CFA INSTITUTE RESEARCH FOUNDATION / **BRIEF**

OPTIMAL DESIGN OF LIFE-CYCLE FUNDS IN EMERGING MARKET COUNTRIES

SEDA PEKSEVIM

CFA Institute Research Foundation

OPTIMAL DESIGN OF LIFE-CYCLE FUNDS IN EMERGING MARKET COUNTRIES

SEDA PEKSEVIM

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.

Photo credit: Lena Ganssmann Photography / Moment / Getty Images

ISBN: 978-1-952927-49-2

CONTENTS

CFA Institute

PROFESSIONAL LEARNING QUALIFIED ACTIVITY
This publication qualifies for 0.75 PL credits under the guidelines of the CFA Institute Professional Learning Program.

OPTIMAL DESIGN OF LIFE-CYCLE FUNDS IN EMERGING MARKET COUNTRIES

Seda Peksevim
Pensión Research & Consulting and ARC Centre of Excellence in Population Ageing Research (CEPAR)

1. Introduction

During the last two decades, defined benefit (DB) plans have largely been replaced by defined contribution (DC) plans worldwide. This trend has also been observed in emerging market (EM) countries, where DC plan assets represented on average about 90% of total (DB plus DC) pension investments as of the end of 2022 (OECD 2022). A serious problem with DC plans is that, more often than not, DC plan members are either incapable of making good investment decisions (because of, for example, financial illiteracy) or unwilling to implement them (because of, for example, behavioral biases). Such shortcomings put retirees at considerable risk of having inadequate retirement income (Benartzi and Thaler 2007; Lusardi and Mitchell 2011).

To address this problem, DC pension plans typically offer default funds that are automatically selected when a plan member does not actively choose an investment strategy. Empirical evidence shows that many participants adopt the default investment option in DC pension plans and tend to remain in this fund afterward (Madrian and Shea 2001).

Already widely used in the United States, life-cycle funds (also called target-date funds) are increasingly becoming the dominant choice as default options in pension plans in many developed and EM countries. These funds are long-term investment vehicles that reduce investors' exposure to risky assets automatically as they approach retirement.

For example, in typical US life-cycle funds, young investors generally have more than 90% equity exposure for several decades, a ratio that decreases with age until retirement (Ayres and Nalebuff 2008). Even in the United States, such a default policy is risky. In EM countries with different demographic characteristics and financial market structures, however, the life-cycle approach may expose pension plan participants to significant financial losses at relatively young ages, discouraging long-term risk-taking (Esch and Michaud 2014). This brief investigates how life-cycle funds can be engineered for EM countries by incorporating risky human capital and parameter uncertainty.

For this study, we selected four EM countries—Mexico, Poland, South Africa, and Turkey—that represent different regions of the world and offer default investment options or life-cycle funds in their mandatory/auto-enrollment pension plans. First, we model human capital for the selected countries stochastically by imposing temporary and permanent shocks to labor income. Second, we estimate portfolio allocations of life-cycle funds based on the stochastic human capital structure, and we conduct a detailed sensitivity analysis in terms of discount rates, contribution rates, risk aversion coefficients, permanent shocks, and correlation between human capital and stock returns. Finally, we analyze the effects of parameter uncertainty on portfolio allocations by incorporating risky human capital.

We can briefly summarize the results regarding the portfolio allocations of life-cycle funds in Mexico, Poland, South Africa, and Turkey as follows:

1. Labor income and capital market assumptions have a significant effect on the portfolio allocation of life-cycle funds.
2. The optimal investment strategy of life-cycle funds is highly sensitive to the level of risk aversion, permanent shocks to labor income, and correlation between human capital and stocks. Specifically, when the correlation between human capital and stock returns exceeds a certain positive threshold, life-cycle funds may allocate bonds to younger investors while favoring stocks for older investors.
3. Contribution rates and discount rates have a relatively limited effect on the asset allocation of life-cycle funds.
4. Parameter uncertainty results in important differences in portfolio allocations, particularly in countries with high stock market volatility.

Our findings can contribute to the understanding of long-term portfolio optimization and the design of life-cycle funds as default fund options in EM countries, which have increasingly adopted mandatory and auto-enrollment pension systems. In Section 2, we provide a short summary of the related literature. Section 3 introduces the data. Section 4 describes the methodology for modeling human capital, parameter uncertainty, and the portfolio optimization problem. Section 5 presents the results. Finally, Section 6 concludes and offers some recommendations for pension fund managers, policymakers, and investors.

2. Related Literature

This study relates to two strands of literature: (1) the life-cycle theory of investing and its relation to human capital and (2) mean reversion and parameter uncertainty.

The Life-Cycle Theory and Human Capital

Life-cycle funds are long-term investment products designed on the theory of life-cycle investing (Bodie, Merton, and Samuelson 1992; Campbell and Viceira 2002). According to this theory, human capital (i.e., the present value of future labor income) and financial capital together are considered one of the key components of an individual's total wealth.

In the conventional life-cycle approach, human capital is assumed to be a riskless asset and plays the same role as a large endowment of risk-free bonds (Bodie, Merton, and Samuelson 1992). Thus, to maintain a stable risk profile for their total wealth, young investors with relatively more human capital should invest in riskier assets, whereas older investors (who have less human capital) should prefer a more conservative asset allocation. Target-date funds offered as a part of US retirement plans (e.g., pension funds from companies such as Vanguard, Fidelity, and T. Rowe Price) illustrate this theory in action. These funds' portfolio structure supports a substantial (~90%) allocation to equities for younger individuals, shifting gradually to a less risky portfolio approach as investors age.

A growing number of studies have challenged the riskless human capital assumption, arguing that human capital is in fact a risky asset because of temporary and permanent fluctuations in labor income (random shocks to the wage process) that individuals face during their working lives. Temporary shocks (e.g., maternity leave or short periods of unemployment) have transitory effects on workers' future earnings, whereas permanent shocks (e.g., disability or promotion) can substantially change the expected value of labor income over an individual's lifetime. Depending on the size of these random shocks and their correlation with stocks, an ideally configured life-cycle fund may have a portfolio structure that differs dramatically from that of the typical US-type target-date fund (Cocco, Gomes, and Maenhout 2005; Benzoni, Collin-Dufresne, and Goldstein 2007). For this reason, risky human capital has significant implications for both long-term portfolio optimization and for maximizing investors' retirement portfolios (Bagliano, Fugazza, and Nicodano 2014, 2019).

Prior academic and industry studies on incorporating human capital into the design of life-cycle funds have predominantly focused on the United States. In this respect, our findings also complement previous work by the CFA Institute Research Foundation, which provides key insights for life-cycle fund design in US pension plans (Bodie, McLeavey, and Siegel 2007; Ibbotson, Milevsky, Chen, and Zhu 2007; Bailey and Winkelmann 2021; Idzorek and Kaplan 2024).

