries provides confirmation that the recent low (even negative) bond yields were truly exceptional.

Alongside real bond yield data, we have very long-run estimates of growth in *per capita* income across countries, assembled by the Groningen Growth and Development Centre (see Bolt and van Zanden 2020). Certain classic economic theories suggest that equilibrium real yields and real growth should be similar. However, very long-run empirical evidence suggests the opposite. Real economic growth was 0.1%–0.4% per year before the First Industrial Revolution, whereas the past two centuries have seen approximately 1%–2% real annual growth in advanced economies (last row of Exhibit 17.3). Thus, the recent two centuries of relatively fast economic growth and higher inflation coincided with low real yields, whereas the earlier centuries of slow growth and low inflation witnessed much higher required yields—contrary to the prediction cited previously.

Do Long Histories Give Us Clear Evidence on Excess Returns to Credit Risk?

We turn next to corporate credits. The credit premium is defined as the (expected or realized) excess return of corporate bonds over comparable government bonds. We discuss evidence on both realized excess returns and forward-looking credit spreads, and because the latter need to be adjusted for defaults, we also comment on the realized default experience. For much of the long histories we study, there are no available credit ratings, so we cannot split the results by rating class or between investment-grade and speculative-grade bonds. These and other related data issues make it nearly impossible to measure the credit premium in early corporate bond markets.

The financing needs of the railroads stimulated the growth of large corporate bond markets from the mid-nineteenth century onward in the United States and the United Kingdom. Consequently, there are a few studies that add to our knowledge in this area. Giesecke, Longstaff, Schaefer, and Strebulaev (2011) estimated annual value-weighted percentage default

[9]Real yield estimation requires estimates of inflation expectations, which are often based on rolling historical average inflation. The estimation challenge is made harder by structural changes in inflation and real rate processes. Farmer, Nakamura, and Steinsson (2024) stressed how pernicious gradual structural changes are because we learn about them very slowly.

rates for US non-financial corporate bonds over 1866–2008. The authors reported the annual time series of default rates and observed a decline over time, with rates averaging 4%, 1.4%, and 0.3% for 1866–1899, 1900–1945, and 1946–2008, respectively.[10]

To estimate the credit spread, Giesecke et al. (2011) used Homer and Sylla's (2005) yield data on high-grade railroad bonds and high-grade New England municipal bonds for 1866–1914 and for prime corporate bonds and long-term government bonds after 1914. These category definitions can only crudely take account of credit differences across firms. We also again note the problems of proxying US government bond yields before 1914.

Using these data, Giesecke et al. (2011) reported an average credit spread of 1.5% for the entire sample period of 1866–2008 (without disclosing the annual time series). The average default rate is also 1.5%. Given their broad-brush assumption of a 50% average recovery rate of losses upon default, the authors estimated the average credit risk premium to be approximately 0.75%.[11] This figure compares with an average credit premium of 1% for investment-grade corporate bonds from 1973 to 2020 (Ilmanen 2022).

Coyle and Turner (2013), studying the period 1861–2002, reported annualized real returns on UK corporate bonds of 2.4% and a credit spread of approximately 1% versus government bonds. The spread was higher, at 1.7%, for 1861–1913 than afterward. Because *ex post* default losses were negligible, the credit premium is of a similar magnitude. As with the United States, however, no information is available on corporate credit quality in the nineteenth and early twentieth centuries. Given that the sample comprised all corporate bonds traded on the London stock market, where listing requirements were relatively strict, we might infer that the credit quality of this bond sample was generally high.

A further data point on corporate bonds was provided in the recent study by Van Mencxel et al. (2024) of Belgium from 1838 to 1939. As mentioned previously, the Brussels stock market was relatively large in the 1800s, and there is an abundance of data. This study reports a small, positive corporate credit spread over government bonds of approximately 0.4%. There is no discussion of default losses and recovery rates to enable us to estimate the credit premium.

Overall, we can only measure corporate credit spreads and credit premiums quite crudely. In the absence of bond rating data for corporate bonds before the 1920s, it seems difficult for scholars to be able to provide more precise estimates of the corporate credit premium than the few we have. The existing sparse evidence suggests that there was a modest credit premium in the nineteenth and twentieth centuries. Given that Kizer, Grover, and Hendershot (2019) and McQuarrie (2020) found problems even with the US corporate bond return data in the early decades after 1926, it is likely to remain the case that the most reliable evidence on the credit premium begins only in 1973.

Finally, we have an estimate of the sovereign credit premium. Meyer, Reinhart, and Trebesch (2022) estimated a credit spread before default losses of 4.3% on foreign-currency government bonds over UK and US government bonds between 1815 and 2016. This spread was

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[10]Van Mencxel (2023) estimated default rates for Belgian corporate bonds in the late nineteenth and early twentieth centuries.

[11]Giesecke et al. (2011, p. 243) cited research by Hickman (1960) that implies an average recovery rate of 62.5% of par value for 1900–1944.

approximately 1 percentage point lower for the first 100 years, 1815–1914. In credit events (sovereign debt restructurings), the typical realized haircut was less than half, implying an average annual default loss near 1%. The resulting average *ex post* sovereign credit premium of approximately 3% is considerably higher than that for corporate bonds.

Conclusion

The various approaches to research on long-run asset returns summarized in this chapter deserve both credit and encouragement. We especially salute Alfred Cowles, Lawrence Fisher, James Lorie, and Roger Ibbotson, who inspired many subsequent empirical researchers to create and analyze new series of raw historical data. Partly thanks to technological advances that made historical data extraction easier, we are experiencing a golden age in the research of financial history.

A growing cohort of applied researchers are addressing interesting questions using very long data histories from a variety of sources. Anarkulova, Cederburg, and O'Doherty (2022) deployed data from Finaeon to show that the frequency of negative long-horizon returns over almost 200 years is an order of magnitude higher when studying a global equity dataset than when looking at US-only equity returns. Arnott and Bernstein (2002) used data from Ibbotson Associates to study the components and determinants of the US equity premium. Some researchers combine both aspects—compiling new data and undertaking novel empirical tests. Baltussen, van Vliet, and van Vliet (2023) extended the CRSP dataset of US stocks back to 1866–1926 to study the robustness of cross-sectional return predictability (factor premiums), and Baltussen, Swinkels, van Vliet, and van Vliet (2023) analyzed asset class performance in different inflation environments.

It is increasingly important to evaluate best practices for research on long-term financial history. We emphasize the importance of good documentation of data sources, discussion of choices and assumptions, and a sharp focus on possible biases. The most obvious empirical research on US and UK equity and bond markets before 1900 has already been done, but it is desirable to refine these return series by improved estimates of delisting bias, default rates, broad payout measures, and so forth.

Another natural path is to extend empirical research beyond these core stock and bond markets to other countries and other asset classes. Any global comparisons will require data on foreign exchange rates (if unhedged), relevant short rates (if hedged), or purchasing power parity estimates. Some equity analyses could be extended before 1800 following the pioneering steps of Le Bris, Goetzmann, and Pouget (2019) and Golez and Koudijs (2018), among others. Relatedly, we reviewed the long-term returns from commodities and real estate in Chambers et al. (2024), and the long-term returns from aesthetic assets were examined in Dimson, Pukthuanthong, and Vorsatz (2026).

We chose to focus our empirical survey on the average returns of major asset classes. Further analysis of forward-looking expected returns (time-series predictability), as well as volatility and other higher moments, can supplement the analysis of historical average returns. Most importantly, relating asset returns to macro developments and various risk factors is essential for asset-pricing models. Longer and better-quality data histories of all these series will allow both larger samples and improved evaluation of long-horizon relationships.

Finally, very long historical datasets face methodological challenges. Their potential usefulness for long-horizon predictability studies is balanced by the statistical problems highlighted by Boudoukh, Israel, and Richardson (2019, 2022). Similar econometric research may help deal effectively with structural changes, missing data and gradually improving asset breadth and data quality.

Key Takeaways

- Long-term index histories can provide valuable evidence on investment returns, but the quality of old financial data is limited. We highlighted four pervasive challenges: easy-data bias, macro-consistency, replicability, and total return estimation. Researchers should consider potential data biases and how they can be mitigated.
- Easy-data bias arises when researchers study intervals that are not representative of the long term. Macro-consistency is an issue when indices fail to measure the aggregate returns of investors as a whole. Replicability is important because investors should be able to reproduce index returns by buying index constituents. Index returns should incorporate both income and capital appreciation.
- We used the best available series for both the United States and the United Kingdom to study several important topics. In the nineteenth and twenty-first centuries, stock and bond returns were lower than in the widely cited twentieth century. The equity–bond risk premium was exceptionally high in the twentieth century. The current century may not provide as large a reward for risk as the last century did.

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SECTION 4

The Future

CHAPTER 18. POPULARITY AND PREMIUMS

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Introduction

The analysis of equity returns has, in large part, concentrated on identifying common factors in individual security returns. Factors already discussed in Chapters 2, 4, and elsewhere include small size, value, and illiquidity, as well as the "market factor," or beta factor, which all stocks have in common to a greater or lesser degree.

This chapter looks at the root cause of factors, identified and not yet identified, through the lens of a formal demand-side asset pricing theory that we call the popularity asset pricing model (PAPM). It addresses some of the weaknesses of the capital asset pricing model (CAPM) and considers all the asset characteristics that might make an investor like or dislike a security, affecting its price and thus its expected return. Summed up in one sentence, the PAPM says that assets with popular characteristics have lower expected returns because their popularity has caused them to have higher prices.

Popularity is not a "factor" in and of itself; rather, it is what drives demand—the collective, aggregated, wealth-weighted preferences of investors. It is the attribute that links together all possible factors—those that a given investor prefers or likes and those to which the investor is averse or that the investor dislikes. Aggregating across investors, the PAPM reflects the demand for a security and thus falls into the category of demand-side models of expected return, as described later.

The PAPM itself says nothing *a priori* about whether investors *should* like or dislike a characteristic; it only asks whether they *do* like or dislike it. Other information, however, can be used to determine whether a characteristic is likely to be regarded by investors as "good" or 'bad."

Some asset characteristics are almost universally liked or disliked. For instance, investors like expected returns and dislike risk; expected returns are popular, and risk is not. These two deep-seated investor *preferences*—desiring expected return and disliking risk—are the fundamental drivers of the risk–expected return paradigm. The tension between them explains much about the risk premiums discussed in this book.

But there is more to the story. Investor preferences—their likes and dislikes—go beyond risk and expected return, are nuanced, and evolve over time. It is the collective actions of investors acting on their return expectations and preferences that determine asset prices and create *priced* factors with expected return premiums, as well as other factors that help explain realized stock returns but that do not offer expected return premiums.

Chapter 2 highlights the various *realized* "risk" premiums measured in 1976 by Roger Ibbotson and Rex Sinquefield and in later work by Ibbotson with various coauthors—an equity premium, a small-cap premium, a value premium, a liquidity premium, a horizon premium, and a default premium. The assumption that the premiums persist was the basis for forecasting the future via simulations. But why should such premiums persist?

Research by Roger Ibbotson, Thomas Idzorek, Paul Kaplan, and James Xiong provides an answer: the theory of popularity and, as we noted at the outset, its formal model, the popularity asset pricing model.

In this chapter, we review the theory of popularity and the creation of the PAPM. Looking backward, we examine various realized premiums and discounts through the popularity lens. Looking forward, we apply the theory of popularity and provide our forecasts or express confidence about which premiums are likely to persist into the future.

The Theory of Popularity

The theory of popularity provides a plausible explanation for most realized historical premiums and, as such, is a powerful framework for thinking about which premiums can be expected to persist over the long term. A wide variety of risk-related and non-risk-related "characteristics" is associated with securities, investments, or companies that investors *like* or *dislike*, all of which can influence investor portfolio formation and thus asset prices.

If enough investors *like* a particular characteristic, investments with that characteristic will tend to be in *high* demand or *popular*, which makes them relatively *expensive*, providing new purchasers at that *high* price with *lower* expected returns. Conversely, if enough investors *dislike* a particular characteristic, investments with that characteristic will tend to be in *low* demand or *unpopular*, which makes them relatively *inexpensive*, providing new purchasers at that *low* price with *higher* expected returns. Of course, any given investment is a bundle of a wide variety of characteristics—some that investors like and others that they dislike.

In the 1980s, in a Graham and Dodd Scroll Award–winning article in the *Financial Analysts Journal*, "The Demand for Capital Market Returns: A New Equilibrium Theory," the seeds of what would become the theory of popularity and the PAPM were first sown by Roger Ibbotson, Jeffrey Diermeier, and Laurence Siegel (1984). They argued that investors care about characteristics beyond risk, which include liquidity and taxation.

In the 2010s, Idzorek, Xiong, and Ibbotson (2012) and, in another Graham and Dodd Scroll Award–winning article, Ibbotson, Chen, Kim, and Hu (2013) documented liquidity as a key characteristic that investors like. Looking at either funds or individual securities, portfolios with lower liquidity outperformed portfolios with higher liquidity. High liquidity is unambiguously popular, leading to a liquidity discount or illiquidity premium. The CAPM, the dominant asset pricing model, is silent on liquidity.

Seeking a better asset pricing theory, Ibbotson and Idzorek (2014) and Idzorek and Ibbotson (2017) built on and provided additional rationales for the New Equilibrium Theory, presenting the theory of popularity as a broad, unifying investor-preference-driven explanation for observed anomalies and premiums. In a CFA Institute Research Foundation book, *Popularity: A Bridge Between Classical and Behavioral Finance*, Ibbotson, Idzorek, Kaplan, and Xiong (2018) built on the previous work, put forth new empirical evidence supporting popularity, and, thanks largely to Paul Kaplan, put forth a formal equilibrium model: the PAPM.

Most recently, in a Harry M. Markowitz Award–winning article in the *Journal of Investment Management*, Idzorek, Kaplan, and Ibbotson (2025) expanded the PAPM to allow investors to *disagree* on the future payoffs of assets. In doing so, the PAPM addresses what Fama and French (2007) identified as the two most significant weaknesses of the CAPM. In their article "Disagreement, Tastes, and Asset Prices," Fama and French identified as the two key weaknesses of the CAPM (1) the assumption that all investors "agree" on the distributions of future payoffs of all assets (i.e., no disagreement) and (2) the assumption that the only investor "taste" (what we call preference) is risk tolerance.

The PAPM addresses both weaknesses, simultaneously allowing for disagreement and any number of investor tastes or preferences. In contrast with the CAPM, in which each investor solves the Markowitz mean–variance problem (although that is actually unnecessary given that all investors "agree" on the capital market assumptions), in the PAPM, each investor solves an expanded Markowitz mean–variance problem that includes an additional term capturing their nonpecuniary preferences.

In both equilibrium models—the CAPM and the PAPM—it is the collective, aggregated, wealth-weighted actions of investors that lead to equilibrium prices. With the CAPM, all investors agree on expected returns and covariances, and the only preference is risk tolerance. With the PAPM, each investor creates a *personalized* portfolio based on the agreed-on covariance matrix of returns, their personal expected returns, and any number of additional preferences for characteristics.[1] The CAPM is actually a special and highly unrealistic case of the PAPM, in which investors all agree on expected returns and the only preference is risk tolerance.

Given that markets are relatively informationally efficient, disagreements that lead to outperformance and underperformance are generally short lived and do not result in expected premiums. In contrast, a number of investor preferences are relatively permanent (e.g., disliking risk, preferring more liquidity, and disliking taxes) and thus, from our perspective, are likely to result in expected long-term premiums.

Of course, changes in investor preferences can occur that lead to short-term movement around long-term mean expectations. One example is the desire for liquidity during a market crisis: As a crisis begins, investors pay up for liquidity, and as the crisis ends, the gains of the run-up are ceded. Another example of changes in investor preferences might be the recent period when environmental, social, and governance (ESG) investing increased in relative popularity with regulatory tailwinds and then became less popular as it became highly politicized and regulatory tailwinds turned into headwinds. Looking forward, regulatory changes can cause large-scale shifts in investor demand. For example, allowing retail investors to purchase private equity and credit funds could shift the demand (popularity) for private funds.

[1] For more information on personalized portfolio construction based on the PAPM, see Idzorek and Kaplan (2022, 2024) and Idzorek (2023).

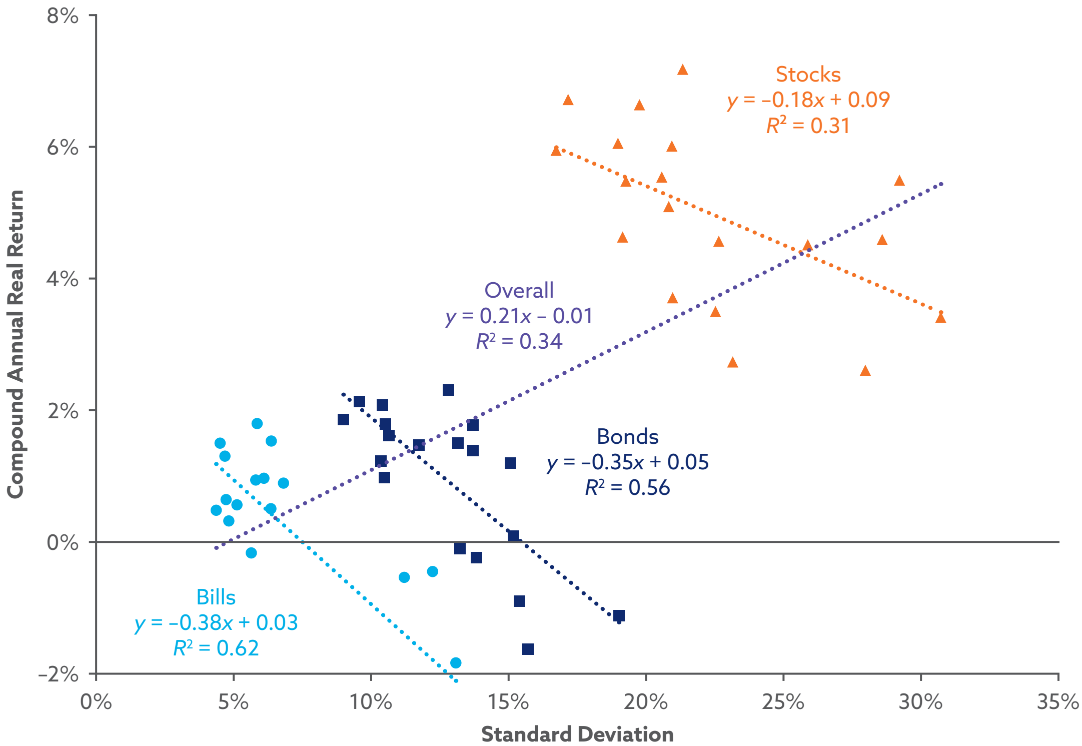
Our primary interest is to understand how popularity provides an explanation for various realized premiums. We then use the theory of popularity to look ahead and identify which premiums are most likely to persist into the future.

Realized Premiums from a Popularity Perspective

Investors dislike risk. This is arguably the most powerful investor preference and, in our opinion, the most plausible explanation for why the risk–return paradigm tends to hold *across* asset classes with different inherent levels of risk. This phenomenon was abundantly clear from the 100-year wealth charts in Chapter 2, in which US bonds beat US bills, US large-cap stocks beat US bonds, and US small-cap stocks beat US large-cap stocks. *Within* an asset class in which investments tend to have similar levels of risk, additional investor preferences help explain realized premiums.

This principle is perhaps best illustrated by leveraging the 126-year history documented by Elroy Dimson, Paul Marsh, and Mike Staunton (2002) in *Triumph of the Optimists*, updated through 2025 in UBS's *Global Investment Returns Yearbook 2026* (Dimson, Marsh, and Staunton 2026) and summarized in Chapter 11 of this book. In **Exhibit 18.1**, we plot the realized compound

Exhibit 18.1. Risk and Realized Real Return of Stocks, Bonds, and Bills for 19 Countries, 1900–2025



Sources: Updated analysis from Ibbotson et al. (2018). Author calculations based on data from Dimson et al. (2026).