Mean Reversion and Parameter Uncertainty

Prior research suggesting that stocks are less volatile in the long run attempts to explain this phenomenon with mean-reversion behavior (Fama and French 1988; Spierdijk and Bikker 2017). Mean reversion describes a negative correlation between realized returns and expected future returns, wherein stock prices tend to oscillate around a particular mean or trend. When mean reversion is present, stock prices become partially predictable, thereby contributing to lower stock market volatility in the long term.

Recent studies add the idea that parameter uncertainty should be taken into account in long-term portfolio optimization. According to the main argument in this literature, the expected return and variance parameters cannot be known precisely, significantly affecting portfolio allocation in the long run. Barberis (2000), Schotman, Tschernig, and Budek (2008), and Hoevenaars, Molenaar, Schotman, and Steenkamp (2014) report that when parameter uncertainty is considered, the optimal stock allocation is lower than when parameters are known or deterministic. These studies are based on the vector autoregression (VAR) methodology combined with distributional assumptions to model parameter uncertainty. Alternatively, Harvey, Liechty, Liechty, and Müller (2010) apply the Markov chain Monte Carlo (MCMC) simulation approach, in which the distribution type is not necessarily specified. Most studies in this literature focus on developed countries, especially the United States.

In one of the most comprehensive studies on parameter uncertainty, Pástor and Stambaugh (2012) propose that stocks are more volatile in the long run than in the short run. Their research considers four different types of uncertainty (independent and identically distributed uncertainty, uncertainty about future expected returns, uncertainty about current expected return, and estimation risk). By applying the MCMC methodology, Pástor and Stambaugh conclude that stocks are more volatile in the long run because of these uncertainties dominating the mean-reversion effect. In contrast, however, a more recent study conducted by Carvalho, Lopes, and McCulloch (2018) shows that unless investors possess extreme beliefs (priors) about expected return and variance parameters, the mean-reversion effect is dominant and stocks are less volatile in the long run.

3. Data

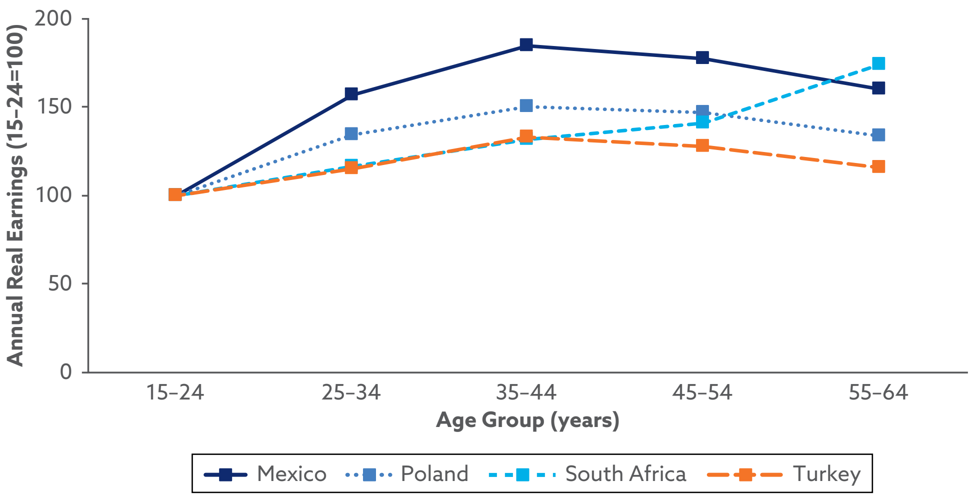
Our study uses two different datasets. The first is life-cycle earnings data by age group. The selected EM countries for the analysis are Mexico, Poland, South Africa, and Turkey, all of which have mandatory or auto-enrollment systems and offer default investment options in their pension plans. The age-earnings data in 2022 for the selected countries is constructed from the following sources:

- Mexico: Instituto Mexicano del Seguro Social (IMSS);
- Poland: Główny Urząd Statystyczny;
- South Africa: Statistics South Africa; and
- Turkey: Turkish Statistical Institute (TURKSTAT).

The estimated nominal earnings by age group are adjusted for inflation using each respective country's consumer price index. The five age groups cover 10-year ranges, from 15 years old to 64 years old.

Exhibit 1 shows annual real labor income (standardized to 100 for the 15–24 age group) across different age groups in Mexico, Poland, South Africa, and Turkey. In Mexico, Poland, and Turkey, a slight to moderate hump-shaped pattern appears in the labor income profiles, peaking in the 35–44 age cohort and then decreasing moderately until the 55–64 age group. The hump-shaped structure of labor income is comparable to that observed in the United States and Germany (Lagakos, Moll, Porzio, Qian, and Schoellman 2018). In South Africa, however, labor income steadily increases with age, reaching a peak in the 55–64 age group at about 1.75 times the labor income of the earliest age cohort.[1]

Exhibit 1. Labor Income Profiles, by Country and Age Group



Sources: IMSS, Główny Urząd Statystyczny (2022), Statistics South Africa (2022), TURKSTAT (2022).

[1]In South Africa, a high level of unemployment results in low labor income for young workers compared with older workers (Bhorat, Naidoo, Oosthuizen, and Pillay 2015).

Exhibit 2. Capital Market Assumptions by Country, 2004–2022

Assets	Expected Return	Standard Deviation	Correlation Coefficient
Mexico			
Stocks	4.6%	16.8%	3.9%
Bonds	2.8%	1.3%	
Poland			
Stocks	2.2%	20.6%	11.4%
Bonds	1.3%	1.2%	
South Africa			
Stocks	4.9%	15.5%	12.6%
Bonds	3.0%	1.6%	
Turkey			
Stocks	5.3%	27.3%	8.0%
Bonds	2.7%	4.1%	

Source: Thomson Reuters Database.

The second dataset in this study contains real-return capital market assumptions for stocks and bonds. **Exhibit 2** presents the annual expected return, standard deviation, and correlation coefficient assumptions for Mexico, Poland, South Africa, and Turkey, respectively. The expected returns for equities and bonds are based on historical real return averages, calculated using monthly data from the Thomson Reuters Database for the period 2004–2022. We chose this time period because of data availability for the selected countries. For equities, we used the following benchmark indexes from each country: S&P/BMV IPC Index (Mexico), WIG Index (Poland), FTSE/JSE All Share Index (South Africa), and BIST 100 Index (Turkey). The assumptions for bonds are based on 10-year government bond yields. Nominal returns are adjusted for inflation using the consumer price index of the respective country and annualized.

4. Methodology

Human Capital Model

Based on studies by Cocco, Gomes, and Maenhout (2005) and Benzoni, Collin-Dufresne, and Goldstein (2007), we model the logarithm of an investor's labor income (w_x) as follows:

$$ln(w_x) = f(x, Z_x) + v_x + \epsilon_x,$$

where $f(x, Z_x)$ is a deterministic function of age x and income level Z_x; $\epsilon_x \sim N(0,\sigma_\epsilon^2)$ makes the assumption that the temporary shock follows a normal distribution; and $v_x = v_{x-1} + u_x$, where $u_x \sim N(0,\sigma_u^2)$ describes the permanent shock.

The model's two random components representing permanent and temporary shocks are assumed to be uncorrelated. We obtain the magnitude of the shocks as a fraction of labor income from Cocco, Gomes, and Maenhout (2005) and Viceira (2010). In their estimation, the expected values of both permanent and temporary shocks are zero, and the annual standard deviations are 10.95% and 13.89%, respectively.[2]

Following Campbell and Viceira (2002), we estimate human capital as follows:

$$HC_x = \sum_{j=0}^{J} \left\{ w_{x+j} exp\left[-j(r_f + \xi) \right] \right\},$$

where HC_x measures total human capital, hc_x measures the labor income at age x, r_f is the risk-free rate, and ξ is the risk premium of human capital over the risk-free rate.[3]

Parameter Uncertainty

The parameter uncertainty model is based on the independent and identically distributed compounding of stock index returns at time *t*:

$$r_t = \mu + \epsilon_t,$$

where $\epsilon_t \sim N(0,\sigma^2)$. Because the expected return μ and variance σ^2 cannot be known precisely from an investor's perspective, their distribution should also be modeled. We do so by specifying the prior distributions and estimating the posterior distributions using the Bayesian approach.

In line with Barberis (2000) and Hoevenaars, Molenaar, Schotman, and Steenkamp (2014), an investor facing parameter uncertainty is assumed to have a noninformative prior:

$$p(\mu,\sigma^2) \propto \frac{1}{\sigma^2}.$$

For the noninformative prior, the posterior distribution of σ^2 is the inverse gamma distribution (Zellner 1971):

$$\sigma^2 \mid r \sim IG\left(\frac{T-1}{2}, \frac{1}{2} \sum_{t=1}^{T} (r_t - \bar{r})^2 \right),$$

where $\bar{r} = \frac{1}{T} \sum_{t=1}^{T} r_t$ and $r = (r_1, r_2, \ldots, r_T)$. After the variance has been sampled from the posterior inverse gamma distribution, it can be used to derive the posterior distribution of the expected return:

$$\mu \mid \sigma^2, r \sim N\left(\bar{r}, \frac{\sigma^2}{T} \right).$$

---

[2]Despite the intuitive disparity in magnitude between negative and positive shocks, the expected value of both shocks is zero. Although it may feel more impactful to lose an entire income upon job loss, compared with the incremental gains from raises or promotions, the statistical expectation commonly adopted in the literature assumes this symmetry for simplicity.

[3]In the portfolio analysis of life-cycle funds, we do not decompose the total discount rate into a risk-free rate and the risk premium of human capital. Instead, we define benchmark values for discount rates, such as 5%, 10%, and 15%. The main reason for this approach is that even high discount rates have no major impact on the asset allocation of life-cycle funds.

The posterior distributions of the expected return and variance are obtained after 100,000 Monte Carlo simulations.

An investor with no parameter uncertainty can choose portfolios with a distribution based on the average values of the expected excess return and variance parameters. In this case, the investor will use the distribution of stock returns, $p(R_{T+\hat{T}}\,|\,r,\mu,\sigma^2)$, conditioned on the fixed parameters. Here, $R_{T+\hat{T}} = r_{T+1} + r_{T+2} + \ldots + r_{T+\hat{T}}$ (cumulative stock returns over $\hat{T}$ periods), where $\hat{T}$ is the investment horizon for an investor. Because of exposure to parameter uncertainty, however, the investor also takes into account uncertainty of the expected return and variance parameters and will use the estimated distribution $p(R_{T+\hat{T}}\,|\,r)$ based on $r = (r_1, r_2, \ldots, r_T)$ when modeling stock returns.

In this study, we consider two degrees of parameter uncertainty: medium and high. Under medium parameter uncertainty, investors are assumed to have confidence in stock return parameters as though they had observed them for 50 years. On the other hand, high parameter uncertainty assumes the parameters are based on observations over only 10 years.[4]

Optimal Portfolio Allocations

The optimal portfolio allocations are estimated based on a one-period portfolio optimization framework with annual rebalancing.[5,6] An investor's wealth maximization problem follows a constant relative risk aversion function:

$$max_{q_x} E[U_{x+1}],$$

where $U_{x+1} = \frac{\left(FC_{x+1} + HC_{x+1}\right)^{1-\gamma}}{1-\gamma}$ and $\gamma > 0$, and financial capital—including stocks and bonds—follows a stochastic process.

FC = financial capital

HC = human capital

γ = risk aversion coefficient

q = allocation to stocks ($0 \le q \le 1$)

x = age

[4]The alternative periods for medium and high levels of parameter uncertainty have also been tested. However, the optimal equity allocation does not change significantly in terms of the difference between no parameter uncertainty, medium parameter uncertainty, and high parameter uncertainty cases.

[5]In the life-cycle fund optimization framework, it is assumed that people consume the portion of their income not invested in financial markets. In this respect, consumption is exogeneous over the life cycle and hence excluded from the optimization problem.

[6]To simplify methodology and assumptions, we employ a one-period portfolio optimization framework with annual rebalancing. Recent studies, such as Moallemi and Sağlam (2017) and Warren (2019), have adopted a dynamic (multiperiod) approach in their portfolio optimization frameworks. These studies focus solely on financial capital, however, and do not account for human capital in their models.

5. Results

Stochastic Human Capital Analysis

We report the findings for stochastic human capital based on a representative investor who begins working at age 20 and will retire at age 65 (with the assumption of zero human capital at that age). The simulation process is based on 100,000 Monte Carlo replications of the labor income process.

Exhibits 3 through 6 present the stochastic human capital distributions, along with their medians and standard deviations, in four EM countries—Mexico, Poland, South Africa, and Turkey—for ages 20, 30, 45, and 60. In Mexico and South Africa, median human capital rises slightly between age 20 and age 30 and then declines at age 45, reaching its lowest level at age 60. Conversely, in Turkey and Poland, median human capital declines slightly from ages 20 to 30 to 45, reaching its lowest level at age 60.