Notes: The 19 countries are Australia, Belgium, Canada, Denmark, Germany, Ireland, Japan, the Netherlands, Finland, France, Italy, Norway, New Zealand, South Africa, Spain, Sweden, Switzerland, the United Kingdom, and the United States. There were no returns on bonds or bills for Germany for 1922 and 1923, so those years for Germany are omitted.

annual real returns (in local currencies) and standard deviations associated with stocks, bonds, and bills for 19 countries.[2] Based on all 57 plot points, the best-fit regression line has a positive slope of 0.21 and an R^2 of 0.34. In other words, there is a moderately positive relationship between risk and realized return across the 57 asset classes, but it is far from a perfect fit.

Notice that we color-coded the plot points for stocks (orange triangles), bonds (dark blue squares), and bills (light blue dots), leading to three distinct asset class color clusters. We then calculated three more best-fit regression lines for the three asset classes, each of which shows a negative risk–return relationship!

So, although risk is the dominant characteristic that investors dislike *across* asset classes, *within* asset classes that tend to have similar risk characteristics it is the nuanced collective preferences of investors that lead to anomalies relative to what standard asset pricing models would have predicted (see Idzorek et al. 2025).

Turning to some of the most well-known anomalies and *historical* premiums and discounts, in **Exhibit 18.2** we list various realized premiums and discounts and their popularity-based explanations.

Exhibit 18.2. Popularity-Based Explanations for Realized Premiums and Discounts

Premium or Discount	Popularity-Based Explanation
Equity premium	Investors dislike: risk (prefer safety)
Illiquidity premium	Investors dislike: illiquidity
Small-cap premium	Investors dislike: risk (prefer safety), illiquidity, information costs
Value premium	Investors dislike: boring, nonglamorous; like the opposite
Low-beta premium	Active fund managers prefer high beta to outperform benchmarks
Severe downside risk premium	Investors dislike: severe risk (prefer safety)
ESG/green discount	Investors like: ESG and green
Good reputation discount	Investors like: good reputations
Credit/default premium	Investors dislike: risk (prefer safety)
Horizon/duration premium	Investors dislike: interest rate risk, reinvestment risk, duration mismatches

[2] The data are for 20 countries, but we omitted Austria because of the extreme volatility of its bond index. Also, there are no returns on bonds and bills for Germany for 1922 and 1923, so for German bonds and bills, we used the remaining 124 years. For all stock indices and for all other bond and bill indices, we used the full 126-year history.

One anomaly omitted from Exhibit 18.2 is momentum. From a popularity perspective, momentum might be explained as a series of short-term changes in relative popularity, in which some event triggers a momentum-building cycle for a particular investment. During the first part of the cycle, investor attention, trading, and liquidity—characteristics that investors tend to like—all increase. At some point, the price rises to a point at which sellers outnumber buyers, and then the price falls. Thus, momentum cannot be a permanently priced factor, but it can have a powerful effect on returns while it is taking place. Momentum is an example of mispricing.

In the next section, we elaborate on the popularity-based explanations of the premiums and discounts, with an eye toward the future.

Forecasting Long-Term Expected Premiums

Researchers have identified hundreds of possible factors—the so-called "factor zoo."[3] In "Domesticating the Factor Zoo with Economic Theory," from the 50th anniversary issue of the *Journal of Portfolio Management*, Idzorek, Kaplan, and Ibbotson (2024) used the PAPM to analyze and identify long-term *priced* factors.

Empirical attempts to tame the factor zoo are helpful, especially from a backward-looking perspective, but a forward-looking perspective should be based on theory. When attempting to domesticate the factor zoo with theory, it is important to distinguish between *priced* factors that lead to expected premiums/discounts and *attribution* (explanatory) factors that do not.

The ever-growing factor zoo includes hundreds of possible attribution factors that at some point helped explain realized return variation among stocks. Attribution factors are numerous, do not emanate from an asset pricing model, and have a zero expected long-term mean; thus, they *should not* influence long-term investment policy.

In contrast, priced factors are quite rare, should emanate from an asset pricing model, and have a nonzero expected long-term mean; thus, they *should* influence long-term investment policy. Through a forward-looking popularity lens, we make conjectures on the premiums and discounts, including whether they will persist into the future.

- *Equity risk premium—high confidence:* Investors uniformly dislike risk, and based on their risk tolerance, a large subset of investors therefore choose to diversify away from equities, avoid equities altogether, or move in and out based on their view of the equity risk premium. To be incentivized to hold equities, based on their respective risk preferences, investors require the expectation of a return premium as compensation for taking on additional risk. We note that even though we have high confidence in the equity risk premium, there is no guarantee that equities will outperform bills or bonds. It is unlikely but possible that equities could underperform for multiple decades. Similar disclaimers apply to all the *expected* premiums because no premium is guaranteed.
- *Illiquidity premium—high confidence:* Investors uniformly dislike illiquidity and like liquidity. A large number of investors will thus continue to avoid less liquid investments, preferring to own more liquid ones. Both of these preferences and corresponding behaviors should continue to create an illiquidity premium.

[3] John Cochrane (2011) used the term "factor zoo" during a 2011 presidential address to the American Finance Association.

- *Small-cap premium—moderate confidence:* To the degree that small-cap stocks are more risky than large-cap stocks, investors require the expectation of a premium. Small caps are less liquid and less well known, with less information than large-cap stocks, which are characteristics that investors dislike and contribute to a "bundled" small-cap premium.

  At least three practices counteract a small-cap premium. First, the widespread belief in a small-cap premium leads to a group of "small-cap premium harvesters," whose collective action bids up the prices of these stocks and thus mutes the premium. Second, private companies that choose to stay private decrease the supply of public small-cap companies, which (all else equal) makes small-cap companies relatively expensive. Third, many quant managers overinvest in small-cap stocks because they often equally weight their portfolios.
- *Value premium—low confidence:* Between the discovery of the value premium by Basu (1977) and the subsequent publication of Fama and French (1992, 1993), which made the existence of the premium in historical data more widely known, the value premium largely disappeared. We attribute the value premium to both disagreement and tastes/preferences, with a group of investors systematically overestimating the growth and profitability expectations for glamorous growth stocks and another large group of investors simply preferring glamorous, high-growth investments. The discovery of the value premium gave rise to "value premium harvesters," whose collective actions dampen the magnitude of this premium. We believe investors will continue to overestimate the future growth and profitability of growth stocks, with a partially overlapping group of investors continuing to prefer growth stocks for other reasons. As has been the case since the early 1990s, value premium harvesters will mute the value premium moving forward.
- *Severe downside premium—high confidence:* Investors uniformly dislike risk and especially dislike severe downside risk. A large number of investors will thus continue to avoid investments perceived to have severe downside risk. This avoidance should continue to create a severe downside risk premium.
- *Low-beta premium—low confidence:* From a popularity-based perspective, the low-beta anomaly, in which low-beta stocks tend to outperform high-beta stocks on a risk-adjusted basis, results from active managers seeking to outperform their benchmarks without using leverage. Such managers overweight high-beta stocks as an imperfect substitute for holding a leveraged portfolio. Xiong, Idzorek, and Ibbotson (2023) documented the dramatic and steady decrease in active mutual funds as a percentage of the market. We expect this trend to continue, suggesting that the low-beta anomaly should decrease and might disappear. Leverage aversion will continue to contribute to a small premium.
- *ESG/green discount—moderate confidence:* ESG/green investing and sustainability have unfortunately been politicized. All else equal, a large group of investors prefer investments that appear to be ESG-friendly or "greener." New investors will thus pay a premium price—that is, they will receive lower expected returns. Conversely, investors willing to purchase investments with bad ESG characteristics should realize a premium.
- *Brand/reputation discount—moderate confidence:* Similar to the ESG/green discount, all else equal, a large group of investors prefers investments with strong brands and/or reputations. Investors will therefore pay a premium price for such stocks and will thus receive lower expected return. We call this effect on return the brand/reputation discount. Conversely, those willing to purchase investments with poor brands and reputations should realize a premium.

- *Credit/default premium—high confidence:* Analogous to the equity premium, investors uniformly dislike risk, causing a large subset of investors to diversify away from credit risk. To be motivated to hold bonds with higher levels of credit risk, investors require a yield in excess of their expected default losses to compensate them for taking on default risk.
- *Horizon/duration premium—mixed confidence, depending on horizon:* We are confident that bonds will continue to provide a horizon/duration premium over bills. Within the bond market, however—because of large demand from institutional investors seeking to match the duration of their liabilities, which are often long term—we have less confidence that long-duration bonds will provide a significant premium over intermediate-duration bonds.

Key Takeaways

- The PAPM is a demand-side model in which the aggregated, wealth-weighted, personalized portfolio construction decisions of investors, based on their expected returns and any number of risk- and non-risk-related preferences, collectively lead to equilibrium asset prices.
- The theory of popularity helps us understand the realized premiums of the past, differentiate between *attribution* factors and *priced* factors, and predict which priced factors are likely to persist.
- Disliked characteristics, such as high risk, low liquidity, long duration, low growth, boring businesses, and polluters, are unpopular, causing stocks with these characteristics to have relatively low current prices and relatively higher expected returns.
- Conversely, liked characteristics, such as low risk, high liquidity, short duration, high growth, glamorous businesses, and a green environmental profile, are popular, causing stocks with these characteristics to have relatively high current prices and relatively lower expected returns.

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CHAPTER 19. PARAMETRIC FORECASTING

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In 1976, Ibbotson and Sinquefield published a pair of articles in the *Journal of Business* that would have great impact on our understanding of capital markets. In the first (Ibbotson and Sinquefield 1976a), they documented monthly returns on stocks, bonds, and bills, as well as monthly inflation rates, over the period 1926–1974. In the second (Ibbotson and Sinquefield 1976b), they applied a bootstrap method to the historical data to make probabilistic forecasts about cumulative wealth over several decades into the future. In Chapter 20, Roger G. Ibbotson, William N. Goetzmann, and Otto S. Manninen apply this bootstrap method using 100 years of data.

Lewis, Kassouf, Brehm, and Johnston (1980) demonstrated how the results of Ibbotson and Sinquefield (1976b) can largely be replicated using a parametric model based on the lognormal distribution. Their lognormal forecasting model has only two inputs: the mean and standard deviation of return. These are the first two moments of any distribution. Using only mean and standard deviation raises the question, Would it make a difference if higher moments—namely, the third (skewness) and the fourth (excess kurtosis)—are taken into account? The answer to this question depends on how far off the higher moments are from those of a lognormal distribution at long horizons. For well-diversified portfolios, the lognormal model works quite well and is the model of choice. As I demonstrate in this chapter, however, there are cases in which the lognormal model largely understates long-term left-tail risk. In such cases, we need another forecasting model.

In this chapter, I present the lognormal forecasting model and illustrate it using large-cap stocks. I then introduce a new forecasting model that takes into account all four moments and compares the results of the two models using large-cap, midcap, and small-cap stocks. Because this model is based on Johnson (1949) distributions, I call it the Johnson forecasting model.[1] I will show that although the lognormal and Johnson models are nearly indistinguishable for large-cap, midcap, and small-cap stocks, they clearly differ for low percentiles at long horizons. For small-cap stocks, these differences are especially large. In this way, the Johnson model captures the long-term left-tail risk of midcap and small-cap stocks not captured by the lognormal model.

Another kind of parametric forecasting is the formation of capital market assumptions for mean–variance optimization. Assuming an annual rebalancing period, these consist of the expected annual return on each asset class, the annualized standard deviation of return for each asset class, and the correlation of annualized returns between each pair of asset classes. Although the standard deviations and correlations are usually estimated using historical return data, it is important that the expected returns be calibrated to an internally consistent model. I will show how do this at the end of this chapter.

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[1] Johnson distributions are different from stable Paretian distributions. The moments of a Johnson distribution are finite, whereas the second and higher moments of a stable Paretian distribution are infinite. See Kaplan (2012a, 2012b) to see how stable Paretian distributions can be used to model asset class returns.

In this chapter, I will cover the following topics:

- Estimating the first four monthly moments
- Probabilistic wealth forecasting
- The lognormal forecasting model
- The first four moments of wealth distributions
- The Johnson forecasting model
- Annualizing the first four moments, covariances, *and* correlations
- Calibrating expected returns for mean–variance optimization

Estimating the First Four Monthly Moments

I refer to mean, standard deviation, skewness, and excess kurtosis collectively as the first four moments. **Exhibit 19.1** presents the mathematical definitions of the first four moments and the

Exhibit 19.1. Formulas for Estimating the First Four Moments of Monthly Returns

Moment	Definition	Estimator
Mean (ER stands for expected return)	$ER_1 = \mathrm{E}[\tilde{R}_1]$	$\widehat{ER}_1 = \frac{1}{N}\sum_{i=1}^{N} R_{1i}$
Standard deviation (SD)	$SD_1 = \sqrt{\mathrm{E}[(\tilde{R}_1 - ER_1)^2]}$	$\widehat{SD}_1 = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(R_{1i} - \widehat{ER}_1)^2}$
Skewness	$s_1 = \frac{\mathrm{E}[(\tilde{R}_1 - ER_1)^3]}{SD_1^3}$	$\hat{s}_1 = \frac{N}{(N-1)(N-2)}\sum_{i=1}^{N}\left(\frac{R_{1i} - \widehat{ER}_1}{\widehat{SD}_1}\right)^3$
Excess kurtosis	$\kappa_1 = \frac{\mathrm{E}[(\tilde{R}_1 - ER_1)^4]}{SD_1^4} - 3$	$\hat{\kappa}_1 = \frac{N(N+1)}{(N-1)(N-2)(N-3)}\sum_{i=1}^{N}\left(\frac{R_{1i} - \widehat{ER}_1}{\widehat{SD}_1}\right)^4 - \frac{3(N-1)^2}{(N-2)(N-3)}$

$\tilde{R}_1$ = a random monthly return

R_{1i} = historical return in month i

N = number of months in sample

Note: Throughout this chapter, numerical subscripts indicate the number of months in the period of a variable or a parameter. In this exhibit, since all the parameters and variables are monthly, the subscript for the number of months in the period is 1.

formulas for estimating them from historical monthly returns.[2,3] **Exhibit 19.2** presents the estimated values of the first four moments of nine asset class indices presented in this book, using all 1,200 months of real (inflation-adjusted) return data on those indices.

An important caveat in using the formulas in Exhibit 19.1 is that they assume that over the entire 1,200-month sample period, the real returns on each asset class are serially independent and drawn from the same distribution. This assumption could be violated in at least three ways:

- The returns could be serially correlated. The last column of Exhibit 19.2 shows the monthly serial correlation coefficient for each of the nine asset class indices. From these results, we see that serial correlation is a major concern only for the cash indices.
- Conditional variance could be dynamic (that is, the variance itself varies over time), as in the GARCH model of Bollerslev (1986).
- The unconditional distribution changes over time. In other words, the monthly distribution is nonstationary.

Exhibit 19.2. Estimates of the First Four Moments of Monthly Real Asset Class Indices, January 1926–December 2025

Asset Class	Mean	Standard Deviation	Skewness	Excess Kurtosis	Serial Correlation
Large-cap stocks	0.69%	5.10%	0.17	6.94	0.08
Midcap stocks	0.83%	6.35%	0.86	12.01	0.13
Small-cap stocks	0.89%	7.41%	1.36	14.77	0.16
US 20-year Treasury bonds	0.19%	2.73%	0.40	3.31	0.11
US 10-year Treasury bonds	0.18%	2.03%	0.37	3.26	0.13
US 5-year Treasury bonds	0.16%	1.43%	0.20	4.06	0.20
US 1-year Treasury bills	0.09%	0.66%	−0.35	7.56	0.43
US 6-month Treasury bills	0.07%	0.57%	−0.93	9.81	0.46
US 30-day Treasury bills	0.03%	0.53%	−1.35	13.54	0.50

Source: Calculations by the author using Ibbotson Indices data.

[2] Ideally, the estimator for mean return should be based on current market conditions, not solely on historical returns. Ibbotson, Goetzmann, and Manninen do this in Chapter 20. In this chapter, to illustrate parametric forecasting, I use historical averages.

[3] Throughout this chapter, I follow the standard practice in probability theory and statistics of using a tilde (~) as part of the name of a random variable and using a circumflex (^) as part of the name of an estimator.

It is possible that one or more of these problems applies to the return histories that form the inputs to the forecasting models presented in this chapter. In particular, dynamic conditional variance and nonstationarity could be the source of high levels of measured excess kurtosis. Using inflation-adjusted returns should somewhat mitigate these issues.

Because the bootstrap model presented in Chapter 20 has results similar to those of the parametric models presented here, however, these issues may not be a major concern. So, for the purposes of the forecasting models, I assume that the monthly returns of each asset class are serially independent and identically distributed and have the first four moments shown in Exhibit 19.2.

Probabilistic Wealth Forecasting

Suppose that at time 0, an investor has W_0 in wealth. Each month, she holds the same portfolio, which she rebalances and holds without additions or withdrawals. After T months, her wealth will be

$$\tilde{W}_T = W_0 \prod_{t=1}^{T} (1+\tilde{R}_{1t}), \tag{19.1}$$

where $\tilde{R}_{1t}$ is the return in month t.

A probabilistic wealth forecast is a percentile of the distribution of $\tilde{W}_T$.[4] Let p be a probability—so, a number between 0% and 100%. $W_T(p)$ is said to be the 100pth percentile of $\tilde{W}_T$ if[5]

$$\Pr[\tilde{W}_T \leq W_T(p)] = p. \tag{19.2}$$

Compound annual return (CAR) for T months is

$$\widetilde{CAR}_T = \left(\frac{\tilde{W}_T}{W_0}\right)^{\frac{12}{T}} - 1. \tag{19.3}$$

Therefore, percentiles of CAR can be calculated from wealth percentiles:

$$\widetilde{CAR}_T(p) = \left(\frac{\tilde{W}_T[p]}{W_0}\right)^{\frac{12}{T}} - 1. \tag{19.4}$$

The Lognormal Forecasting Model

Based on the central limit theorem, Lewis et al. (1980) showed how to form probabilistic forecasts using the lognormal distribution. (See the "Central Limit Theorem and the Lognormal Distribution" sidebar.) A monthly return distribution is said to be lognormal if $\log(1+\tilde{R}_1)$ follows a normal distribution. Let μ_1 and σ_1 be the expected value and standard deviation of this

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[4] A percentile is a value (1 = nearly the lowest, 99 = nearly the highest) for which a random variable falls below with a specified probability. For example, in Exhibit 19.4, the 75th percentile of wealth per dollar invested at 20 years is 6.50. This means that at 20 years, there is a 75% probability that wealth per dollar invested is 6.50 or less.

[5] In decimal form, p is between 0 and 1. So, the percentile number is 100p. For example, if p = 5% = 0.05, the percentile number is 100p, which equals 5 for the 5th percentile.

normal distribution. These parameters can be calculated from the mean and standard deviation of $\tilde{R}_1$ as follows:

$$\sigma_1 = \sqrt{\log\left[1+\left(\frac{SD_1}{1+ER_1}\right)^2\right]}. \tag{19.5a}$$

$$\mu_1 = \log(1+ER_1) - \frac{1}{2}\sigma_1^2. \tag{19.5b}$$

The 100*p*th percentile of wealth in the lognormal model is

$$W_T(p) = W_0 \exp[T\mu_1 + \sqrt{T}\sigma_1 z(p)], \tag{19.6}$$

where $z(p)$ is the 100*p*th percentile of a standard normal random variable. **Exhibit 19.3** shows values of $z(p)$ for common percentiles.