Exhibit 3. Human Capital Distributions in Mexico, by Age

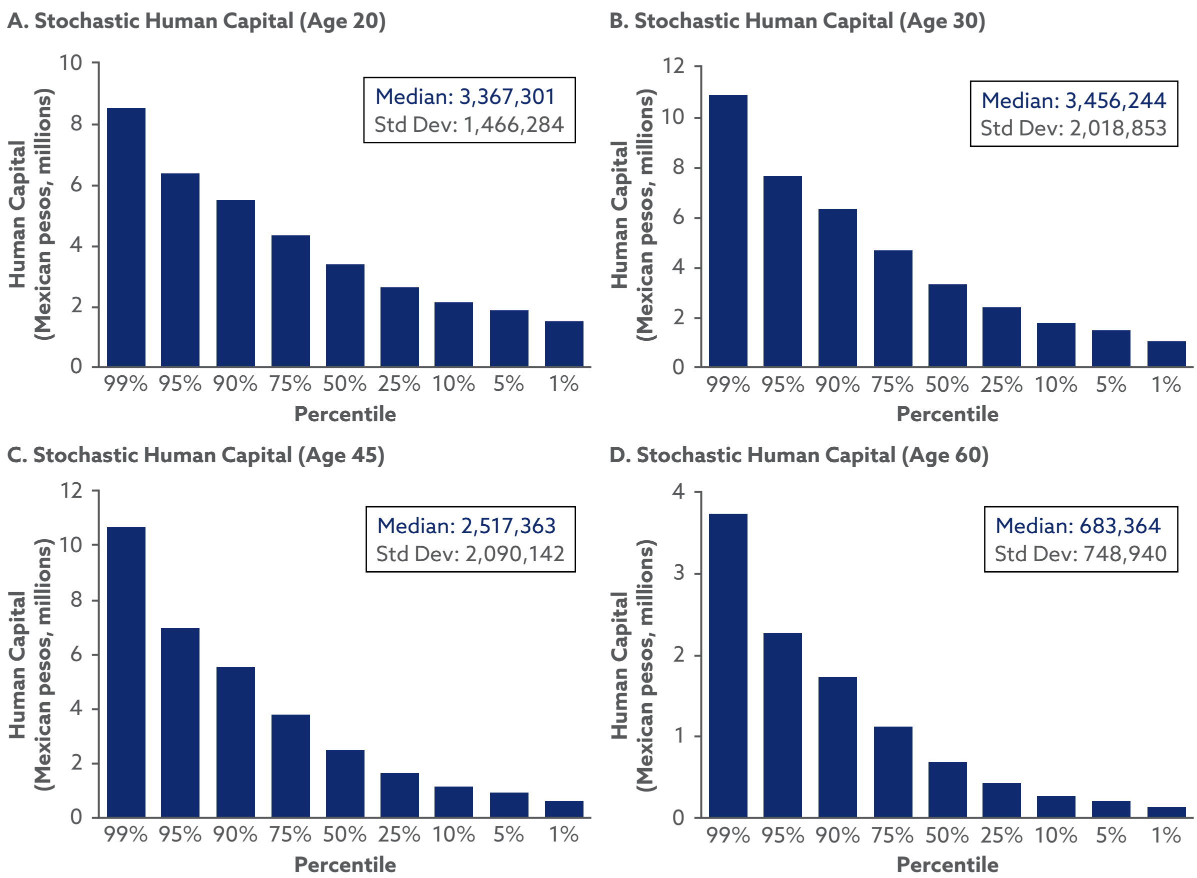
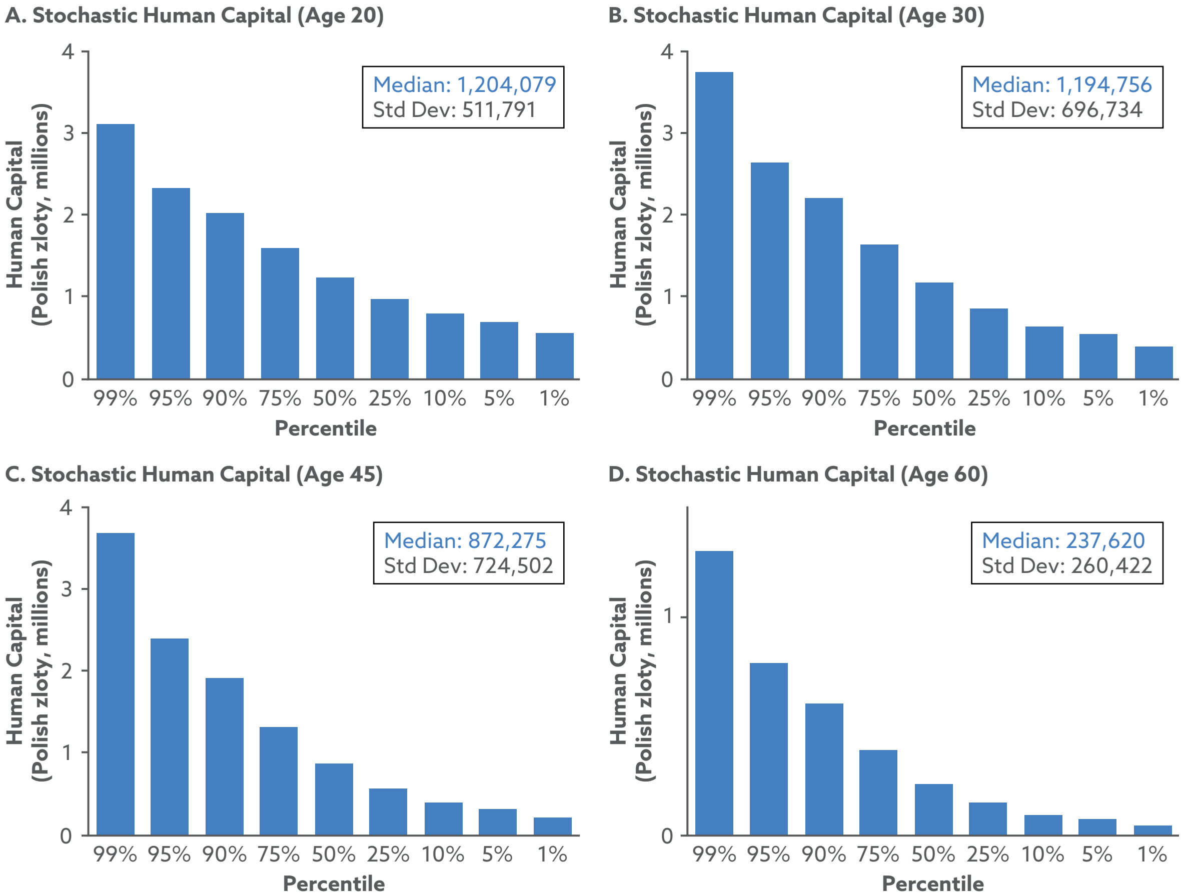