The 100*p*th percentile of compound annual return in the lognormal model is

$$CAR_T(p) = \exp\left[12\mu_1 + \frac{12}{\sqrt{T}}\sigma_1 z(p)\right] - 1. \tag{19.7}$$

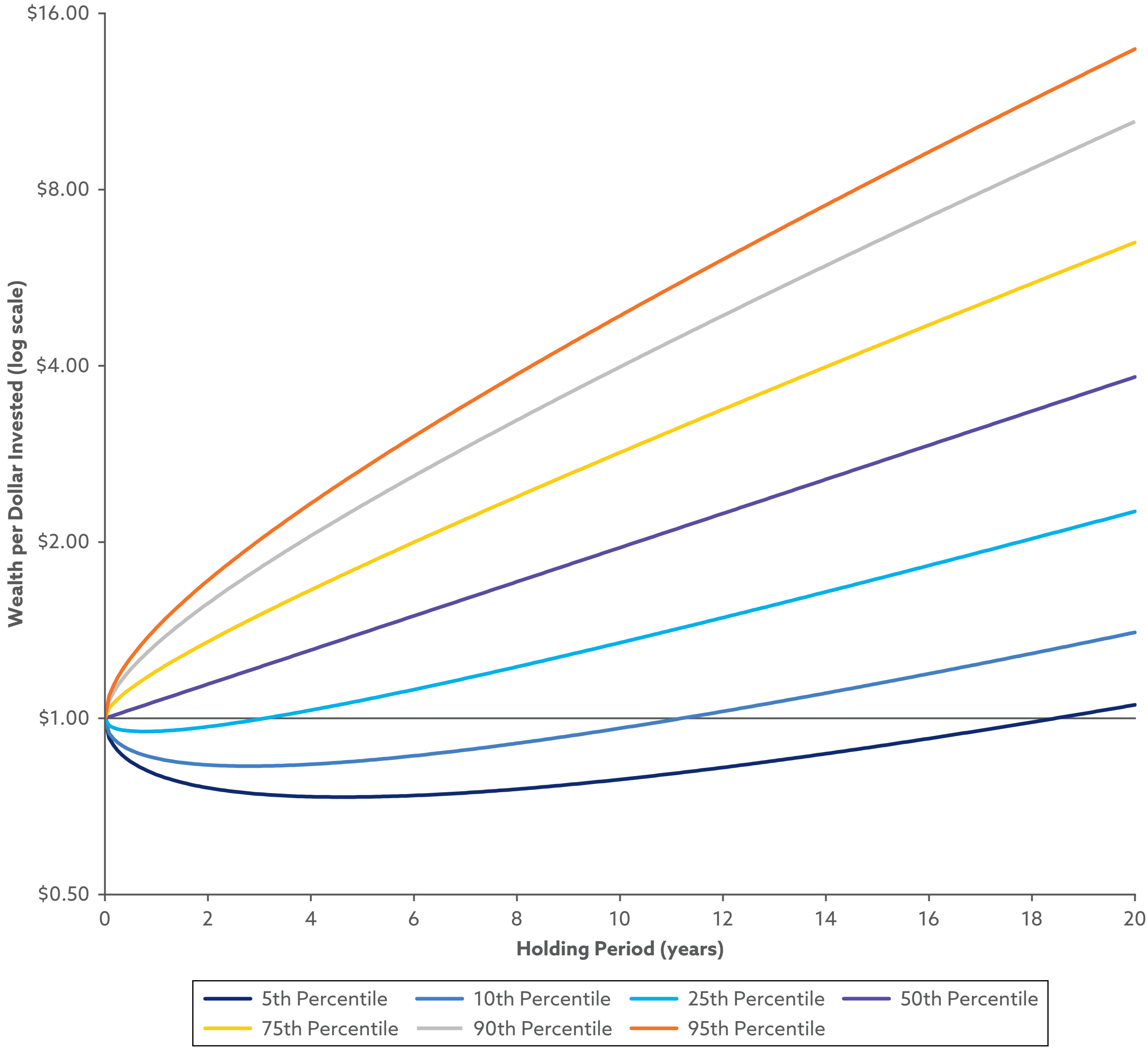
Exhibit 19.4 shows the percentiles of future wealth for large-cap stocks with W_0 = \$1 for the lognormal model. **Exhibit 19.5** shows percentiles for CAR. In these two exhibits, the horizontal axis depicts $T/12$, so it is in years.

Exhibit 19.3. Percentiles of the Standard Normal Distribution

Percentile	Standard Normal Value
5th	–1.6449
10th	–1.2816
25th	–0.6745
50th	0.0000
75th	0.6745
90th	1.2816
95th	1.6449

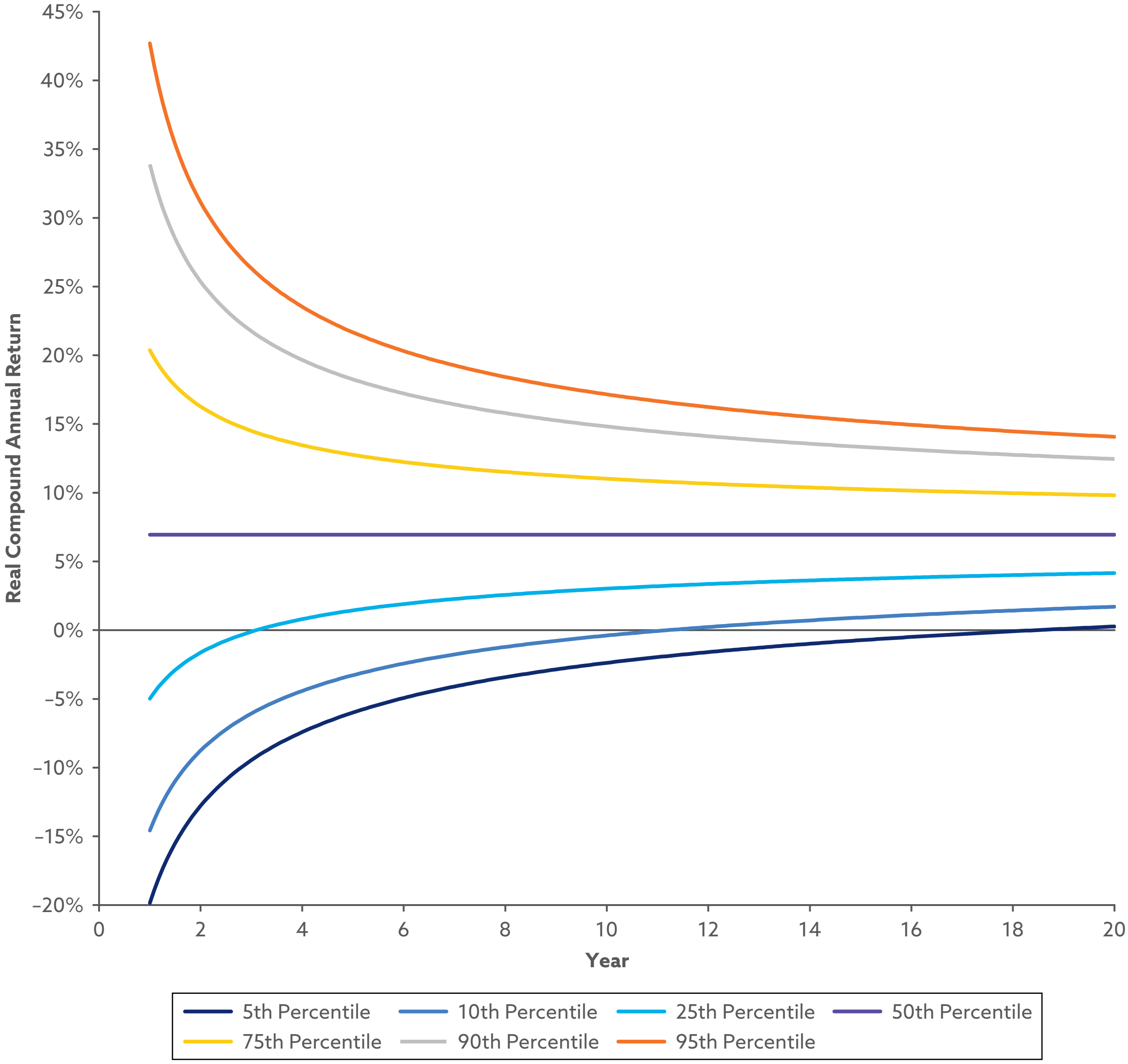
Source: Standard calculations.

Exhibit 19.4. Percentiles of Future Wealth Under the Lognormal Model: Large-Cap Stocks



Source: Calculations by the author using Ibbotson Indices data.

Exhibit 19.5. Percentiles of Future Compound Annual Return Under the Lognormal Model: Large-Cap Stocks



Source: Calculations by the author using Ibbotson Indices data.

The Central Limit Theorem and the Lognormal Distribution

Suppose that we have a sequence of T independent and identically distributed (i.i.d.) random variables, $\tilde{X}_1, \tilde{X}_2, \cdots, \tilde{X}_T$, all with the same mean, μ, and all with the same standard deviation, σ.[6] These variables may or may not be normally distributed. The mean of this sequence is[7]

$$\tilde{\bar{X}}_T = \frac{1}{T}\sum_{t=1}^{T}\tilde{X}_t. \tag{19.S1}$$

Let

$$\tilde{Y}_T = (\tilde{\bar{X}}_T - \mu)\sqrt{T}. \tag{19.S2}$$

$\tilde{Y}_T$ is the mean of the sequence, centered to have a mean of zero and scaled to have a standard deviation of σ. The central limit theorem says that as $t \to \infty$, $\tilde{Y}_T$ approaches a normally distributed random variable with a mean of zero and a standard deviation of σ. Hence, the mean and, therefore, the sum of a sequence of T i.i.d. random variables is well approximated by a normally distributed variable for large values of T.

To apply the central limit theorem to probabilistic forecasting of cumulative wealth, take logarithms of both sides of Equation 19.1:

$$\log(\tilde{W}_T) = \log(W_0) + \sum_{t=1}^{T}\log(1+\tilde{R}_{1t}). \tag{19.S3}$$

Assuming that returns are i.i.d., applying the central limit theorem to Equation 19.S3, one can conclude that for large values of T, $\log(\tilde{W}_T)$ is well approximated by a normally distributed random variable with a mean of $\mu_1 T$ and a standard deviation of $\sigma_1\sqrt{T}$.

A random variable is lognormally distributed if its logarithm is normally distributed. Hence, because $\log(\tilde{W}_T)$ is well approximated by a normally distributed variable, it follows that $\tilde{W}_T$ is well approximated by a lognormally distributed random variable with logarithmic parameters $\mu_1 T$ and $\sigma_1\sqrt{T}$. It also follows that compound annual return, as defined by Equation 19.3, is well approximated by a lognormal distribution with logarithmic parameters μ_1 and $\sigma_1/\sqrt{T}$.

[6] That is, the realization of any one random variable in the sequence is completely unrelated to that of any other random variable in the sequence, and all the random variables in the sequence are drawn from the same distribution. A simple way to illustrate a sequence of i.i.d. random variables is to flip the same coin repeatedly. Note that the central limit theorem applies to any sequence of i.i.d. random variables, not just to time series.

[7] Following standard practice, I use a bar as part of the name of a variable to indicate that it is an average. Hence, the combination of a bar and a tilde indicate that the average itself is a random variable.

Restating this conclusion in plain English, when forecasting wealth at the end of T periods or (equivalently) the compound annual return over those T periods, the distribution can be assumed to be lognormal. Therefore, most such forecasts use the lognormal distribution. In this chapter, some of the forecasts use the lognormal distribution and others use an alternative distribution assumption called the Johnson distribution.

Although the lognormal distribution is considered to be heavy tailed, its tails decay too rapidly to be considered fat tailed.

The First Four Moments of Wealth Distributions

In the lognormal model, skewness and excess kurtosis are not specified by explicit parameters. Rather, these moments are functions of the logarithmic standard deviation given in Equation 19.5a.

To see how skewness and excess kurtosis relate to logarithmic standard deviation, consider the three-parameter lognormal distribution, which is a generalization of the lognormal distribution. If $\tilde{Z}$ is a standard normal random variable, $\tilde{X}$ follows a three-parameter lognormal distribution if[8]

$$\tilde{X} = \xi + \lambda \cdot \exp(\mu + \sigma \tilde{Z}). \tag{19.8}$$

In Equation 19.8, ξ is the third parameter of the three-parameter lognormal distribution. It shifts the distribution. The additional parameter, λ, determines whether the distribution is right skewed (+1) or left skewed (–1).

As discussed later, the three-parameter lognormal distribution is a limiting case of the Johnson distribution that will be used for parametric forecasting. For the remainder of this chapter, the term *lognormal distribution* will refer to the three-parameter lognormal distribution, with the two-parameter return distribution as a special case.

The major limitation of the lognormal model is that it does not explicitly take into account the shape of the short-term wealth distributions. (As discussed in the sidebar, according to the central limit theorem, the long-term distributions should be nearly lognormal.) This limitation can be seen from the formulas for the skewness and excess kurtosis of a lognormal distribution. Letting

$$\omega = \exp(\sigma^2), \tag{19.9}$$

the skewness is

$$s = \lambda(\omega + 2)\sqrt{\omega - 1} \tag{19.10a}$$

and the excess kurtosis is

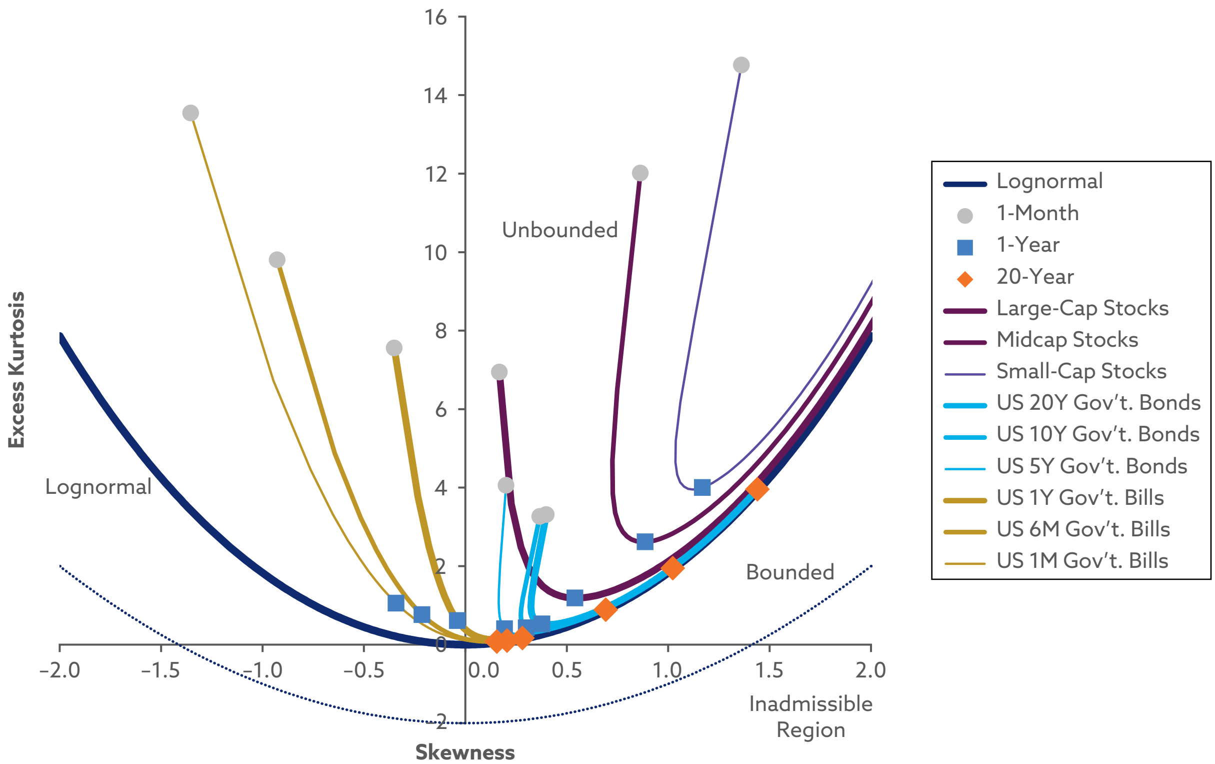
$$\kappa = \omega^4 + 2\omega^3 + 3\omega^2 - 6. \tag{19.10b}$$

[8] In equations that do not refer to a specific period of time, I omit the time period subscripts on the parameters.

The skewness and excess kurtosis of a lognormal distribution simultaneously satisfy Equations 19.10a and 19.10b. **Exhibit 19.6** shows possible combinations of skewness and excess kurtosis. The curve labeled "Lognormal" represents combinations for lognormal distributions implied by Equations 19.9 and 19.10. The gray dots depict the combinations for the asset class indices given in Exhibit 19.2. The asset classes are indicated by the color and thickness of the curves that emanate from the circles, as shown in the table just below the chart. Note that these combinations are far above the lognormal curve, indicating that monthly returns are far from lognormal. A different distribution, which I will introduce in the next section, is necessary.

In order to make probabilistic forecasts with Johnson distributions, the first four moments for any holding period need to be calculated. This calculation has two steps.

Exhibit 19.6. Combinations of Skewness and Excess Kurtosis for Stocks, Bonds, and Bills, and Regions for Johnson Distributions



	Color	Thick	Medium	Thin
Stocks	Purple	Large Cap	Mid Cap	Small Cap
US Treasury bonds	Light Blue	20 Years	10 Years	5 Years
US Treasury bills	Yellow	1 Year	6 Months	1 Month

Source: Calculations by the author using Ibbotson Indices data.

Step 1: Calculate the First Four Raw Monthly Moments

The *n*th monthly raw moment is defined as follows:

$$M_n = E[(1+\tilde{R}_1)^n]. \tag{19.11}$$

The raw moments from the moments are as follows:

$$M_1 = 1 + ER_1. \tag{19.12a}$$

$$M_2 = SD_1^2 + M_1^2. \tag{19.12b}$$

$$M_3 = s \cdot SD_1^3 + 3M_2M_1 - 2M_1^3. \tag{19.12c}$$

$$M_4 = (\kappa + 3)SD_1^4 + 4M_3M_1 - 6M_2M_1^2 + 3M_1^4. \tag{19.12d}$$

Step 2: Derive the First Four Moments for the Holding Period

If monthly returns are assumed to be independent over time and identically distributed, then

$$\mathrm{E}\left[\prod_{t=1}^{T}(1+\tilde{R}_{1t})^n\right] = M_n^T, \tag{19.13}$$

where T is the number of months of the holding period. Based on Equations 19.12 and 19.13, the first four moments for the holding period can be derived from the monthly raw moments as follows:

$$ER_T = M_1^T - 1. \tag{19.14a}$$

$$SD_T = \sqrt{M_2^T - M_1^{2T}}. \tag{19.14b}$$

$$s_T = \frac{M_3^T - 3M_2^T M_1^T + 2M_1^{3T}}{SD_T^3}. \tag{19.14c}$$

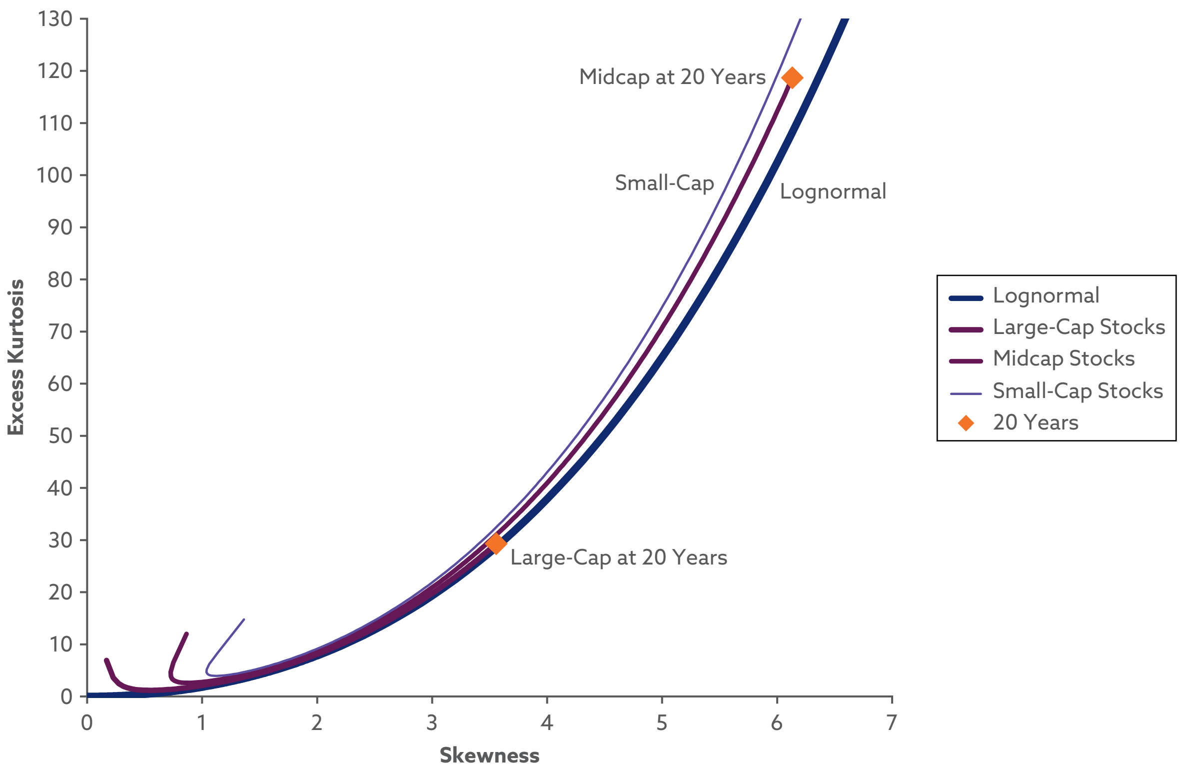
$$\kappa_T = \frac{M_4^T - 4M_3^T M_1^T + 6M_2^T M_1^{2T} - 3M_1^{4T}}{SD_T^4} - 3. \tag{19.14d}$$

Exhibit 19.6 shows the progression of combinations of skewness and excess kurtosis for the bond and bill asset class indices as the holding period is increased one month at a time. These curves start at 1 month (shown by the gray dots) and end at 240 months (20 years, shown by the orange diamonds). In each case, as the holding period increases, at first, the combination moves closer to the lognormal curve. Once the combination is near the curve, it moves in parallel to the curve. As discussed in the sidebar, this is a manifestation of the central limit theorem.