Exhibit 4. Human Capital Distributions in Poland, by Age



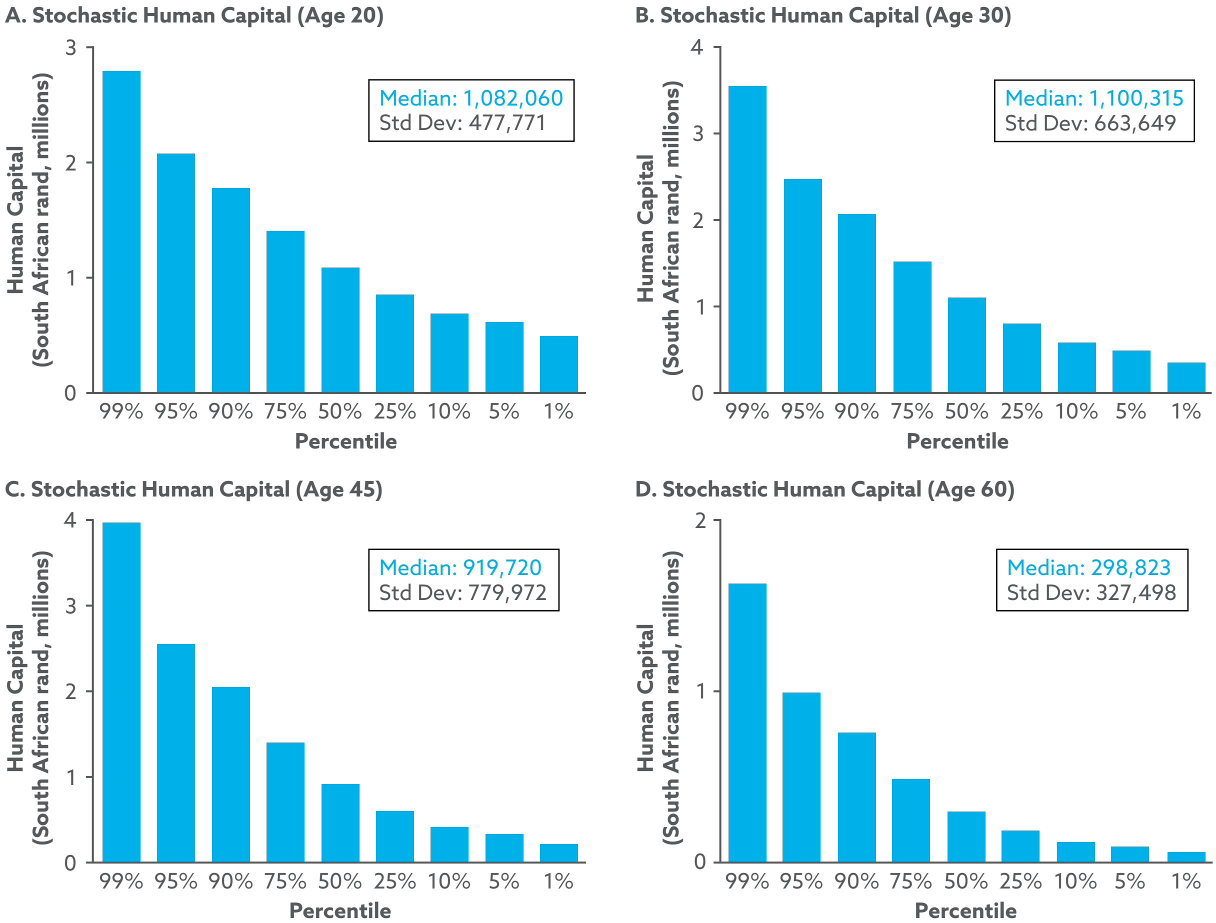
Because labor income shocks and discount rates are modeled identically for each country,[7] these differences are primarily attributed to the differences in labor income profiles shown in Exhibit 1. For example, in countries where labor income either decreases moderately (Mexico) or increases steadily (South Africa) at older ages, human capital at age 20 is higher compared with age 30. In Poland and Turkey, however, flatter labor income profiles result in lower human capital accumulation at age 20 relative to age 30, as earnings increase more gradually during early working years.

The amount of human capital owned at each age, shown in Panels A through D of Exhibits 3 through 6, is influenced by random shocks to labor income. In all countries, the standard deviation of human capital increases from age 20 to ages 30 and 45 because of investors being exposed to both temporary and permanent labor income fluctuations during their working lives. More importantly, the ratio of human capital volatility to median human

---

[7]In the stochastic human capital analysis, the annual standard deviations of permanent and temporary shocks are 10.95% and 13.89%, respectively. The analysis uses a 5% benchmark discount rate.

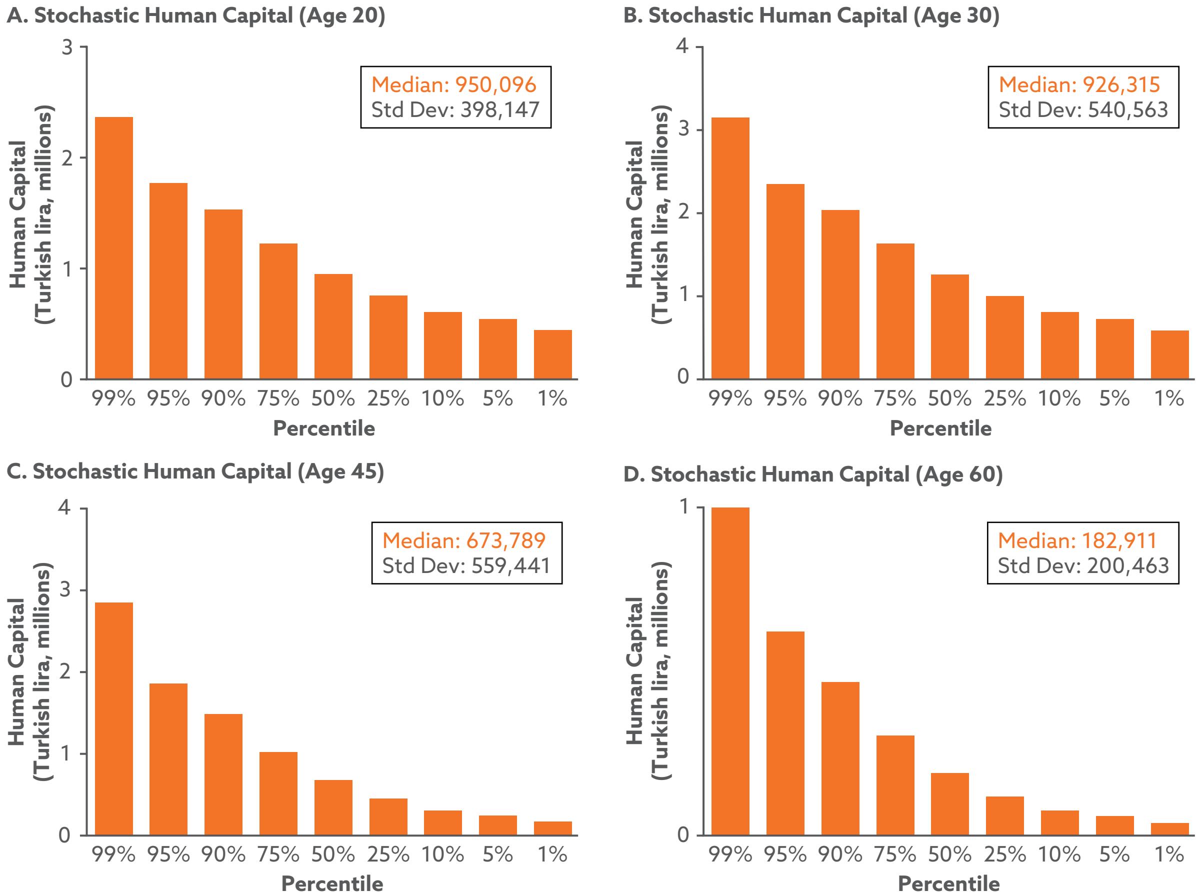
Exhibit 5. Human Capital Distributions in South Africa, by Age



capital increases with age in every case. For example, the ratio of the standard deviation to median human capital at age 20 is less than 0.5, but it exceeds 1 at age 60 (Panels A and D of Exhibits 3 through 6).

This growth in relative volatility stems mainly from uncertainty resulting from so-called permanent shocks in labor income. Although temporary shocks, such as maternity leave and short-term unemployment, affect labor income equally for all age ranges, the magnitude of permanent shocks for scenarios such as disability and promotions, as modeled by the AR(1) process, grow cumulatively with age. As a result, as an individual ages, the standard deviation of human capital approaches and can even exceed the median value—for example, the standard deviation of a 60-year-old investor's human capital is higher than its median value in Mexico, Poland, South Africa, and Turkey (Panel D of Exhibits 3 through 6).

Exhibit 6. Human Capital Distributions in Turkey, by Age



Optimal Portfolio Allocations under Stochastic Human Capital

We used the following baseline assumptions in modeling life-cycle funds:

- Starting age of investment: 20 years
- Retirement age: 65 years
- Risk aversion coefficient (γ): 5
- Discount rate: 5%
- Contribution rate: 10%
- Standard deviation of temporary and permanent shocks: (13.89%, 10.95%)
- Utility function: $U = \frac{(FC_{t+1} + HC_{t+1})^{1-\gamma}}{1-\gamma}$ for $\gamma \neq 1$

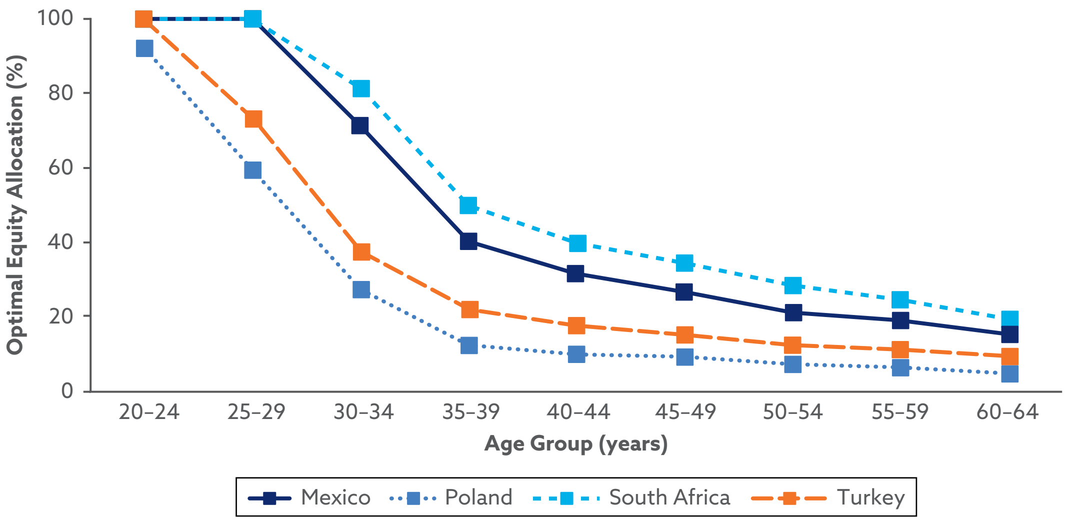
$$U = \ln(FC_{t+1} + HC_{t+1}) \text{ for } \gamma = 1$$

Exhibit 7 shows the optimal equity allocation for life-cycle funds, assuming stochastic human capital, across different age groups in Mexico, Poland, South Africa, and Turkey.[8] Based on the foregoing assumptions, the equity allocation declines with age in all countries, consistent with the general pattern observed in US target-date funds. The allocations are significantly lower in these EM countries, however, compared with the US target-date funds, where investors typically allocate 90%–100% of their assets to equities for several decades, up to age 50 or older.

Based on the foregoing assumptions, our analysis shows that Mexico and South Africa exhibit aggressive equity allocations at younger ages, starting at 100% for the 20–24 age group. This result reflects the rapid income growth for an individual over time in those countries, because under such circumstances higher future earnings result in greater human capital at younger ages. Mexico and South Africa's relatively favorable capital market conditions—higher expected stock returns coupled with moderate volatility—further support these higher equity exposures. Equity allocations decline sharply by midlife (35–39 age group) and stabilize at around 15% to 20% in the pre-retirement phase (60–64 age group).

Poland and Turkey follow a more conservative approach, however, with equity allocations lower for all age groups compared with Mexico and South Africa. This difference is attributed to flatter labor income profiles, which result in slower human capital accumulation at younger ages and less favorable capital market conditions. In Poland, lower expected stock returns and high volatility result in less aggressive allocations, whereas in Turkey, the high volatility of stocks offsets their favorable returns. In the pre-retirement phase, equity allocations in both countries stabilize at 5% to 10%.

Exhibit 7. Optimal Equity Allocations in Life-Cycle Funds, by Country



[8]The simulation process for modeling human capital and financial capital is based on 100,000 Monte Carlo replications. **Appendix A** reports optimal equity allocations for different numbers of simulations.

The results emphasize the critical role of labor income profiles and capital market assumptions in designing life-cycle funds. Countries with steeper income growth and favorable market conditions, such as Mexico and South Africa, allow for more aggressive equity allocations, whereas such countries as Poland and Turkey necessitate more conservative strategies. These findings highlight the importance of tailoring life-cycle fund designs in EM countries to reflect their unique demographic and financial characteristics.

Appendix B reports the simulated wealth accumulation paths for life-cycle funds, and **Appendix C** illustrates the expected accumulation of human capital and financial capital over the life cycle in Mexico, Poland, South Africa, and Turkey.

Sensitivity Analysis

This subsection presents sensitivity analysis for life-cycle funds in Mexico, Poland, South Africa, and Turkey, focusing on discount rates, contribution rates, risk aversion coefficients, permanent shocks, and correlation between human capital and stock returns.