The ranges of values of skewness and excess kurtosis for the stock indices exceed the ranges of possible values in Exhibit 19.6, which is the reason only parts of the curves for these indices appear in this exhibit. To show the full progressions from 1 to 240 months of the combinations of skewness and excess kurtosis for large-cap and midcap stocks, in **Exhibit 19.7** I extend the range of possible values for skewness out to 7 and excess kurtosis out to 130. (This exhibit also shows part of the curve for small-cap stocks. The full curve is in **Exhibit 19.8**.) The curve for large-cap stocks comes very close to the lognormal curve, but the curve for midcap stocks is a bit above it, even at 20 years. In the next section, I will discuss the consequences of this finding for the Johnson forecasting model.

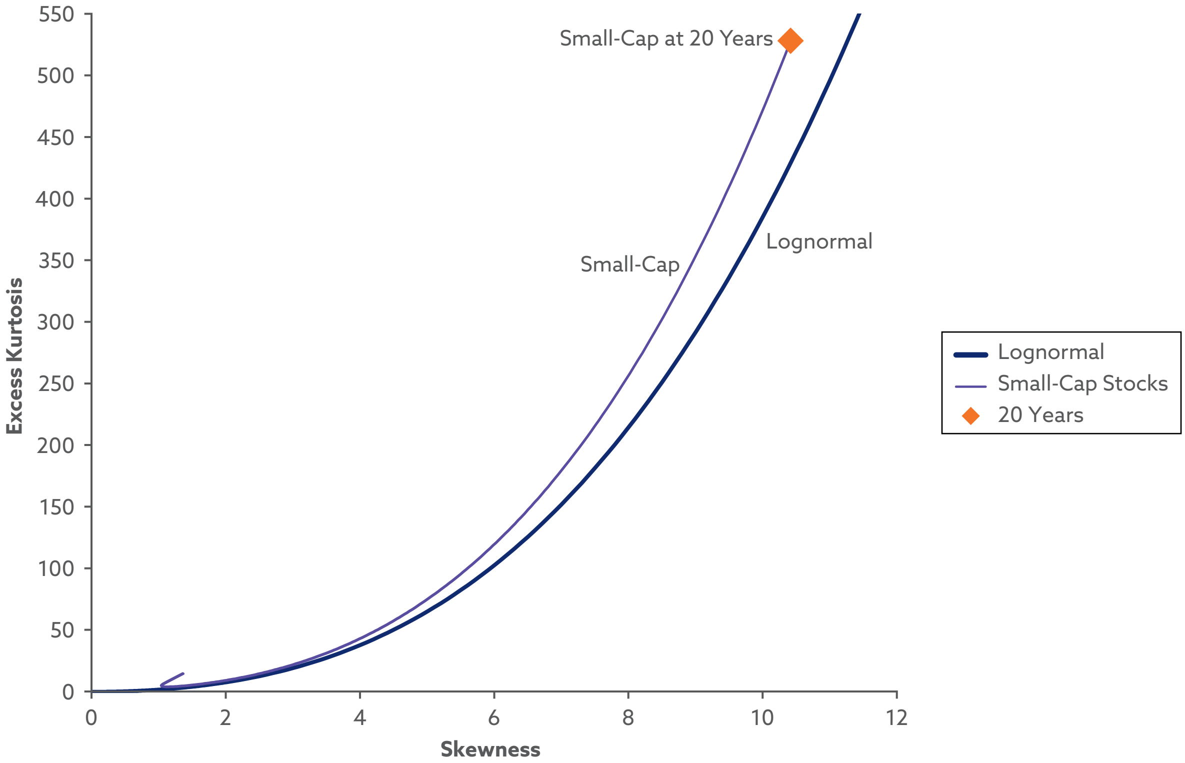
To show the full progression from 1 to 240 months of combinations of skewness and excess kurtosis curve for small-cap stocks, in Exhibit 19.8 I extend the range of possible values of skewness to 12 and excess kurtosis out to 550. The curve for small-cap stocks is considerably above the lognormal curve, even at 20 years, which has major repercussions in the Johnson forecasting model, discussed next.

Exhibit 19.7. Combinations of Skewness and Excess Kurtosis for Stocks



Source: Calculations by the author using Ibbotson Indices data.

Exhibit 19.8. Combinations of Skewness and Excess Kurtosis for Small-Cap Stocks



Source: Calculations by the author using Ibbotson Indices data.

The Johnson Forecasting Model

Johnson (1949) created a system of distributions based on combinations of skewness and excess kurtosis, depicted in Exhibit 19.6. First, not all combinations are possible. A combination is possible only if

$$\kappa \geq s^2 - 2. \tag{19.15}$$

The curve labeled "Admissible Region" in Exhibit 19.6 depicts Equation 19.15 as the dividing line between admissible and inadmissible combinations.

Among the admissible combinations, there are four cases:

- If $s = \kappa = 0$, the distribution is normal.
- If (s, κ) is on any other point on the lognormal curve, the distribution is lognormal.
- If (s, κ) is below the lognormal curve, the distribution is a bounded Johnson distribution.
- If (s, κ) is above the lognormal curve, the distribution is an unbounded Johnson distribution.

Because the combinations for all the asset class indices are above the lognormal curve, I will focus on the unbounded Johnson distribution. Thus, a four-parameter distribution is defined as follows for monthly returns:

$$1+\tilde{R}_1=\lambda_1\sinh\left(\frac{\tilde{Z}-\gamma_1}{\delta_1}\right)+\xi_1, \tag{19.16}$$

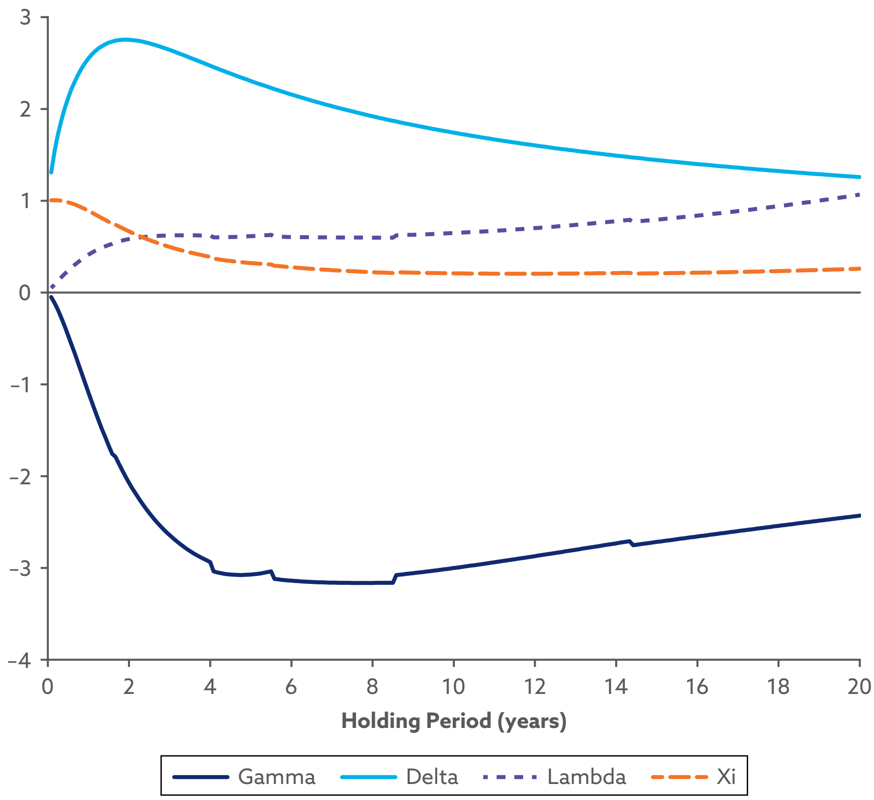
where sinh(·) is the hyperbolic sine function defined as

$$\sinh(x)=\frac{1}{2}[\exp(x)-\exp(-x)]. \tag{19.17}$$

Four parameters—λ_1, ξ_1, γ_1, δ_1—are calculated from the first four monthly moments using the algorithm developed by Hill, Hill, and Holder (1976).

To form probabilistic forecasts with the unbounded Johnson distribution, the four parameters are calculated for the Johnson distribution at *T* months from the first four moments given in Equation 19.14 using the Hill et al. (1976) algorithm. **Exhibit 19.9** shows the progression of the

Exhibit 19.9. Evolution of Parameters of the Johnson Distribution: Large-Cap Stocks



Source: Calculations by the author using Ibbotson Indices data.

parameters of the Johnson distribution for $T = 1, 2, \ldots, 240$ for large-cap stocks (the horizontal axis is in years, so it shows $T/12$).

From the parameters for a holding period of T months, the 100pth percentile of wealth is calculated as

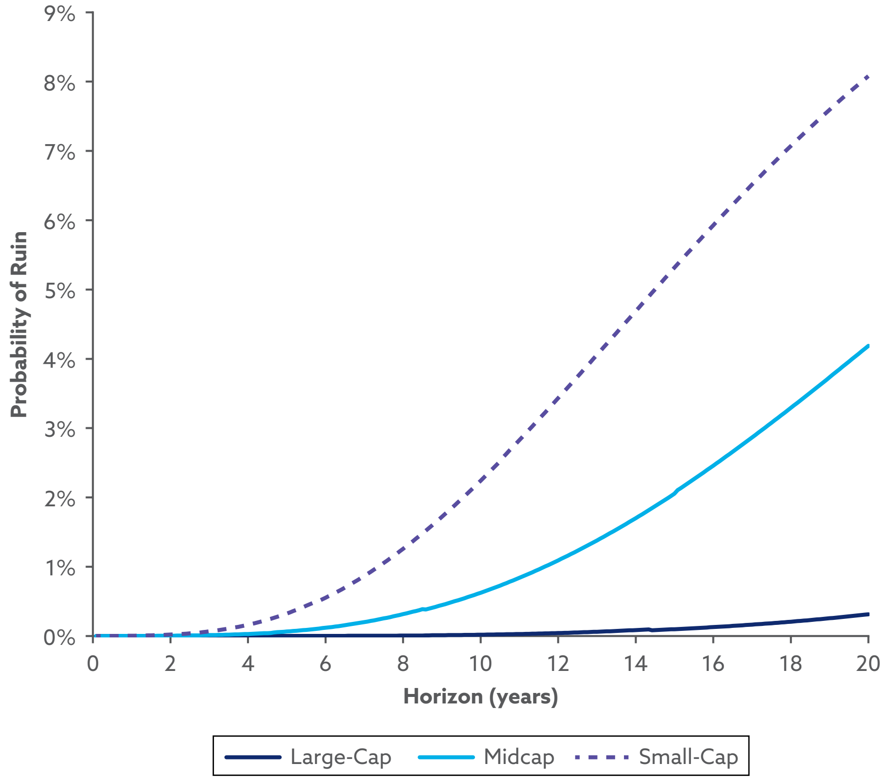
$$W_T(p) = W_0\left[\lambda_T \sinh\left(\frac{z(p)-\gamma_T}{\delta_T}\right)+\xi_T\right]. \tag{19.18}$$

Equation 19.18 can result in a negative value. Such an outcome can be interpreted to mean that a return of –100% is realized over the holding period, resulting in complete ruin; I define $\bar{p}(T)$ as the "probability of ruin" for the holding period of T months.[9] It is the value that satisfies

$$W_T\left[\bar{p}(T)\right] = 0. \tag{19.19}$$

Exhibit 19.10 shows the "probability of ruin" for large-cap, midcap, and small-cap stocks over holding periods from 1 to 240 months (20 years). **Exhibit 19.11** shows the "probability of

Exhibit 19.10. "Probability of Ruin" for Stocks: 1–240 Months



Source: Calculations by the author using Ibbotson Indices data.

[9] Later, I will explain why I put "probability of ruin" in quotes.

Exhibit 19.11. "Probability of Ruin" for Stocks at 240 Months and the Implied Frequency of Ruinous Monthly Returns

Asset Class	"Probability of Ruin"	Frequency of Ruinous Returns
Large-cap stocks	0.31%	1 month in 76,453 (6,371 years)
Midcap stocks	4.19%	1 month in 5,611 (468 years)
Small-cap stocks	8.08%	1 month in 2,849 (237 years)

Source: Ibbotson Indices. Calculations by the author.

ruin" for these stock indices at 240 months and the implied frequency of a monthly return of –100%.[10]

As Exhibit 19.10 shows, the "probability of ruin" increases with the holding period. The reason is that it takes only one ruinous return to wipe out all accumulated wealth. Exhibits 19.10 and 19.11 also show large differences in the "probability of ruin" between large-cap, midcap, and small-cap stocks. These differences result from the differences in the gaps between the paths of skewness and excess kurtosis for each asset class index and the lognormal curve in Exhibits 19.7 and 19.8.

For large-cap stocks, there is almost no gap; consequently, the "probability of ruin" is only 0.31% at 240 months. For midcap stocks, a small but noticeable gap exists, resulting in a "probability of ruin" of 4.19% at 240 months. For small-cap stocks, however, the gap is quite large, resulting in a "probability of ruin" of 8.08% at 240 months. Note that although a "probability of ruin" at 240 months of 8.08% may seem large, it implies that the frequency of ruinous returns is just one month in 237 years.

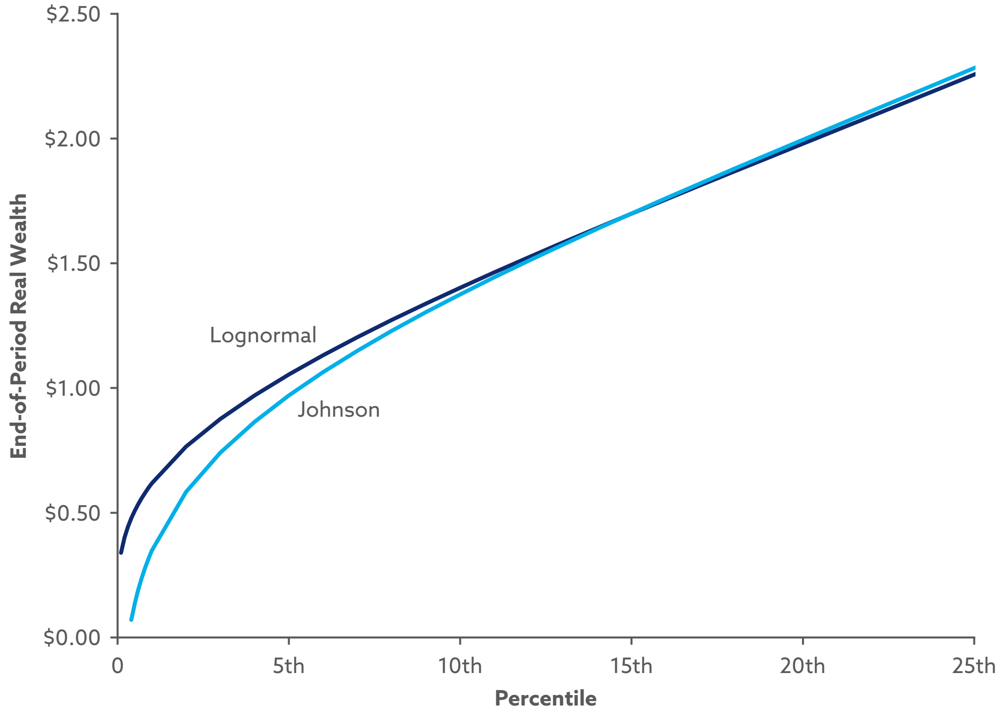
Of course, these values for the "probability of ruin" should not be taken literally. This is why I have placed the phrase "probability of ruin" in quotation marks. Although it might be possible for a single stock to lose 100% of its market value, such a loss is highly unlikely for a diversified portfolio of stocks. At each point in time, each stock index consists of many stocks, with the composition changing over time. In a given month, some stocks might lose 100% of their market value, but not all components of an index will do so at the same time (except in extreme circumstances, such as a revolution or losing a war).

What the values for the "probability of ruin" shown in Exhibit 19.10 and 19.11 do show is that the lognormal model can understate the riskiness of asset classes with return distributions that are far from being lognormal. The "probability of ruin" is not a forecast; rather, it is an output of the Johnson model that indicates the presence of risks not captured by the lognormal model.

The differences in the paths of skewness and excess kurtosis relative to the lognormal curve also result in corresponding differences between the wealth percentile curves from the lognormal and Johnson models. In the case of large-cap stocks, because the paths of skewness and kurtosis are very close to that of the lognormal, the results are also very close. Differences are

[10] The implied frequency of ruinous monthly returns is 1 in $\dfrac{1}{1-[1-\bar{p}(T)]^{\frac{1}{T}}}$ months.