Discount Rates

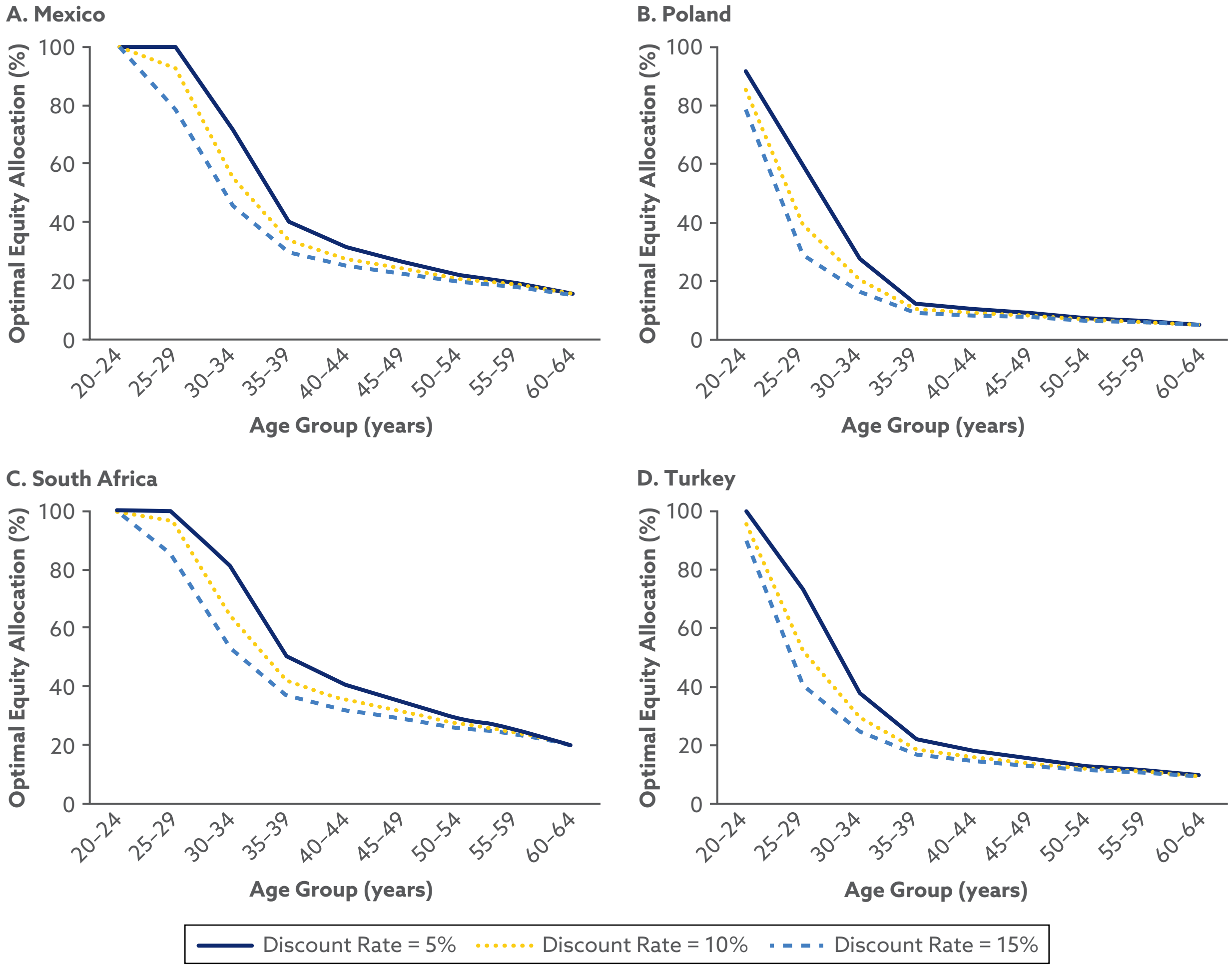
The first sensitivity analysis examines the effect of various nominal discount rates (5% [baseline], 10%, and 15%) on the optimal equity allocation of life-cycle funds (**Exhibit 8**). Among the four countries, we observe no substantial differences in the optimal equity allocations under different discount rates. Although higher discount rates reduce the amount of human capital, the effect on optimal stock allocations is small because human capital dominates financial capital in the wealth maximization problem until roughly age 50.

Moreover, for the 60–64 age group, the equity allocation under the three discount rate assumptions converges to (approximately) a single number for each country. This number is approximately 15%, 5%, 19%, and 9% in Mexico, Poland, South Africa, and Turkey, respectively. The reason for this irrelevance of the discount rate at older age groups is that the stock ratio is primarily optimized for financial capital rather than human capital in those age groups. Because the discount rate is used to model human capital, its effect becomes insignificant as human capital approaches zero in older age groups.

Contribution Rates

Exhibit 9 illustrates the optimal equity allocations of life-cycle funds for different contribution rates (3%, 5%, 10% [baseline], and 15%). Note that these contribution rates are purely hypothetical and do not reflect actual contribution rates used in these countries. As the contribution rate increases, pension plan participants allocate a larger portion of their labor income to financial capital, allowing investors to accumulate larger pension savings during the pre-retirement period (60–64 age group). As a result, at higher contribution rates, participants reduce the share of equities in their portfolios at a younger age, whereas lower contribution rates lead to the opposite behavior. In Mexico and South Africa, for example, the optimal allocation to equities starts decreasing after the 35–39 age group for a 3% contribution rate, compared with the 20–24 and 25–29 age groups for a 15% contribution rate. Similarly, in Poland and Turkey, the equity allocation starts decreasing after the 25–29 age group for a 3% contribution rate, whereas it declines from the youngest age group for a 15% contribution rate.

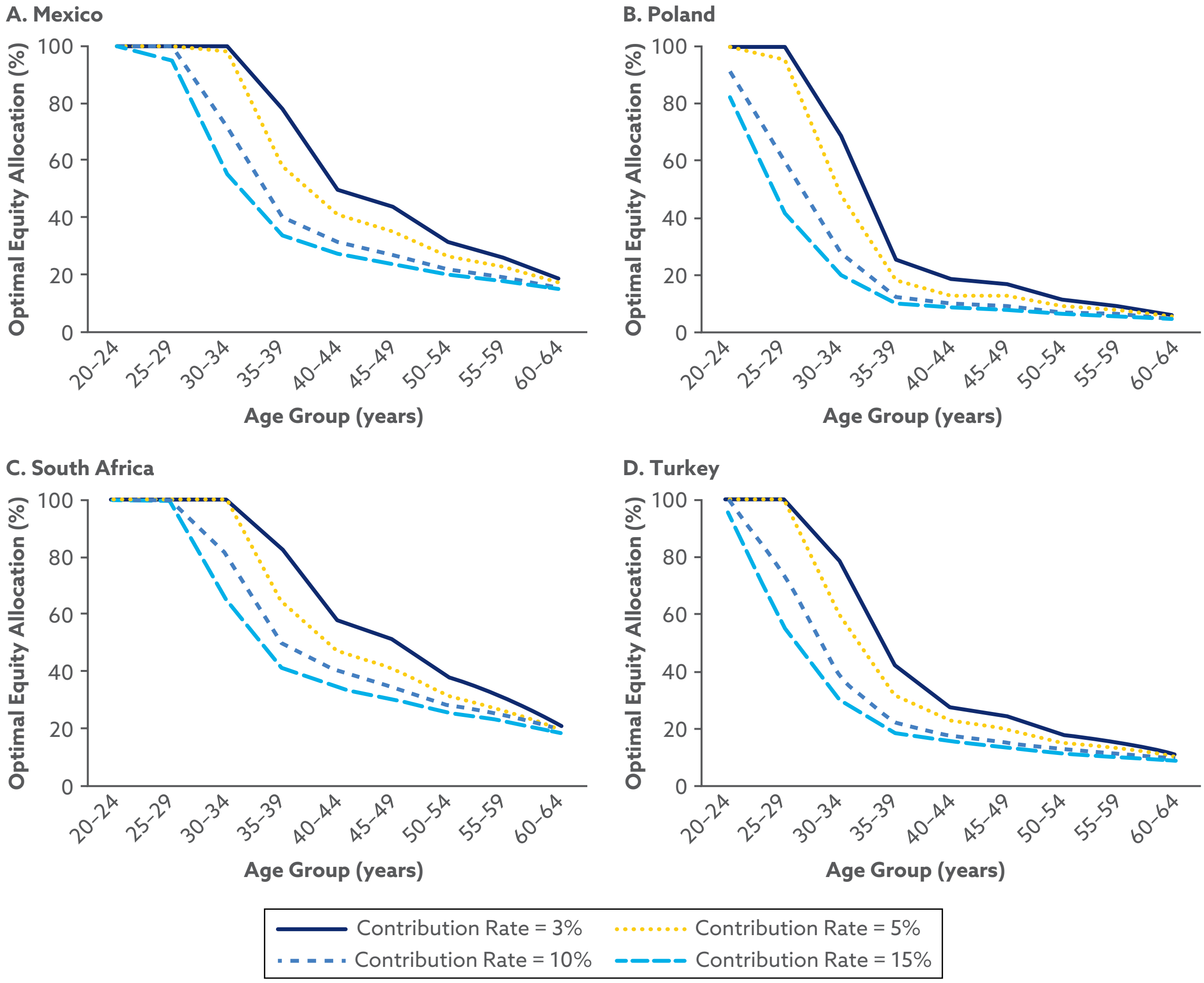
Exhibit 8. Optimal Equity Allocations for Different Discount Rates, by Country