Exhibit 19.12. Low Percentiles of Wealth at 20 Years for Large-Cap Stocks: Lognormal and Johnson Models



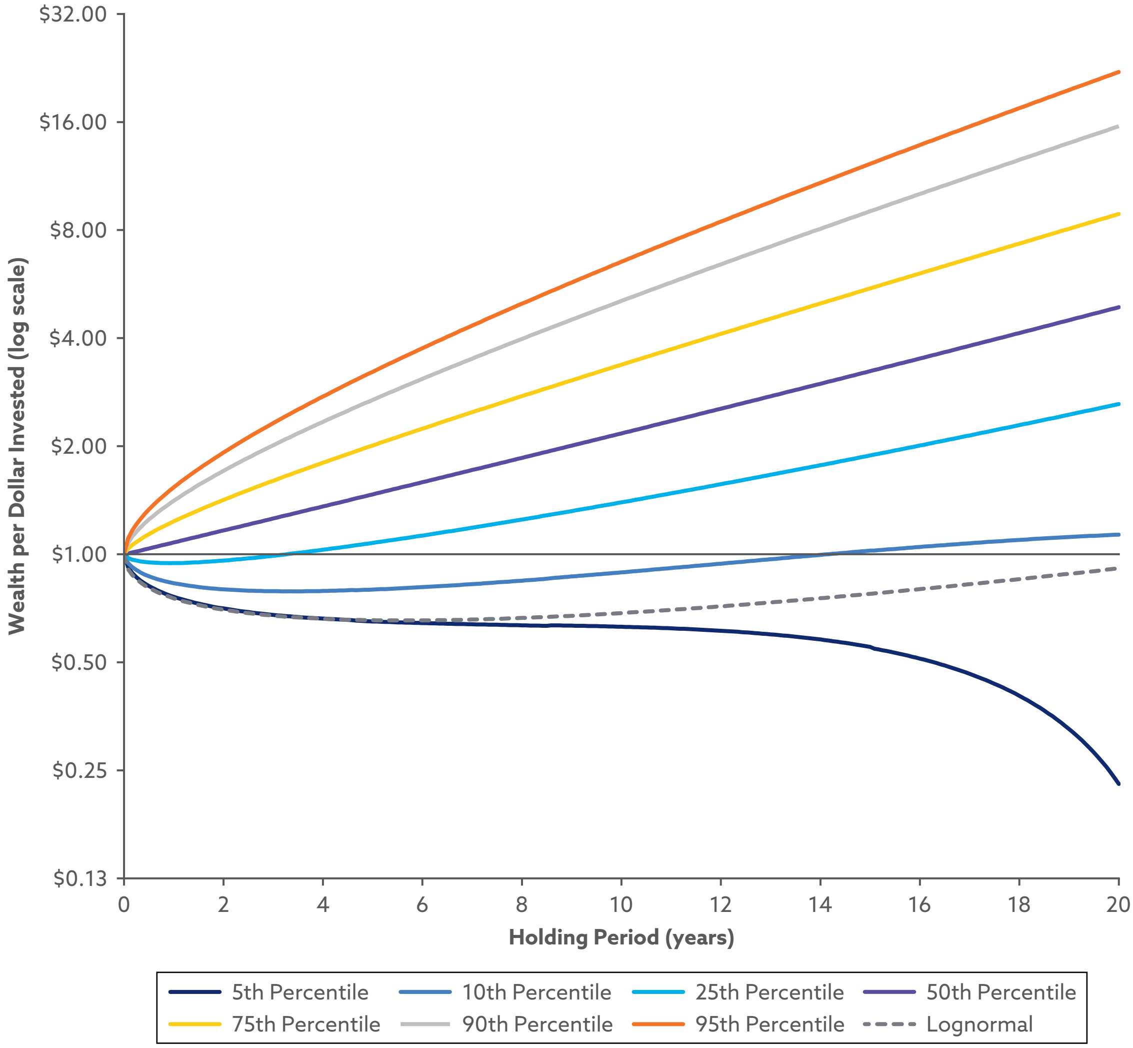
Source: Calculations by the author using Ibbotson Indices data.

apparent only for very low percentiles at long holding periods. To illustrate this, **Exhibit 19.12** shows percentiles of wealth in 20 years for both the lognormal and Johnson models, at percentiles varying from the 0.1th to the 25th. It is only at these extremes that the Johnson model is clearly more pessimistic than the lognormal model.

Exhibit 19.13 shows wealth percentiles for midcap stocks using the Johnson model. It also shows the 5th percentile using the lognormal model as a dashed curve. At the 5th percentile, the two models begin to deviate at a holding period of about six years, with the Johnson model always being more pessimistic. At about 12 years, while the lognormal curve continues to slope upward, the Johnson curve slopes downward, thus becoming even more pessimistic as the holding period increases. These differences between the 5th percentiles of wealth for the two models are further manifestations of the gap between the path of skewness and excess kurtosis for midcap stocks and the lognormal curve in Exhibit 19.7.

Exhibit 19.14 shows wealth percentiles for small-cap stocks using the Johnson model. It also shows the 5th and 10th percentiles using the lognormal model as burgundy dashed (5th) and gray dotted (10th) curves. At the 10th percentile, the two models begin to deviate at a holding period of about 12 years, with the Johnson model always being more pessimistic. While the lognormal curve continues to slope upward, the Johnson curve slopes downward, becoming even more pessimistic as the holding period increases.

Exhibit 19.13. Wealth Percentiles for Midcap Stocks Under the Johnson Model

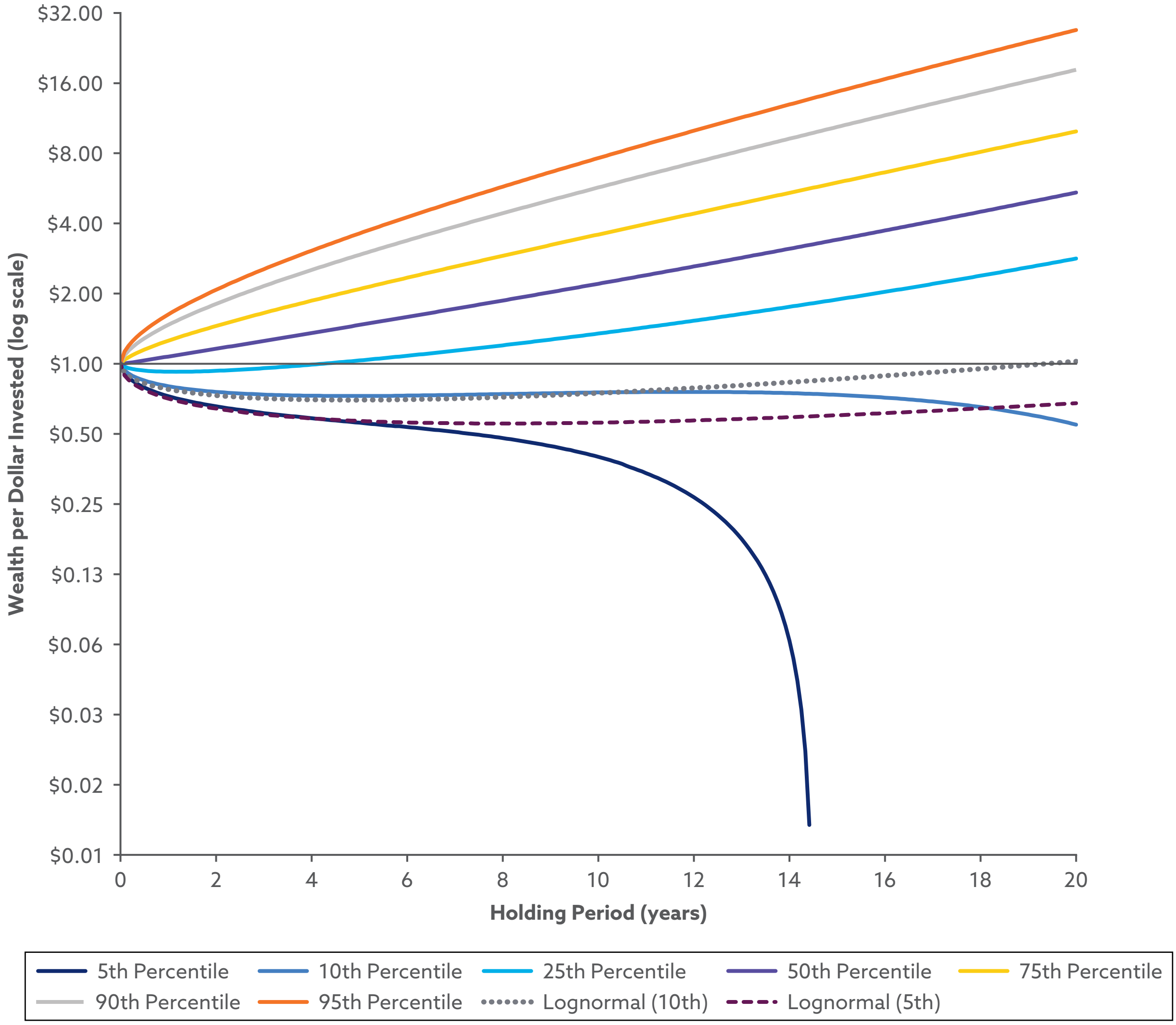


Source: Calculations by the author using Ibbotson Indices data.

The 5th percentile curve for the Johnson model begins to deviate from the lognormal model at about six years. It then drops—and at an increasing rate. It reaches $0 at 14.5 years because, as Exhibit 19.10 shows, this is where the "probability of ruin" for small-cap stocks reaches 5%.[11]

[11] Because the vertical axis of Exhibit 19.14 is logarithmic, wealth cannot actually be shown going to $0 in that exhibit. Instead, the curve ends at 14.5 years with a value of $0.01.

Exhibit 19.14. Wealth Percentiles for Small-Cap Stocks Under the Johnson Model



Source: Calculations by the author using Ibbotson Indices data.

These differences between the 10th and 5th percentiles of wealth for the lognormal and Johnson models result from the large gap between the paths of skewness and excess kurtosis for small-cap stocks and the lognormal curve in Exhibit 19.8.

Annualized Parameters and Applications

Asset class return models are typically stated in terms of annual returns. By setting $T = 12$ and applying Equations 19.11 and 19.12, the first four moments can be annualized. **Exhibit 19.15**

Exhibit 19.15. Annualized Estimates of the First Four Moments of Real Asset Class Indices, January 1926–December 2025

Asset Class	Mean	Standard Deviation	Skewness	Excess Kurtosis
Large-cap stocks	8.60%	19.19%	0.54	1.19
Midcap stocks	10.45%	24.36%	0.89	2.62
Small-cap stocks	11.21%	28.72%	1.17	4.00
US 20-year Treasury bonds	2.34%	9.67%	0.38	0.53
US 10-year Treasury bonds	2.23%	7.18%	0.30	0.43
US 5-year Treasury bonds	1.97%	5.03%	0.19	0.41
US 1-year Treasury bills	1.08%	2.29%	−0.04	0.61
US 6-month Treasury bills	0.82%	2.00%	−0.21	0.77
US 1-month Treasury bills	0.32%	1.83%	−0.34	1.06

Source: Calculations by the author using Ibbotson Indices data.

shows the results of doing this for the monthly statistics in Exhibit 19.2. Exhibit 19.6 showed how the annualized combinations of skewness and kurtosis are much closer to the lognormal curve.

Covariance and Correlation

Asset class return models need to model not only the distribution of each asset class but also the covariance of returns between every pair of asset classes. The monthly covariance of the returns of asset classes *j* and *k* is estimated as follows:

$$\hat{C}_{1jk} = \frac{1}{N-1}\sum_{i=1}^{N}(R_{1ji} - \widehat{ER}_{1j})(R_{1ki} - \widehat{ER}_{1k}). \tag{19.20}$$

Because covariances can be hard to interpret, correlations are often reported instead, because a correlation must be between −1 and +1. The monthly correlation of the returns of asset classes *j* and *k* is estimated as follows:

$$\hat{\rho}_{1jk} = \frac{\hat{C}_{1jk}}{\widehat{SD}_{1j}\,\widehat{SD}_{1k}}. \tag{19.21}$$

Exhibit 19.16 presents the estimated monthly correlations between all pairs of asset class indices.

Exhibit 19.16. Estimates of Monthly Correlations of Real Asset Class Indices, January 1926–December 2025

Asset Class	1	2	3	4	5	6	7	8	9
(1) Large-cap stocks	1.0000								
(2) Midcap stocks	0.9396	1.0000							
(3) Small-cap stocks	0.8749	0.9684	1.0000						
(4) US 20-year Treasury bonds	0.0948	0.0580	0.0213	1.0000					
(5) US 10-year Treasury bonds	0.1018	0.0694	0.0352	0.9342	1.0000				
(6) US 5-year Treasury bonds	0.0980	0.0692	0.0395	0.8341	0.9243	1.0000			
(7) US 1-year Treasury bills	0.1195	0.1032	0.0834	0.5442	0.6259	0.7561	1.0000		
(8) US 6-month Treasury bills	0.0910	0.0733	0.0578	0.4175	0.4825	0.6023	0.9509	1.0000	
(9) US 1-month Treasury bills	0.0741	0.0503	0.0397	0.2968	0.3477	0.4513	0.8476	0.9490	1.0000

Source: Calculations by the author using Ibbotson Indices data.

The formula for annualizing covariances is

$$\hat{C}_{12jk} = [\hat{C}_{1jk} + (1+\widehat{ER}_{1j})(1+\widehat{ER}_{1k})]^{12} - [(1+\widehat{ER}_{1j})(1+\widehat{ER}_{1k})]^{12}. \qquad (19.22)$$

The annualized correlation of the returns of asset classes j and k is given by

$$\hat{\rho}_{12jk} = \frac{\hat{C}_{12jk}}{\widehat{SD}_{12j}\,\widehat{SD}_{12k}}. \qquad (19.23)$$

Exhibit 19.17 presents the annualized correlations between all pairs of asset class indices. All the off-diagonal entries are slightly lower in magnitude than their monthly counterparts.

Exhibit 19.17. Annualized Correlations of Real Asset Class Indices, January 1926–December 2025

Asset Class	1	2	3	4	5	6	7	8	9
(1) Large-cap stocks	1.0000								
(2) Midcap stocks	0.9382	1.0000							
(3) Small-cap stocks	0.8714	0.9673	1.0000						
(4) US 20-year Treasury bonds	0.0940	0.0573	0.0209	1.0000					
(5) US 10-year Treasury bonds	0.1010	0.0686	0.0346	0.9339	1.0000				
(6) US 5-year Treasury bonds	0.0973	0.0685	0.0389	0.8334	0.9241	1.0000			
(7) US 1-year Treasury bills	0.1187	0.1021	0.0822	0.5433	0.6254	0.7596	1.0000		
(8) US 6-month Treasury bills	0.0904	0.0726	0.0569	0.4168	0.4821	0.5883	0.9508	1.0000	
(9) US 1-month Treasury bills	0.0736	0.0497	0.0391	0.2962	0.3473	0.4397	0.8475	0.9490	1.0000

Source: Calculations by the author using Ibbotson Indices data.

Capital Market Assumptions for Mean–Variance Optimization

The annualized asset class expected returns, standard deviations, and correlations in Exhibits 19.15 and 19.17 together form a set of capital market assumptions (CMAs) that are the inputs to Markowitz (1952, 1959, 1987) mean–variance optimization (MVO). It is not good practice, however, to perform MVO with CMAs, especially expected returns, that are based purely on historical data, because doing so amounts to assuming that the future will be just like the past.

Idzorek and Kaplan (2024) developed a method for creating a set of expected returns that are calibrated to a complete contingent claims market model. Financial economists often use this type of approach to model capital markets. In this type of model, there is a single random variable—called the stochastic discount factor (SDF), sometimes called a "pricing kernel"—for pricing all securities. Kaplan and Idzorek (2025) explained their approach in more detail. The following discussion is based on Kaplan and Idzorek (2025).

Reverse Optimization

I begin the process of setting expected returns with the reverse optimization process devised by Sharpe (1974). Reverse optimization, as the name implies, is mean–variance optimization run in reverse.

In the standard *forward* mean–variance optimization model, portfolios of discrete investments or mixes of asset classes are constructed to minimize portfolio variance for a given level of portfolio expected return. The model requires two inputs:

$\mathbf{E}_{\mathbf{AC}}$ = a vector, or list, of K asset class expected returns.

$\mathbf{V}_{\mathbf{AC}}$ = a $K \times K$ covariance matrix of asset class returns.

Note that in writing formulas, *italic* font is used for scalars and **bold** font is used for vectors and matrices.

E_p is used to denote the target expected return for the portfolio, and **h** is used to denote the vector of portfolio weights, or holdings. The MVO model solves the following constrained quadratic program:

$$V_{MVO}(E_P) = \min_{\mathbf{h}} \mathbf{h}^{\mathrm{T}} \mathbf{V}_{\mathbf{AC}} \mathbf{h} \text{ s.t. } \mathbf{h}^{\mathrm{T}} \mathbf{E}_{\mathbf{AC}} = E_P, \sum_{i=1}^{K} h_i = 1, \mathbf{h} \geq 0. \tag{19.24}$$

Equation 19.24 states that the optimization procedure finds the portfolio weights (**h**) for the K asset classes that *minimize* portfolio variance subject to (s.t.) three constraints: (1) The portfolio return must equal E_p, (2) the weights of the portfolio must sum to 1—that is, 100%—and (3) each weight must be zero or greater.

Forward optimization begins with a set of *expected returns* ($\mathbf{E}_{\mathbf{AC}}$) and arrives at efficient *weights* (**h**). By varying μ_p from the highest asset class expected return to the expected return of the minimum-variance portfolio, the Markowitz efficient frontier can be traced out.

In *reverse* optimization, one starts with a single set of *weights* (**h**) from a reference portfolio ($\mathbf{h}_{\mathbf{R}}$) presumed to be efficient, such as a market-capitalization-weighted portfolio, and calculates the set of *expected returns* ($\boldsymbol{\mu}_{\mathbf{AC}}$) that make those weights efficient. With this construct, a closed-form solution exists, and a quadratic program is unnecessary. For the reference portfolio to be on the efficient frontier, the following condition must be true:

$$\mathbf{E}_{\mathbf{AC}} = r_f + (E_R - r_f)\boldsymbol{\beta}, \tag{19.25}$$

where r_f is the expected return on a portfolio with a beta of zero. (This expected return is denoted r_f because it is set to the risk-free rate.) E_R is the expected return of the reference portfolio discussed below, and $\boldsymbol{\beta}$ is the vector of asset class betas (defined below) with respect to the reference portfolio.

Similar to the capital asset pricing model (CAPM) formula for expected returns, Equation 19.25 states that the expected total return of an asset class equals the risk-free rate plus a risk premium multiplied by the beta of the asset class relative to the reference portfolio.[12] The most common reference portfolio is a market-cap-weighted portfolio. The vector of asset class betas is given by

$$\beta = \frac{1}{\mathbf{h}_R^{\mathrm{T}}\mathbf{V}_{\mathbf{AC}}\mathbf{h}_{\mathbf{R}}}\mathbf{V}_{\mathbf{AC}}\mathbf{h}_{\mathbf{R}}. \tag{19.26}$$

In Equation 19.26, each asset class beta is calculated by dividing the covariance of each asset class, calculated relative to the reference portfolio, by the variance of the reference portfolio.

The expected return of the asset classes ($\mathbf{E_{AC}}$) can then be written as a function of μ_R and r_f as follows:

$$\mathbf{E_{AC}}(E_R, r_f) = r_f + (E_R - r_f)\boldsymbol{\beta}. \tag{19.27}$$

Based on Equation 19.27, **Exhibit 19.18** shows

- the reference portfolio that is assumed for this example;
- the betas computed from the reference portfolio, the standard deviations in Exhibit 19.15, and the correlations in Exhibit 19.17; and
- the expected returns on the asset classes using Equation 19.26, with r_f = 2% and E_R = 4.57%.

The next section explains how we set E_R by calibrating the expected returns.

Calibration of Expected Returns

Now E_R and r_f can be included as parameters that provide the expected returns on the asset classes ($\mathbf{E_{AC}}$) in an efficient frontier function:[13]

$$V_{MVO}(E_P; E_R, r_f) = \min_{\mathbf{h}} \mathbf{h}^{\mathrm{T}}\mathbf{V}_{\mathbf{AC}}\mathbf{h} \text{ s.t. } \mathbf{h}^{\mathrm{T}}\mu_{\mathbf{AC}}(E_R, r_f) = E_P, \sum_{i=1}^{K} h_i = 1,\ \mathbf{h} \geq 0. \tag{19.28}$$

Equation 19.28 is very similar to Equation 19.24, except that it has two additional parameters—the assumed expected return on the reference portfolio (E_R) and the risk-free rate (r_f). By varying across the range of possible portfolios returns (E_P), Equation 19.28 leads to an entire efficient frontier.

I chose to write many of the equations as functions of other values to clarify and automate the eventual calibration process, in which one altered value cascades across the various formulas. In this case, by changing the *assumed* expected total return on the reference portfolio, E_R, or the risk-free rate, r_f, or both, one arrives at a new set of expected returns ($\mathbf{E_{AC}}$) and, ultimately, a new

[12] In the CAPM, the reference portfolio is the market portfolio. Reverse optimization is more general than the CAPM in that the reference portfolio can be any portfolio assumed to be on the efficient frontier.

[13] In Markowitz (1952, 1959, 1987), the efficient frontier is a plot of the efficient frontier function as defined in Equation 19.28. Common practice, however, is to reverse the axes and plot the standard deviation rather than the variance of return. I follow the common practice in this chapter. See Exhibit 19.19.

Exhibit 19.18. Betas and Expected Returns from Reverse Optimization

Asset Class	Equity Portfolio	Reference Portfolio	Beta	Expected Return	Standard Deviation
Large-cap stocks	70.00%	42.00%	1.43	5.68%	19.19%
Midcap stocks	20.00%	12.00%	1.78	6.58%	24.36%
Small-cap stocks	10.00%	6.00%	1.99	7.10%	28.72%
US 20-year Treasury bonds	0.00%	13.33%	0.21	2.55%	9.67%
US 10-year Treasury bonds	0.00%	13.33%	0.16	2.42%	7.18%
US 5-year Treasury bonds	0.00%	13.33%	0.11	2.28%	5.03%
US 1-year Treasury bills	0.00%	0.00%	0.04	2.11%	2.29%
US 6-month Treasury bills	0.00%	0.00%	0.03	2.07%	2.00%
US 1-month Treasury bills	0.00%	0.00%	0.02	2.05%	1.83%
Equity portfolio	100.00%	—	1.56	6.00%	20.72%
Reference portfolio	—	100.00%	1.00	4.56%	12.98%

Source: Calculations by the author using Ibbotson Indices data.

efficient frontier. In practice, only the expected total return on the reference portfolio is varied and the risk-free rate is taken as a given.

To create consistency between the utility functions in many economic models and the MVO model, the mean–variance problem is set up using the mean–variance approximation of expected utility proposed by Levy and Markowitz (1979).[14] We assume a constant relative risk aversion (CRRA) utility function with risk tolerance parameter θ.

Based on Equation 19.28, it is possible to find the point on the efficient frontier that maximizes the Levy–Markowitz CRRA utility function for given values of θ, E_R, and r_f as follows:

$$\mu_\theta^{MVO}(E_R, r_f) = \arg\max_{\mu_P} U_\theta[E_P, V_{MVO}(E_P; E_R, r_f)], \tag{19.29}$$

where $U_\theta(\cdot,\cdot)$ is the Levy–Markowitz CRRA utility function with risk tolerance θ described by Kaplan (2020), Idzorek and Kaplan (2024), Kaplan and Idzorek (2025), and Kaplan (2025).

[14] See Kaplan (2020), Idzorek and Kaplan (2024), Kaplan and Idzorek (2025), and Kaplan (2025).

The standard deviation at the point on the efficient frontier that maximizes the Levy-Markowitz CRRA utility function is

$$S_{\theta}^{MVO}(E_R,r_f)=\sqrt{V_{MVO}[E_{\theta}^{MVO}(E_R,r_f);E_R,r_f]}. \tag{19.30}$$

Kaplan (2025) explained how to use *parametric* quadratic programming to find the corner portfolios of the efficient frontier, identify them using the Levy-Markowitz utility function, and create the entire efficient frontier.

Inputting reverse optimized expected returns into a mean-variance optimizer and maximizing the Levy-Markowitz CRRA utility function, with various values of the risk tolerance parameter, θ, allows the calibration of the CMAs to the implied CMAs embedded in the complete contingent claims market model.

To do so, two sets of points are formed for a set of n values of θ in expected return-standard deviation space—one from the complete contingent claims market of the life-cycle model described in Kaplan and Idzorek (2025, Appendix A) and one from a mean-variance-efficient frontier based on the Levy-Markowitz CRRA utility function. Taking r_f as given, E_R is selected to minimize the sum of the squared Euclidean distances between the n corresponding points from each model, as follows:

$$E_R^*=\arg\min_{E_R}\sum_{j=1}^{n}\left[E_{\theta_j}^{SDF}-E_{\theta_j}^{MVO}(E_R,r_f)\right]^2+\left[S_{\theta_j}^{SDF}-S_{\theta_j}^{MVO}(E_R,r_f)\right]^2, \tag{19.31}$$

where

$\theta_1, \theta_2, \ldots, \theta_n$ = the n values of θ

$E_{\theta_j}^{SDF}$ = the expected return from the complete contingent claims market model with risk tolerance θ_j

$S_{\theta_j}^{SDF}$ = the standard deviation of return from the complete contingent claims market model with risk tolerance θ_j

To calculate $E_{\theta_j}^{SDF}$ and $S_{\theta_j}^{SDF}$, start with the definition of the SDF. The SDF is a random variable $\tilde{Q}$ such that the market price of any security with a random payout $\tilde{X}$ is $E[\tilde{Q}\tilde{X}]$. Because a risk-free asset always pays \$1,[15]

$$E[\tilde{Q}]=\frac{1}{1+r_f}. \tag{19.32}$$

The ideal portfolio of an investor with risk tolerance θ has a return of

$$\tilde{R}_{\theta}=\frac{\tilde{Q}^{-\theta}}{E[\tilde{Q}^{1-\theta}]}-1. \tag{19.33}$$

[15] A security that costs $\frac{1}{1+r_f}$ today and pays \$1 tomorrow with certainty is paying a riskless interest rate of r_f.

The SDF is assumed to follow a lognormal distribution. Hence,

$$\log(\tilde{Q}) \sim N\left[-\log(1+r_f)-\frac{1}{2}\sigma_{SDF}^2, \sigma_{SDF}^2\right], \tag{19.34}$$

where σ_{SDF}^2 is the logarithmic variance of the SDF. This parameter is to be determined.

To calculate the expected return and the standard deviation of the return given by Equation 19.33, first, the price of a security that pays $\tilde{Q}^{-\theta}$ needs to be calculated:

$$P_\theta = \mathrm{E}[\tilde{Q}^{1-\theta}] = (1+r_f)^{\theta-1}\exp\left[\frac{1}{2}\theta(\theta-1)\sigma_{SDF}^2\right]. \tag{19.35}$$

The expected value of $\log(1+\tilde{R}_\theta)$ is

$$\mathrm{E}[\log(1+\tilde{R}_\theta)] = \theta\left[\log(1+r_f)+\frac{1}{2}\sigma_{SDF}^2\right]-\log(P_\theta). \tag{19.36}$$

The expected return is

$$E_\theta^{SDF} = \exp\left\{\mathrm{E}[\log(1+\tilde{R}_\theta)]+\frac{1}{2}\theta^2\sigma_{SDF}^2\right\}-1. \tag{19.37}$$

The standard deviation of return is

$$S_\theta^{SDF} = (1+E_\theta^{SDF})\sqrt{\exp(\theta^2\sigma_{SDF}^2)-1}. \tag{19.38}$$

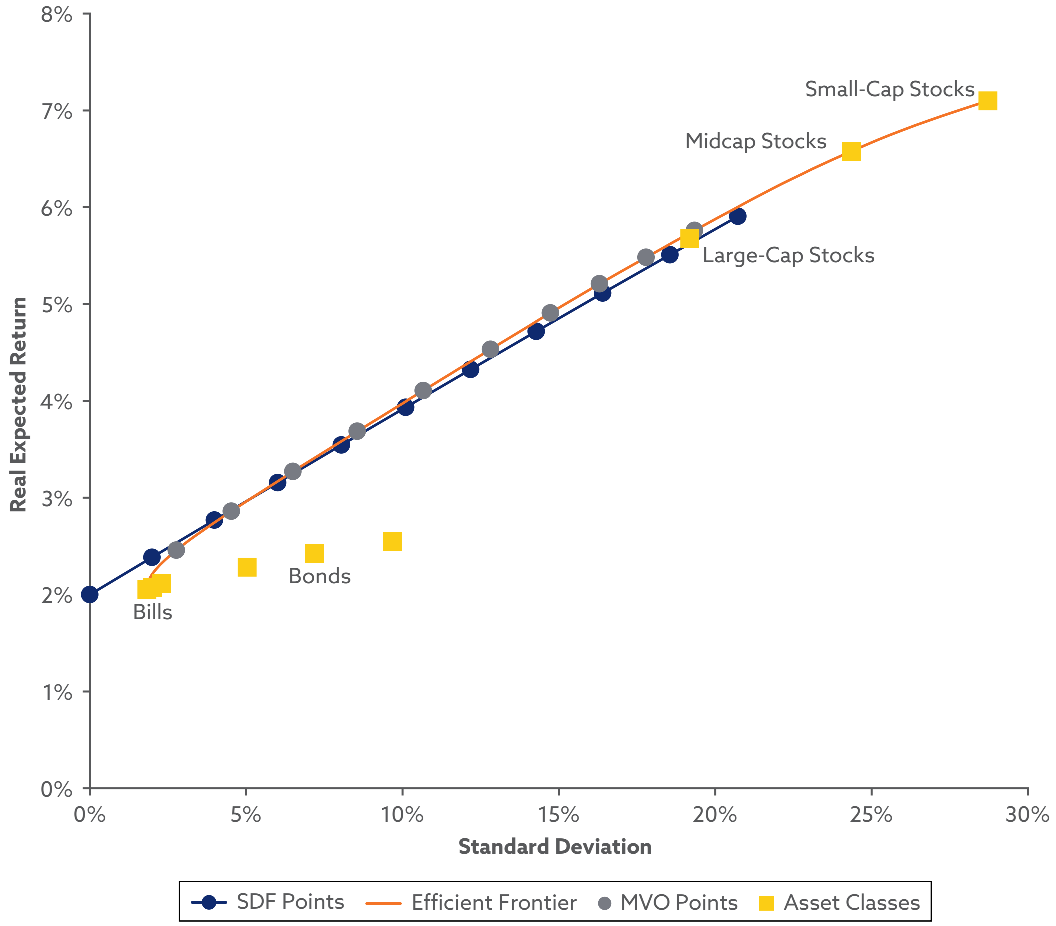
To find σ_{SDF}^2, it is assumed that the portfolio with θ = 100% is the equity portfolio in Exhibit 19.18 (this is the normalized equity subportfolio of the reference portfolio). The annualized covariance matrix shows that the standard deviation of this portfolio is 20.72%. $S_{100\%}^{SDF}$ is equated to this value. Using Equations 19.35–19.38,

$$\left(\frac{S_{100\%}^{SDF}}{1+r_f}\right)^2 = [\exp(\sigma_{SDF}^2)]^2[\exp(\sigma_{SDF}^2)-1]. \tag{19.39}$$

Solving Equation 19.39 for σ_{SDF} results in σ_{SDF} = 19.38%.

Exhibit 19.19, adopted from Idzorek and Kaplan (2024) and Kaplan and Idzorek (2025), illustrates the calibration process. Starting at the bottom, the connected blue dots show the 10 risk–expected return combinations associated with 10 different values for θ — 10%, 20%,…, 100% — coming from Equations 19.37 and 19.38. The gray dots on the orange efficient frontier identify 10 risk–expected return combinations from maximizing the Levy–Markowitz CRRA utility function for the same 10 values of θ. Equation 19.31 is solved for E_R^*, the expected return that minimizes the sum of the squared Euclidean distances between the 10 corresponding risk–expected return points from each model. (The 10 values are used to span the relevant part of the efficient frontier without making the minimization process too computationally intense.) The orange curve is simply the complete mean–variance-efficient frontier as defined in Equation 19.28.

Exhibit 19.19. Calibration Process for Expected Returns in Mean–Variance Optimization



Source: Calculations by the author using Ibbotson Indices data.

Key Takeaways

- Parametric forecasting models allow the formation of probabilistic forecasts of cumulative wealth and compound annual returns from moments of a return distribution. These forecasts consist of percentiles of wealth or return at various holding periods.
- The lognormal forecasting model uses only mean and standard deviation because the skewness and excess kurtosis of a lognormal distribution depend solely on its mean and standard deviation.
- The lognormal forecasting model works well for well-diversified portfolios and is the model of choice in most situations.

- If at long horizons the skewness and excess kurtosis of a wealth distribution do not converge to those of a lognormal distribution, the lognormal forecasting model is not appropriate.
- The Johnson forecasting model is an alternative to the lognormal forecasting model that explicitly takes skewness and kurtosis into account.
- In extreme cases, such as wealth distributions for small-cap stocks, the Johnson forecasting model results in distributions with large left tails at long horizons.
- Although the standard deviations and correlations used as inputs for mean–variance optimization are usually estimated using historical return data, it is important that the expected returns be consistent with an economic model. I present a way for doing this that uses reverse optimization.

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CHAPTER 20. FORECASTING EQUITY AND BOND RETURNS

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Bootstrapping Future Return Distributions

In this chapter, we revisit the landmark forecasting methodology of Ibbotson and Sinquefield (1976b), bringing it forward with modern bootstrapping techniques and comparisons drawn from the five decades of research that followed that original work. Our goal is practical: to produce credible long-horizon return forecasts that are grounded in history, disciplined by current market conditions, and stress tested against the widest available international evidence.

The approach belongs to a family of forecasting methods that are simpler in spirit than the parametric models covered in the previous chapter—and often just as useful. Rather than fitting an explicit statistical model to return data, these methods construct future scenarios by resampling directly from the historical record. The past, rearranged in new sequences, becomes the raw material for the future. That is the core idea of bootstrapping, and it is a powerful one.

Bootstrap methods are particularly well suited to financial data. Asset returns are fat-tailed and skewed—properties that parametric models can struggle to capture cleanly. By drawing directly from observed historical returns, bootstrap forecasts pick up these features automatically, without needing to specify or defend a particular distributional assumption.

The Ibbotson–Sinquefield (IS) model lies in the middle ground between a pure bootstrap and a fully parametric forecast. It resamples historical risk premiums but anchors expectations to the current Treasury yield curve. It also models inflation and real short rates as persistent processes rather than purely random draws. This blend of historical resampling and economic structure is what makes the IS framework robust—and is what has made it a touchstone for long-horizon forecasting for nearly fifty years.

We compare the IS model with the circular block bootstrap (CBB), a fully nonparametric method that preserves short-run time-series dependence without imposing any economic structure. We also apply a global mean adjustment—shifting US return expectations toward the broader international experience—to guard against overextrapolating what may have been an exceptionally favorable century for US markets into the future when making forecasts. The result, using data through 2025 and anchored to the current yield curve, is a forecast of approximately 8.0% nominal and 5.6% real geometric average equity returns over the 2026–50 horizon. Readers interested primarily in the forecasts themselves can skip directly to the final section of this chapter, titled “Forecasts.”

The Ibbotson–Sinquefield Simulation Model

The IS methodology was one of the first to show investors not just a single expected return but a full range of plausible long-horizon outcomes, along with the probability of each. To appreciate how the approach works, it helps to understand what made it possible. The release of the Stocks, Bonds, Bills, and Inflation (SBBI) dataset in the mid-1970s was a landmark in financial research. For the first time, investors and researchers had access to a standardized, long-run record of actual US asset-class returns—one stretching back to 1926—that reflected what investors could realistically have earned.

With nearly five decades of consistent data in hand, it became possible to ask a new kind of question: What does history tell us about the range of outcomes a long-term investor might face? The IS framework answers that question by simulating the future using the past. Rather than modeling each asset class in isolation, it draws returns across all asset classes simultaneously, preserving the natural relationships between them—how stocks, bonds, and bills have historically tended to move together or apart. This analysis matters enormously in portfolio construction, where the interplay between assets is at least as important as the return of any single one.

But the IS model does not simply assume the future will resemble the past. Its anchor is the yield curve. Long-term government bond prices embed the market’s collective expectations about future interest rates and inflation, and the IS model uses those expectations to set the baseline path for all asset classes. Forward rates extracted from the yield curve determine where returns are expected to go—both in nominal terms and after inflation. History then plays a different but equally important role: It tells the model how returns are likely to vary and fluctuate around that market-implied path. Rather than setting the destination, historical data inform the journey. They capture how volatile markets have been, how asset classes have moved relative to one another, and how far outcomes have tended to stray from expectations. The result is a simulation grounded in where markets stand today, enriched by nearly a century of experience about how they actually behave.

To formalize this intuition, we now describe the structure of the model more precisely. We begin with the role of the yield curve in shaping long-run expectations and then outline how returns are decomposed and simulated within the framework.

Yield Curves and “Consensus” Expectations

A key feature of the IS framework is its explicit use of the government bond yield curve to anchor long-run expectations. At the time of the forecast, the observed Treasury yield curve is treated as a summary of current market information about future interest rates. By extracting one-year forward rates from the yield curve, the model recovers the market’s consensus expectations of future short-term nominal interest rates, up to a maturity premium.

Let Y_N denote the yield to maturity on an N-year Treasury bond. The corresponding one-year forward rates $\{F_n\}$ are computed mechanically from the yield curve and interpreted as

$$F_n \approx \mathbb{E}(R_{f,n}) + \hat{\mathbb{E}}(R_H), \tag{20.1}$$

where $\mathbb{E}(R_{f,n})$ is the expected nominal one-year risk-free return n years ahead and $\hat{\mathbb{E}}(R_H)$ is the historical average maturity premium.

Expected nominal short rates are then further decomposed into expected inflation and expected real short rates:

$$\mathbb{E}(R_{f,n}) \approx \mathbb{E}(R_{I,n}) + \mathbb{E}(R_{r,n}). \tag{20.2}$$

Because the yield curve does not specify real rates or inflation, the model uses historical dynamics of real rates to forecast $\mathbb{E}(R_{r,n})$ and adjust the mean of the simulated inflation process so that the resulting nominal short-rate path is consistent with the forward rates implied by the yield curve.

This procedure embodies what Ibbotson and Sinquefield (1976b) described as a "consensus" forecast. The simulated economy evolves according to historically observed dynamics, but its long-run expectations are anchored to information implied by current market prices. Changing the initial yield curve therefore shifts the expected path of inflation, real rates, and expected returns on all asset classes in the simulation.

Decomposition of Returns into Components

Given the expected path of nominal short-term interest rates implied by the yield curve, the IS model constructs asset returns from a small number of economically interpretable components. Rather than modeling each asset class directly, nominal returns are decomposed into inflation, real interest rates, and asset-specific risk premiums.

In the original study (Ibbotson and Sinquefield 1976a), annual nominal total returns were constructed for five US asset categories: common stocks ($R_{m,t}$), long-term government bonds ($R_{g,t}$), long-term corporate bonds ($R_{c,t}$), Treasury bills ($R_{f,t}$), and inflation ($R_{I,t}$). From these series, the following components are defined:

- Inflation, $R_{I,t}$
- The real short rate, $R_{r,t}$
- The equity risk premium, $R_{p,t}$
- The maturity (horizon) premium, $R_{H,t}$
- The default premium, $R_{d,t}$

All these components are defined using exact multiplicative relationships. For example, the equity premium is defined as the excess return on stocks relative to T-bills,

$$R_{p,t} = \frac{1+R_{m,t}}{1+R_{f,t}} - 1, \tag{20.3}$$

and the real short rate is obtained by deflating the bill return by inflation,

$$R_{r,t} = \frac{1+R_{f,t}}{1+R_{I,t}} - 1. \qquad (20.4)$$

In the simulation, however, returns are recombined using an additive approximation:

$$R_f \approx R_r + R_I; \quad R_m \approx R_f + R_p; \quad R_g \approx R_f + R_H; \quad R_c \approx R_g + R_d. \qquad (20.5)$$

Ibbotson and Sinquefield (1976b) noted that the omitted interaction terms are small at annual frequencies. The additive structure greatly simplifies both the interpretation and implementation of the model while remaining close to the underlying accounting identities.

Time-Series Structure and Persistence

To ensure internal consistency with the yield-curve-implied path of expected short rates, the IS model imposes a simple time-series structure on both inflation and real short rates. The motivation for this addition is straightforward: Inflation and interest rates are known to exhibit persistent behavior over time, with shocks tending to have lasting effects. A purely nonparametric resampling of historical inflation rates would fail to capture this persistence, potentially generating unrealistic sequences of outcomes, such as sharp inflation followed immediately by deep deflation, which are rare in actual macroeconomic data.

Inflation and the real short rate are each modeled as first-order autoregressive, or AR (1), processes:

$$R_{I,t} = \gamma_{I0} + \gamma_{I1} R_{I,\,t-1} + \varepsilon_{I,t}; \quad R_{r,t} = \gamma_{r0} + \gamma_{r1} R_{r,\,t-1} + \varepsilon_{r,t}. \qquad (20.6)$$

These AR (1) specifications capture the slow-moving nature of macroeconomic conditions and interest rates, ensuring that simulated paths evolve smoothly around the yield-curve-consistent mean rather than exhibiting implausibly sharp reversals. All coefficients are saved, and the two sets of residuals, $\{\varepsilon_{I,t}\}$ and $\{\varepsilon_{r,t}\}$, are retained for the simulation. These residuals are then resampled during the simulation to generate realistic shocks for inflation and the real short rate, jointly with the fitted coefficients.

By contrast, the equity, maturity, and default premiums are assumed to be serially uncorrelated. In addition, their historical realizations are treated as draws from a stable joint distribution. This approach reflects Ibbotson and Sinquefield's (1976b) view that risk premiums are difficult to forecast through time, even though they exhibit meaningful contemporaneous comovement across asset classes.

Simulation Mechanics and Cross-Asset Dependence

Conditional on the yield-curve-implied path of expected short-term interest rates, the simulation proceeds sequentially, year by year. The initial starting point for inflation and the real short rate is taken from the last observed historical value. Future paths are generated as follows:

- Inflation and the real short rate evolve according to the previously estimated AR (1) processes. Rather than drawing shocks independently, the simulation resamples entire rows of the residual matrix from the AR (1) estimation, so that the inflation shocks, $\{\varepsilon_{I,t}\}$ and $\{\varepsilon_{r,t}\}$, are always drawn from the same historical year, *t*. This approach preserves their empirical correlation. The maturity premium shock is drawn from the same historical year as well, although this is required only when forecasting returns on longer-duration assets.

- Asset-specific premiums, including equity and default premiums, are likewise drawn together. T-bill returns are constrained to be nonnegative by setting any negative draws to zero and rescaling the remaining values to preserve the historical mean.
- Nominal and real returns for each asset class are then built up from their components using the additive identities described in the previous section.

Repeating this procedure over many simulations produces a large ensemble of plausible future return paths, giving us a distribution of possible return paths over the forecast horizon.

Long-Horizon Outcomes

The simulated return paths are compounded into wealth indices, from which geometric mean returns and percentile bands are computed at each horizon. These outputs form the basis of the familiar fan-shaped "tulip" and "trumpet" plots that summarize the conditional distribution of long-run outcomes implied by the IS model.

Viewed as a whole, the IS model occupies a middle ground between purely historical resampling and fully parametric forecasting. It preserves the empirical joint behavior of asset returns, imposes persistence where economically justified, and disciplines expectations using information from financial markets. Because of the anchoring of expectations to the yield curve, the resulting forecasts are sensitive to prevailing interest rate conditions, allowing the model to adapt to changing economic environments.

Overview of Bootstrap Methods

To understand the IS model's connection to bootstrap methods, it helps to start with what bootstrapping actually is.

The central idea is simple: Treat the historical record as the best available guide to how returns are generated, and build simulated future paths by repeatedly drawing from that record with replacement. Each simulated path is made up entirely of past observations, reshuffled into a new sequence, with some years possibly appearing more than once and others not at all.

This approach was formalized by Efron (1979) in what is now called the i.i.d. bootstrap—so named because each draw is independent and identically distributed, meaning that past draws have no influence on future ones. By reshuffling historical outcomes, the model constructs a distribution of synthetic future paths without making any assumptions about the underlying data-generating process. It is precisely this resampling mechanism—drawing residuals from the historical record—that the IS model also uses to simulate inflation, interest rate, and risk premium paths. That shared feature is why the IS model has long been associated with bootstrapping.

The difference lies in structure. The i.i.d. bootstrap imposes none: Draws are independent, with no allowance for persistence, trends, or economic relationships. The IS model wraps the same resampling logic inside an economic framework—the AR (1) processes for inflation and real rates and the yield-curve anchor—that gives the simulated paths realistic dynamics.

In portfolio applications, bootstrap methods are typically applied to joint observations across asset classes rather than to individual assets. Drawing an entire year's returns across stocks, bonds, and bills together preserves the historical relationships between them by construction, making the approach well suited to portfolio analysis, where those relationships matter. This empirical grounding, and the fact that no parametric assumptions are required, has made bootstrapping widely used in finance—from studying long-horizon return predictability (Goetzmann 1990; Goetzmann and Jorion 1995) to analyzing tail risk (Daníelsson and de Vries 1997, 2000).

The absence of time-series structure is both the method's strength and its principal limitation. On the one hand, bootstrap forecasts are transparent and rooted directly in the data. On the other, because draws are independent, the simulation cannot reproduce such features as inflation persistence. An i.i.d. bootstrap could plausibly generate a year of sharp inflation followed immediately by deep deflation—a sequence that is rare in practice. This is precisely the gap the IS model closes through its AR (1) structure for inflation and real rates.

A nonparametric alternative exists for closing the same gap: the block bootstrap. Rather than drawing individual yearly observations, block methods resample contiguous segments of the historical record, preserving the short-run time-series dynamics within each block without imposing a parametric model. We focus on two closely related variants: the moving block bootstrap (MBB) and the circular block bootstrap (CBB). Both are well established in the resampling literature (Lahiri 2003), and we use the CBB as a nonparametric benchmark when comparing forecasting approaches in the "Forecasts" section (see also Künsch 1989; Liu and Singh 1992; Politis and Romano 1994).

The Moving Block Bootstrap

The mechanics of this approach are straightforward. Given a time series $\{r_t\}_{t=1}^{T}$ and a block length L, overlapping blocks are constructed by sliding a window across the sample, yielding $T - L + 1$ blocks:

$$\mathcal{B}_1 = (r_1, \ldots, r_L), \mathcal{B}_2 = (r_2, \ldots, r_{L+1}), \ldots, \mathcal{B}_{T-L+1} = (r_{T-L+1}, \ldots, r_T). \tag{20.7}$$

These blocks are then sampled with replacement and concatenated to form a bootstrap path of approximately the original length. Dependence is preserved within each block, although it is broken across blocks. The block length, L, governs the tradeoff: A length of one year results in the i.i.d. bootstrap, whereas a length of five years, for example, captures a full business cycle of dependence. The increased time-series dependence comes at the cost of fewer distinct segments from which to draw.

The Circular Block Bootstrap

The CBB addresses a subtle problem in the moving block bootstrap. The issue in MBB block formation is that observations near the start and the end appear in fewer blocks, introducing a representativeness bias. The CBB treats the series as circular, allowing blocks to begin at any index $t \in \{1, \ldots, T\}$ and wrap around the sample when they reach the end:

$$(r_{T-1}, r_T, r_1, r_2, \ldots). \tag{20.8}$$

This yields T possible starting points rather than $T - L + 1$, giving every observation an equal amount of representation. Thus, the MBB and CBB methods are closely related and, in fact, equivalent asymptotically. In finite samples, however, the CBB typically provides a more uniform representation of the data. For this reason, although the MBB serves as a useful starting point, we use the CBB as the modern comparative methodology for the IS model.

Block bootstrap methods thus occupy a natural middle ground between the i.i.d. bootstrap and the IS model by preserving short-run time-series dependence without imposing parametric structure or yield-curve anchoring. This makes the CBB a useful benchmark for isolating the contribution of economic structure in the IS model, which is how we use it in the "Forecasts" section. We also experimented with hybrid approaches that resample blocks of AR (1) residuals or risk premiums rather than individual draws, but these yielded results nearly identical to the original IS model, confirming that the AR (1) structure already captures the relevant time-series dependence. We therefore focus on the pure CBB and the original IS model in what follows.

Estimation Biases of Historical Data

All forecasting methods that rely on historical data, whether fully nonparametric bootstraps or hybrid frameworks, such as the IS model, share a fundamental limitation: They assume that the past provides a meaningful guide to the future. Simulated outcomes are constructed from the historical observations and therefore inherit both statistical properties and the economic environment of the sample period. The question is not whether historical data are useful—they clearly are—but how representative they are of the future environment we are trying to forecast.

Several distinct sources of bias are relevant when using US historical data to form long-run return expectations. The first concern is survivorship and selection bias. Markets that experienced permanent closure, default, or prolonged stagnation are typically absent from forecasting exercises. By conditioning on the performance of a market that not only survived but thrived, forecasters risk overstating expected returns relative to what a broader set of possible historical outcomes would imply (see, e.g., Brown, Goetzmann, Ibbotson, and Ross 1992; Brown, Goetzmann, and Ross 1995).

A second source of bias is valuation expansion. To see why valuation changes matter for forecasting, it helps to decompose what drives equity returns over time. At its most basic, the total return on an equity investment comes from three sources: the dividend yield, the growth in earnings, and any change in the price investors are willing to pay per dollar of earnings—the P/E. The first two reflect the underlying economics of the business. The third reflects such factors as risk appetite, market participation, investor sentiment, liquidity, and demographics. Over the twentieth century, US equity valuations expanded dramatically. Investors moved from applying relatively low multiples to corporate earnings—reflecting the uncertainties of an earlier era, limited diversification, and less liquid markets—to the substantially higher multiples that prevailed in recent decades. This rerating added a persistent tailwind to realized returns that is visible in the historical record and therefore embedded in any simulation that resamples from it.

The problem is that valuation expansion of this magnitude may not repeat. For instance, a P/E can expand from 10 to 20, generating a powerful boost to returns over the period in which it occurs. But a multiple cannot expand from 20 to 40 with the same ease, and it certainly cannot keep expanding indefinitely. To the extent that future returns revert toward their fundamental drivers—dividend income and real earnings growth—rather than continuing to benefit from further multiple expansion, a bootstrap simulation anchored in the historical record can systematically overstate what investors should expect in the future.

This effect is not small. Empirical decompositions of historical US equity returns suggest that valuation expansion has accounted for a meaningful share of the total realized premium of stocks over bonds. Stripping it out produces a materially lower estimate of the forward-looking equity premium—one more consistent with what the current level of valuations and dividend yields would imply.

More generally, the macroeconomic and institutional stability of the United States, alongside technological progress, favorable demographics, and geopolitical dominance, has created a unique environment over the past century. Forecasts conditioned solely on this experience may embed an optimism that is difficult to disentangle from the data. These biases point to two simple adjustments that can serve as transparent starting points for thinking about how sensitive forecasts are to sample assumptions.

The first is a valuation adjustment that strips out the contribution of P/E expansion from historical returns. One can construct a return series that better reflects what investors might expect if multiples remain stable in the future. In practice, this approach tends to produce forecasts that are modestly lower than the unadjusted US estimates but still reflect the favorable underlying growth experience of the US economy.

The second is a global mean adjustment, which aligns the mean of the US return series with the broader international experience using data from Dimson, Marsh, and Staunton (2026). Rather than replacing US data entirely, the adjustment shifts the mean while preserving the distributional characteristics of the US return series:

$$r_t^{adj} = r_t^{US} - (\mu_{US} - \mu_{WxUS}), \tag{20.9}$$

where μ_{US} is the historical mean of US returns and μ_{WxUS} is the historical mean of world ex-US returns (GDP weighted across countries). This adjustment captures a wider range of economic and political histories, including episodes of war, prolonged stagnation, and institutional disruption that are not present in the US record.

Because the global adjustment produces lower expected returns than the valuation adjustment while remaining very transparent, it serves as the more conservative of the two, and we adopt it as our preferred baseline in the “Forecasts” section. Presenting forecasts relative to this adjustment gives readers a sense of how much of the US historical return premium may reflect conditions that are unlikely to persist. Importantly, neither adjustment should be interpreted as a formal correction; both are better understood as alternative conditioning assumptions about which historical outcomes are most informative regarding the future.

It is worth noting that much more sophisticated adjustments exist. We focus on these two simple adjustments because they are transparent, replicable, and sufficient to illustrate the sensitivity of long-horizon forecasts to sample assumptions.

Forecasts

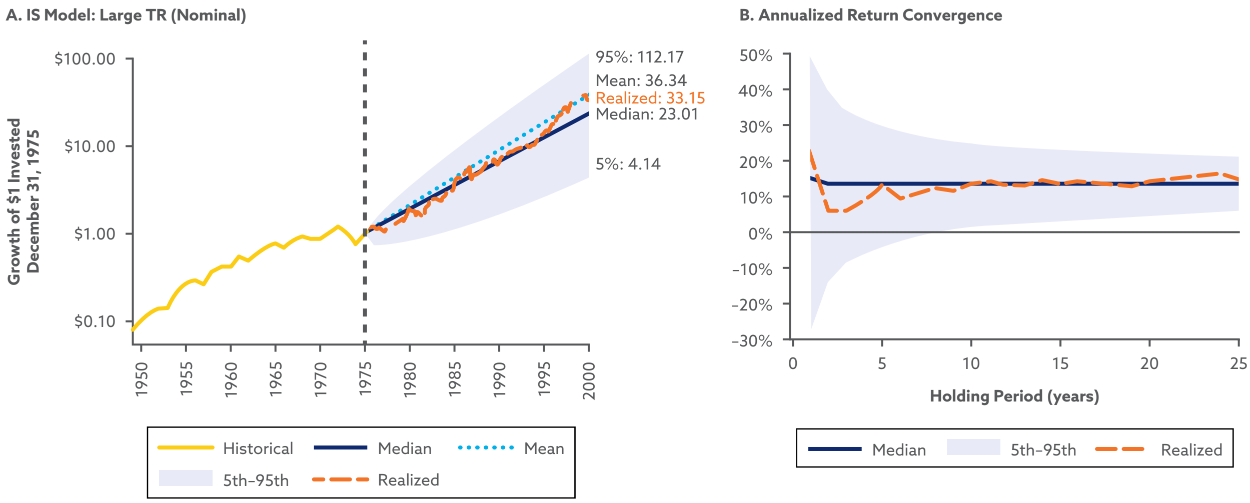
We now present long-horizon forecasts of US equity returns over a 25-year horizon. Each forecast represents a full distribution of potential future outcomes rather than a single point estimate. We summarize these distributions by reporting their mean and highlighting the median and the 5th–95th percentile bands, which together provide a compact description of the potential range of outcomes.

The Original Ibbotson–Sinquefield Forecasts

The original Ibbotson–Sinquefield (1976b) simulations attracted considerable attention both for their novel methodology and their optimistic long-horizon equity return forecasts. Using annual US data from 1926 to 1974 and anchoring expectations to the 1975 yield curve, the authors forecasted a geometric average return of approximately 13% per year for US common stocks over the subsequent 25 years. After adjusting for inflation, this forecast corresponded to an expected real return of roughly 6.3% per year.

Exhibit 20.1 reproduces the original IS forecast for nominal equity returns using the Ibbotson Equity Indices large-cap data. Panel A shows the familiar tulip plot summarizing the distribution of simulated wealth paths, and Panel B presents the corresponding trumpet plot of annualized geometric returns across holding horizons. The realized nominal returns lie close to the center of the simulated distribution for the entire simulation period.

Exhibit 20.1. Replication of the Ibbotson–Sinquefield (1976b) Bootstrap Forecast for US Equities, Anchored to the 1975 Yield Curve, with Realized Returns Overlaid, 1976–2000



Source: Calculated by the authors using Ibbotson Indices data. Underlying data from CRSP and US Bureau of Labor Statistics.

These predictions were later revisited by Ibbotson (2006), who confirmed their exceptional accuracy. Realized returns tracked the forecasted mean nearly identically for the first 20 years before deviating slightly, only to revert back toward the forecast center by the end of the period. Much of the difference between the forecasted and realized results reflects inflation dynamics: The higher-than-expected inflation of the mid-1970s pushed up subsequent nominal forecasts, but as inflation declined sharply over the following decades, realized real equity returns exceeded the model's expectations even as nominal returns tracked the forecasted path closely. The model got the nominal trajectory right for largely the right reasons, even if the underlying real return versus inflation split came out differently than predicted.

The episode offers the right frame for interpreting any long-horizon forecast: The IS methodology is best understood as a statement about the central tendency of a wide distribution—not a guarantee and not immune to history's capacity for surprise. With that backdrop in place, we turn to our own forecast for 2026–2050.

2026–2050 Forecasts

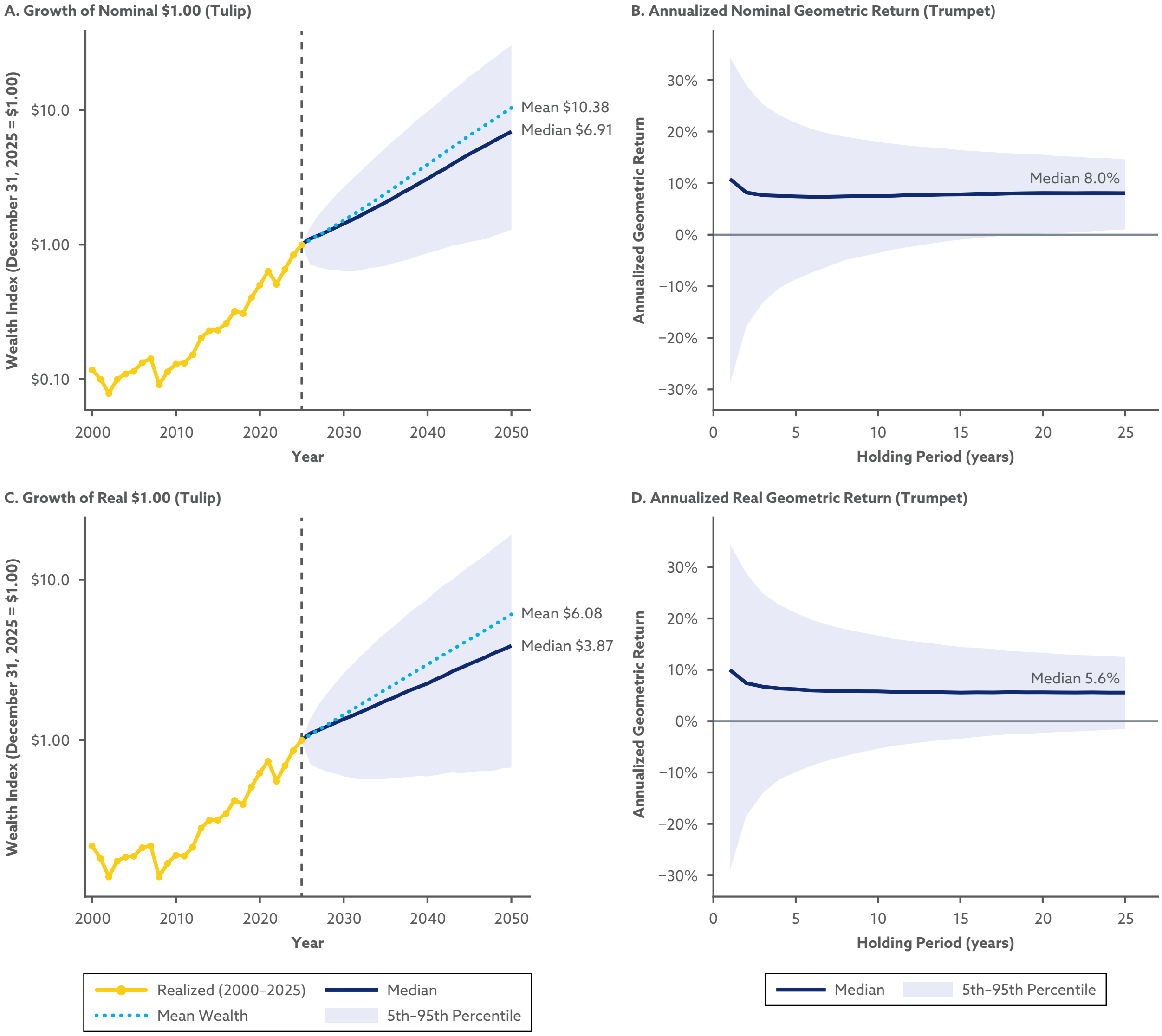
Since the original forecasts proved so accurate over their own 25-year window, we apply the same IS framework to the period 2026–2050 using data from 1926 to 2025, anchoring expectations to the end of 2025 Treasury yield curve. We accompany the IS model forecasts with forecast results generated by the circular block bootstrap (CBB) model as a fully non-parametric comparison, helping assess the role of anchoring expectations to the end of 2025 Treasury yield curve. We run each of the forecast models on two samples: the US record alone and a globally adjusted series. The IS model generates both nominal and real return forecasts, as in the original study, while the CBB is applied only to the real return series due to its indifference about the prevailing interest rate conditions.

On the unadjusted US record, the IS model predicts geometric mean returns of roughly 9.5% nominal and 7.0% real, with the CBB producing a near identical 7.0% real return. Although these figures fall well below the original study—reflecting the change in interest rate environment—many would still call them optimistic, and for a good reason. The very history that these forecasts draw upon—the US experience of the past century—was in many respects an exceptionally fortunate one, and this good fortune is inherited right into our forecasts. We therefore take the globally adjusted IS forecast as our main estimate, one that leans on the broad sweep of global market history rather than the US record alone.

Shifting the sample toward the international experience lowers the forecast by roughly 1.5 percentage points, to approximately 8.0% per year in nominal terms and 5.6% per year in real terms. **Exhibit 20.2** presents the IS forecasts' tulip and trumpet plots using this adjusted US sample. The CBB again tracks the IS model's real figure closely, at 5.5% per year.

The adjustment behind the forecasts retains the distributional shape of the US series, tempering the sample mean toward the broader international experience while leaving its variance intact. The dispersion in the trumpet plots, which tell us the range and relative likelihood of both good and bad outcomes, is therefore still that of the US record, only with the center shifted. This is the same empirical, assumption-free distribution that we highlighted earlier as the strength of non-parametric methods.

Exhibit 20.2. Ibbotson–Sinquefield Bootstrap Forecast for Globally Adjusted US Equities, Anchored to the 2025 Yield Curve, 2026–2050



Sources: Ibbotson Indices; Dimson–Marsh–Staunton global returns database; computations by the authors.

Notes: Panels A and B (top) show nominal return forecasts, with Panel A showing cumulative wealth indices and Panel B compound annual returns; Panels C and D show real return forecasts, with Panel C showing cumulative real wealth indices and Panel D compound annual real returns. The graphs are based on the globally adjusted US return data.

Since the IS and CBB methods produce closely aligned results for the 2026–50 period, the plots between the two are nearly identical. We therefore present the CBB results only as summary statistics in **Exhibit 20.3**. The close agreement between the two methods is partly coincidental and partly structural. At long horizons, short-run time-series dependence—whether captured through the block resampling or an AR (1) process—becomes increasingly irrelevant as returns accumulate, especially because we use annual returns. Thus, the repeated sampling from the same empirical distribution naturally drives estimates toward similar long-run means. In that sense, convergence is expected to an extent.

But the reason that both the IS and CBB forecasts formed using 2025 data are so close to one another is the prevailing macroeconomic environment. US short-term rates and inflation are close to their past-century averages, which means the yield-curve anchoring that distinguishes the IS model from pure resampling happens to add relatively little right now. When the present looks like the historical average, the two approaches rooted to the historical data will mechanically arrive at similar numbers. This is not always the case, however. In 1975, for example, elevated inflation pushed IS nominal forecasts higher, resulting in annual forecasts roughly 4.5 percentage points higher than what the CBB would have predicted. The convergence we see today is therefore as much a statement about current conditions as it is about the methods themselves.

Exhibit 20.3 reports all of the forecasts using both methods (IS and CBB) and both samples (unadjusted US and globally adjusted). The global adjustment lowers the IS forecast by approximately 1.5 percentage points, from 9.5% to 8.0% in nominal terms and from 7.0% to 5.6% in real terms. The CBB real figures also move by the same amount when compared across the two samples. The 8.0% nominal and 5.6% real globally adjusted IS forecast is the one we put forward as our geometric mean forecast for the next 25 years.

We believe these figures are optimistic yet reasonable. A useful way to assess this is to decompose the real forecast into its components. Current real short-term interest rates are

Exhibit 20.3. Forecasted Equity Return Estimates for 2026–2050: Unadjusted and Adjusted Samples

Method	IS	CBB
Unadjusted forecast (2026–2050)		
2026–2050 (Nominal)	9.5%	—
2026–2050 (Real)	7.0%	7.0%
Global returns adjusted forecast (2026–2050)		
2026–2050 (Nominal)	8.0%	—
2026–2050 (Real)	5.6%	5.5%

Sources: Ibbotson Indices; Dimson–Marsh–Staunton global returns database; computations by the authors.

Notes: Reported values are annualized geometric mean return forecasts. “Unadjusted” refers to simulations based on US historical data without international mean adjustment. “Adjusted” refers to simulations incorporating a global mean adjustment.

approximately 0.9% per year.[1] An expected real equity return of 5.6% therefore implies a forecasted equity risk premium of roughly 4.7% over the risk-free rate. This figure fits well in line with the long-run literature. Therefore, we are not forecasting an unusual equity premium for the next quarter century; rather, we are forecasting one that looks very close to what it always has been, and we believe that is the right starting point.

Measuring the Unmeasurable: Indexing and the Reduction of Knightian Uncertainty

There is a deeper reason the adjusted forecast is reasonable, one that connects to the contribution of Ibbotson and Sinquefield. It has to do with how investor attitudes and equity markets have themselves changed over the past century. In equilibrium, expectations about equity returns will influence investor behavior and vice versa. For 1970s investors, the crash of 1929, the volatility of the 1930s, and the sharp market decline after the 1972 oil crisis loomed large in financial market experience. Statistical analysis like that of Ibbotson and Sinquefield had yet to be performed and widely reported, making it difficult for investors to assess the probability of any given outcome. This Knightian uncertainty—the risk of the "unknown unknown"—may explain the high equity risk premium over the fifty years from 1926 to 1975 and motivate a conservative approach to forecasting future returns.

One can debate how much or how little was known about the risk and uncertainty of equity investing between 1926 and 1975. The Great Crash and ensuing Great Depression in the real economy presented investors with a palpable sense that financial life as they knew it might be coming to an end. Radical change was in the air, and although it seemed likely from contemporary accounts that the financial system would survive in some form, a full recovery, a move to new highs, and a superboom later in American history was only one conceivable outcome. Other, less rosy outcomes seemed more likely.

The 1970s were different. Returns were deeply disappointing, there were many corporate bankruptcies and consolidations, and there was civil unrest. But there was little or no talk of dismantling the financial system and starting over. The market would recover, remain low, or go lower, but it would not go away.

Thus, some measure of Knightian uncertainty was resolved in 1926–1975 that didn't need to be resolved in 1976–2026 and still doesn't (looking forward to 2050). This observation supports the idea of assuming a somewhat lower risk premium in the next 25 years than over the last 100 and, in particular, lower than over the first half of the last 100.

Investors today not only have the benefit of a century and more of past market returns but also a statistical toolkit for predicting future return distributions. The empirical project that Ibbotson and Sinquefield began, and that many of the coauthors of this volume have extended, played a catalyzing role in converting market uncertainty into tractable risk metrics. Thanks in large measure to empirical financial research, the long-run record is now far richer than it was when Ibbotson and Sinquefield first ran their simulations. Data collection and modern statistical methods such as bootstrapping and survivorship analysis have accomplished what amounts,

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[1] As of 31 December 2025.

almost by definition, to the reduction of Knightian uncertainty—that is, quantification of the previously unquantifiable.

Over the subsequent five decades, this resolution of deep uncertainty has made equity markets a normal, expected feature of economic life for households, institutions, and policymakers. The widespread adoption of passive equity investing, using strategies that closely match the capital-weighted portfolio strategies studied in the first SBBI volume, is compelling evidence that the accumulated knowledge about distributions has influenced beliefs and behavior. The first retail index fund also appeared in 1976 but was initially greeted with widespread skepticism; five decades later, index funds have surpassed active managers in US equity assets, more than $11 trillion is benchmarked to the S&P 500, and index and target-date funds are the default vehicles of retirement saving.

Investment trends since 1976 bear directly on our forecast. We cannot simply re-run the 1976 analysis in 2026, because the original study and the movement it launched have changed how investors understand equity risk. Part of the past century's high realized return may well have been compensation for an uncertainty that has since been measured and largely resolved; as that uncertainty was priced in, a somewhat lower required premium may have followed—already embedded in current valuations and in the IS model's yield-curve anchoring. Stocks are no safer in any probabilistic sense; the variance remains substantial. But our forecast of 8.0% nominal and 5.6% real is best understood as the market's own long-horizon consensus, in a world where the distribution of equity returns is no longer an unknown unknown.

Conclusion

Fifty years separate the original Ibbotson–Sinquefield simulations from the forecasts in this chapter, and that distance is itself a measure of how far the discipline of finance has come. In 1976, Ibbotson and Sinquefield used the historical record to simulate the full distribution of outcomes a long-term investor might face, anchored to the prevailing yield curve. We have repeated that exercise with half a century of additional data, modern resampling methods, and the widest international evidence now available—and arrive at a forecast in the same spirit as the original: approximately 8.0% nominal and 5.6% real for US equities over 2026–2050, implying an equity risk premium close to its long-run historical value.

That durability is the truest tribute to the original work. The Stocks, Bonds, Bills, and Inflation project did more than document the past; it helped convert the long-run behavior of diversified portfolios from a matter of judgment into a matter of measurement. The half-century of indexing and institutional adoption that followed is evidence of that achievement and the reason any careful forecaster in 2026 must reckon with it. We offer our numbers in that tradition: not a prediction to be defended to the decimal but a distribution, rather than a point, because the future remains, as it always has been, a range of possibilities rather than a certainty.

Key Takeaways

- Using the Ibbotson–Sinquefield model on the globally adjusted US return history, we forecast 8.0% nominal and 5.6% real annualized geometric returns for US equities over 2026–2050.

- Sampling-based long-horizon return forecasts offer a transparent, data-driven way to form expectations of future equity returns. Their strength is that the path from data to forecast is easy to follow, but this same reliance on data is simultaneously their limitation, as the method implicitly assumes that the past is a reasonable guide to the future. The forecasts thus are only as representative as the sample they draw from.
- The Ibbotson–Sinquefield model highlights how incorporating a modest amount of economic structure, such as yield-curve anchoring and persistent inflation dynamics, can produce more economically grounded forecasts. Such forecasts come at the cost of being more sensitive to prevailing market conditions.
- Fully nonparametric block bootstrap methods offer a complementary approach that can also preserve time-series dependence without imposing parametric assumptions.
- The forecast based on US historical data was adjusted by lowering the expected equity risk premium to the international historical equity risk premium mean. The reason for this adjustment is that the US was the best performing equity market, with the US market benefiting during the last 100 years from survivorship, valuation, and institutional circumstances that are not likely to repeat.

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CHAPTER 21. CONCLUSION

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In 1976, Rex Sinquefield and I published "Stocks, Bonds, Bills, and Inflation: Year-by-Year Historical Returns (1926–1974)" in the University of Chicago's *Journal of Business* (Ibbotson and Sinquefield 1976a). This year marks the 50th anniversary of that publication and the 100th anniversary of the 1926 beginning of the Stocks, Bonds, Bills, and Inflation (SBBI) dataset. This year, my coauthors and I introduce a new dataset that we hope will carry the methods and the thinking behind SBBI forward into the future.

Ibbotson Associates updated SBBI continually until 2006, when the firm was sold to Morningstar, Inc. SBBI was updated by Morningstar through 2024, until it was discontinued in early 2025.

The Ibbotson Equity and Bond Indices in this book replace and expand the original SBBI indices. Morningstar announced that it was acquiring CRSP (Center for Research in Security Prices) in September 2025, and the deal closed in February 2026. The indices presented in this book use CRSP (with permission from CRSP) as the underlying data source. Until its acquisition, CRSP was created and affiliated with the University of Chicago's Booth School of Business. I previously served as executive director of CRSP from 1979–1984 while I was a faculty member at Chicago Booth.

In Chapter 2, Tom Idzorek, Larry Siegel, and I describe the summary results of the Ibbotson Equity and Bond Indices over the last 100 years. From 1926 to 2025, the compound total annual return on large-cap stocks was 10.1%. Small caps had a 10.9% return. Long-term US Treasury bonds returned 4.9%, while 30-day Treasury bills returned 3.3%. Inflation was 2.9% over the period.

The partial title of this book is *Exponential Wealth*, reflecting the fact that when total returns are compounded over a long period, with income reinvested and before any taxes or expenses are removed, tremendous wealth can be created. Over the last 100 years, $1 invested at 10.1% in large-cap stocks grew to $14,751. Even after inflation, which caused prices to rise 18-fold, the real value of the original $1 investment is $820. Such exponential wealth does not emerge from the lower returns of bonds and bills: $1 grew in real (inflation-adjusted) terms only 6.5 times for long-term US Treasury bonds and 1.39 times for US Treasury bills.

In general, the higher the risk, the higher the return. Over this 100-year period, there was a positive equity risk premium, horizon (interest rate risk) premium, and small-cap premium, as well as a positive real riskless interest rate. In Chapter 9, Larry Siegel and Carla Nunes study the equity risk premium in detail with various estimation methods. The math and index construction techniques are presented by Jim Harrington and me in Chapter 3.

The US Equity Indices

Otto Manninen, Will Goetzmann, and I computed the Ibbotson Equity Indices from the CRSP data, and we present the results in Chapter 4. The Ibbotson Indices are a set of capitalization-weighted indices that include the top 25 stocks (Mega Cap), Large Cap, Mid Cap, Small Cap, and Micro Cap, along with composite indices that combine these elemental pieces. During the first half of the study period (1926–1975), the cuts are based on decile counts, as the number of stocks in the underlying dataset grow dramatically over time. At the start of the sample in 1926, there were only a few more than 500 eligible stocks in the CRSP database. Thus, Deciles 1 and 2 (large caps) contained, between them, only about 100 stocks. By 1975, after AMEX and Nasdaq stocks had been added to the CRSP database, there were more than 4,600 stocks, with the top two deciles consisting of more than 920 stocks. The large-cap index thus represents the dominant companies of the time, with the same relative positions in terms of importance to the economy.

For the later period, 1976 to present, the index cuts are based on fixed counts. The CRSP datasets continued to grow, reaching a maximum of more than 7,500 stocks in the 1990s. Although the number of stocks has fallen in this century, there are still almost 4,000 stocks today, a sufficient number to provide fixed-count cut-offs. The Large Cap index, for example, consists of the top 300 stocks by capitalization. This number is held constant despite changes in the total count of US stocks being traded on the various exchanges. This is the way that many of today's popular indices, such as the S&P 500 and the Russell 2000, are constructed.

During the full 100-year period, compound annual total returns were 10.07% for large caps, 11.05% for midcaps, 10.95% for small caps, and 11.06% for microcaps. The small-cap premium over large caps is positive, but it is not consistent across all size categories and amounts to only about 1% per year.

In Chapter 5, Will Goetzmann and Otto Manninen analyze the US indices, noting that they are positively skewed with kurtosis, meaning that a few winning stocks account for much of the equity risk premium. These authors, along with coauthor James Tyler, follow up, in Chapter 6, with a study of bubbles, booms, and crashes from 1792 to the present. The authors find that crashes have been rare, mostly unpredictable, and usually followed by recovery rather than a further crash, a finding that enriches our theme of exponential wealth being created by long-term investing in equities.

The US Bond Indices

The Coleman Fisher Ibbotson (CFI) Bond Indices consist of estimated forward interest rates, yield curves, and total returns on US Treasury issues over the period 1926–2025. In Chapters 7 and 8, Tom Coleman and I discuss these yield curves, returns, and methodology. By estimating forward rates, the CFI data can be used to construct any type of yield curve (e.g., par bond, annuity, zero) and price any set of default-free cash flows over the last 100 years. Furthermore, synthetic bond returns of any maturity or duration can be created.

The 100-year history of US Treasury yields can be summarized as follows: Yields fell in the 1930s and then rose, peaking in 1981 and falling thereafter. A graph of the yields looks like a simple, predictable pyramid, with both short- and long-term yields peaking at more than 15% in 1981, although the month-to-month yield changes are nearly random. Because of the rise in yields before 1981, investors experienced capital losses, and because of the later decline in yields, they had capital gains. For the whole period, however, capital gains/losses were near zero, as yields coincidentally started and ended the 100-year period near 4%.

The overall average yields were 3.25% for short-term bills (one month) and 4.86% for long bonds (20 years), providing a historical horizon premium of 1.61%. Because of the rise in yields, the 1925–80 average total return of the long bond was only 2.69%. Because of the later decline in yields, the 1981 to present long bond return averaged 7.62%. Over the entire 100-year period, most of the return came from the yield, whereas most of the volatility came from the change in the yields.

This book features numerous coauthors who have created datasets over the centuries for US and global markets.

Global Markets and Older Data

Ed McQuarrie, in Chapter 10, has backdated the US stock and bond data to 1793, shortly after the Buttonwood Agreement of 17 May 1792, which created the New York Stock Exchange (NYSE). He expands the earlier Goetzmann, Ibbotson, and Peng (2001) work by including stocks beyond the NYSE, as well as additional dividend and capitalization data. His data can potentially be linked to the Ibbotson Indices, starting in 1926. During this pre-1926 period, the United States generally had deflation between wars. US bonds were not riskless but outperformed US equities before the Civil War and almost matched equities for the overall period up to 1926.

In Chapter 11, Elroy Dimson, Paul Marsh, and Mike Staunton provide extensive real total returns for 21 countries, starting in 1900. They show that stocks outperformed bonds and bonds outperformed bills in almost every country. However, the United States, which currently makes up more than half of the global market, is not very representative of the total, because it is the best-performing market over the 126-year period. Later, we adjust our forecasts to reflect the generally lower global returns outside the United States.

The historical London market had a similar experience. In Chapter 12, Will Goetzmann, Fernando Reyes De La Luz, and Geert Rouwenhorst show that during the period from 1870 to 1929, the equity premium over long-term bonds averaged 4.5% per year, with realized returns declining monotonically with the seniority of the asset class in a typical firm's capital structure.

Bryan Taylor also examines stock and bond data in earlier centuries in Chapter 16, summarizing the results of the vast Finaeon dataset. He identifies four financial revolutions, starting with the first Venetian loans in 1171 and then the founding of four East Indian trading companies beginning in the 1600s. He moves on to global stock and bond trading in the 1800s and finally covers the more recent explosion in global issuance and investing.

This book also examines other markets. Geert Rouwenhorst, Rajkumar Janardanan, and Xiao Qiao created a suite of commodity futures. They show in Chapter 13 that the performance of futures returns was distinct from spot returns and that futures were competitive with US stock markets over the period 1871–2025, providing diversification benefits.

Tadaaki Komatsubara, in Chapter 14, measures the remarkable rise in Japanese markets from 1952 to the late 1980s, which ended in a bubble, followed by a two-decade adjustment and a recent recovery. In Chapter 15, Peng Chen documents the Chinese market over 2005–2025, with returns that closely align with longer-term studies of US markets. These results affirm that exponential wealth can be built in a variety of markets around the world, albeit at different rates and times.

David Chambers, Elroy Dimson, Antti Ilmanen, and Paul Rintamäki evaluate and critique the whole index literature in Chapter 17. The authors highlight the challenges: easy-data biases, macro-consistency, replicability, and total return estimation. The authors of Chapter 17 mostly meet these challenges, but of course, index construction is an ongoing learning process as we find out more and more about both markets and history.

The Future

In Chapter 18, "Popularity and Premiums," Tom Idzorek, Paul Kaplan, and I summarize some of our earlier work on how assets are priced—that is, how expected returns are determined. Assets with disliked characteristics (e.g., the assets are risky, lack liquidity, are boring, have a long duration, or are from polluters) are unpopular, with low current prices and relatively high expected returns. The opposite is true for popular assets, with higher prices and lower expected returns.

Paul Kaplan models the future distributions of the various asset class returns in Chapter 19 using statistical tools. He estimates the first four moments of the distribution of stocks, bonds, and bills—that is, the mean, standard deviation, asymmetry (skewness), and kurtosis. He shows that although lognormal distributions work well for diversified portfolios, asymmetry and kurtosis are required to build satisfactory models of specific asset classes, especially the riskier ones.

The book ends with long-term forecasts of the stock and bond markets. In Chapter 20, Will Goetzmann, Otto Manninen, and I use the original Ibbotson and Sinquefield (1976b) estimation methodology to forecast the stock market over 2026–2050 using bootstrapping techniques that incorporate the inflation and real interest rate expectations embedded in the current year-end 2025 yield curve. We then add the full distribution of equity risk premiums derived from the 100-year historical samples.

We do make an adjustment, however. We recognize that, as Dimson, Marsh, and Staunton noted in Chapter 11, the United States was an unusually successful country over the last century. We therefore subtract the return of the US stock market in excess of the GDP-weighted non-US market (about 1.5% per year). Our forecast for the US stock market over the period 2026–2050 is thus 8% nominal and 5.6% real (after inflation).

I hope that future researchers will continue to work on stock and bond total return indices for as long as capital markets continue to exist. The capital markets are vitally important because they enable wide and deep participation in the exponential wealth-building engine documented in this book.

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