Risk Aversion Coefficients

Exhibit 10 presents the optimal equity allocations of life-cycle funds for different risk aversion coefficients (γ) (1, 3, 5 [baseline], 7, and 10). A coefficient of 10 represents the highest degree of risk aversion, while coefficients of 1 or 2 indicate the lowest levels of risk aversion (Cocco, Gomes, and Maenhout 2005; Azar 2006). The degree of risk aversion significantly influences the share of the portfolio allocated to stocks. For example, a representative investor with a risk aversion of 1, despite having risky human capital, selects a life-cycle fund with a 100% equity allocation for the majority of age groups in Mexico and South Africa. This result is also similar to the findings of Pfau (2010), which reported an approximately 100% stock allocation as optimal for individuals with a risk aversion coefficient of 1 in the United States. Conversely, for investors with risk aversion coefficients greater than 1, the optimal equity allocation declines rapidly.

Exhibit 9. Optimal Equity Allocations for Different Contribution Rates, by Country

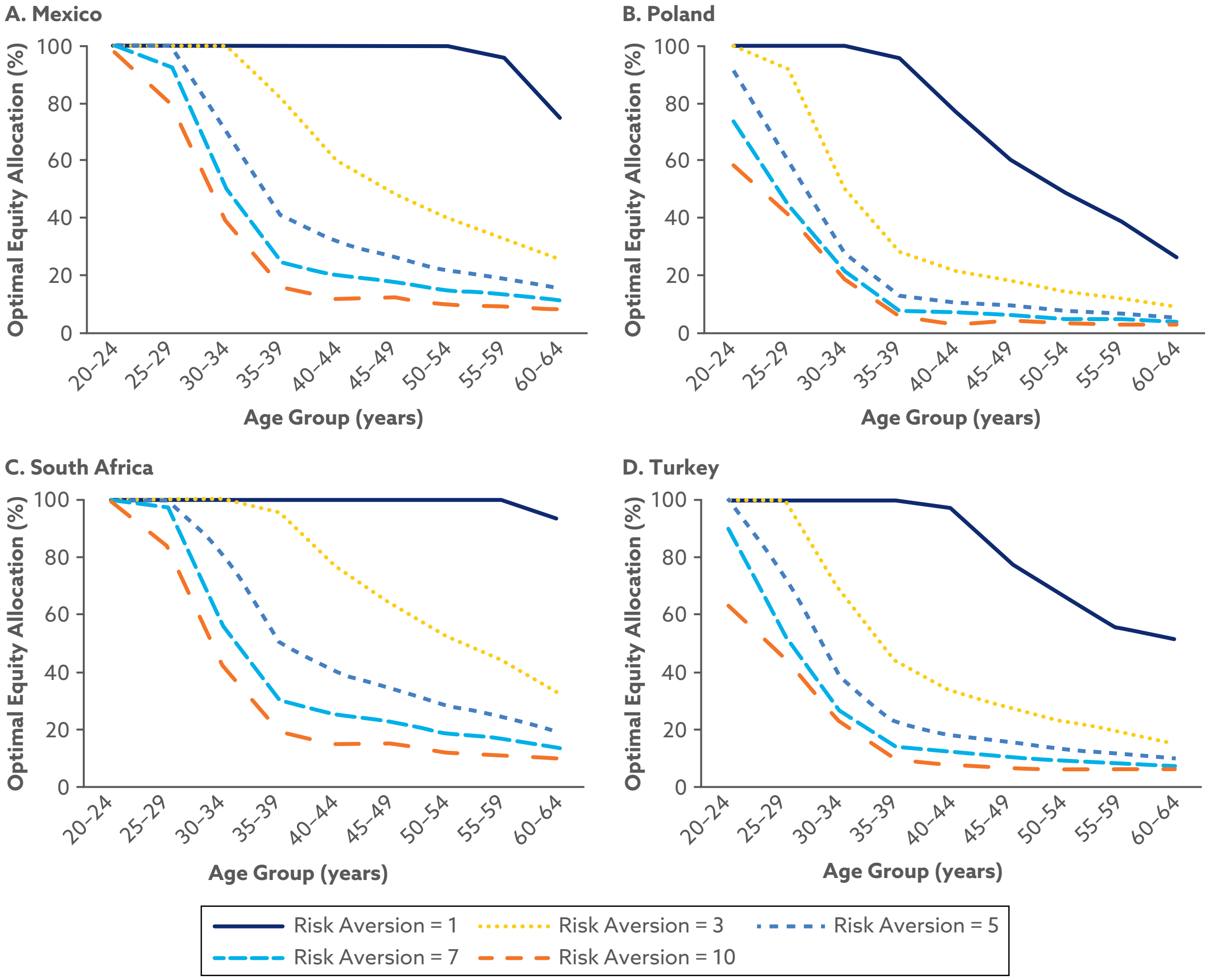


For the oldest age group, investors with the highest risk aversion coefficient ($\gamma = 10$) allocate approximately 8% of their portfolio to stocks in Mexico, 3% in Poland, 10% in South Africa, and 6% in Turkey.

Permanent Shocks

Exhibit 11 illustrates the optimal equity allocations for life-cycle funds across varying magnitudes of permanent shocks (5.48%, 10.95% [baseline], 16.43%, and 21.90%) in Mexico, Poland, South Africa, and Turkey. As expected, higher standard deviations of permanent shocks decrease the optimal share of equities in investors' portfolios. Because permanent shocks are modeled with the AR (1) process and grow cumulatively with age, they significantly affect the portfolio allocation of life-cycle funds.

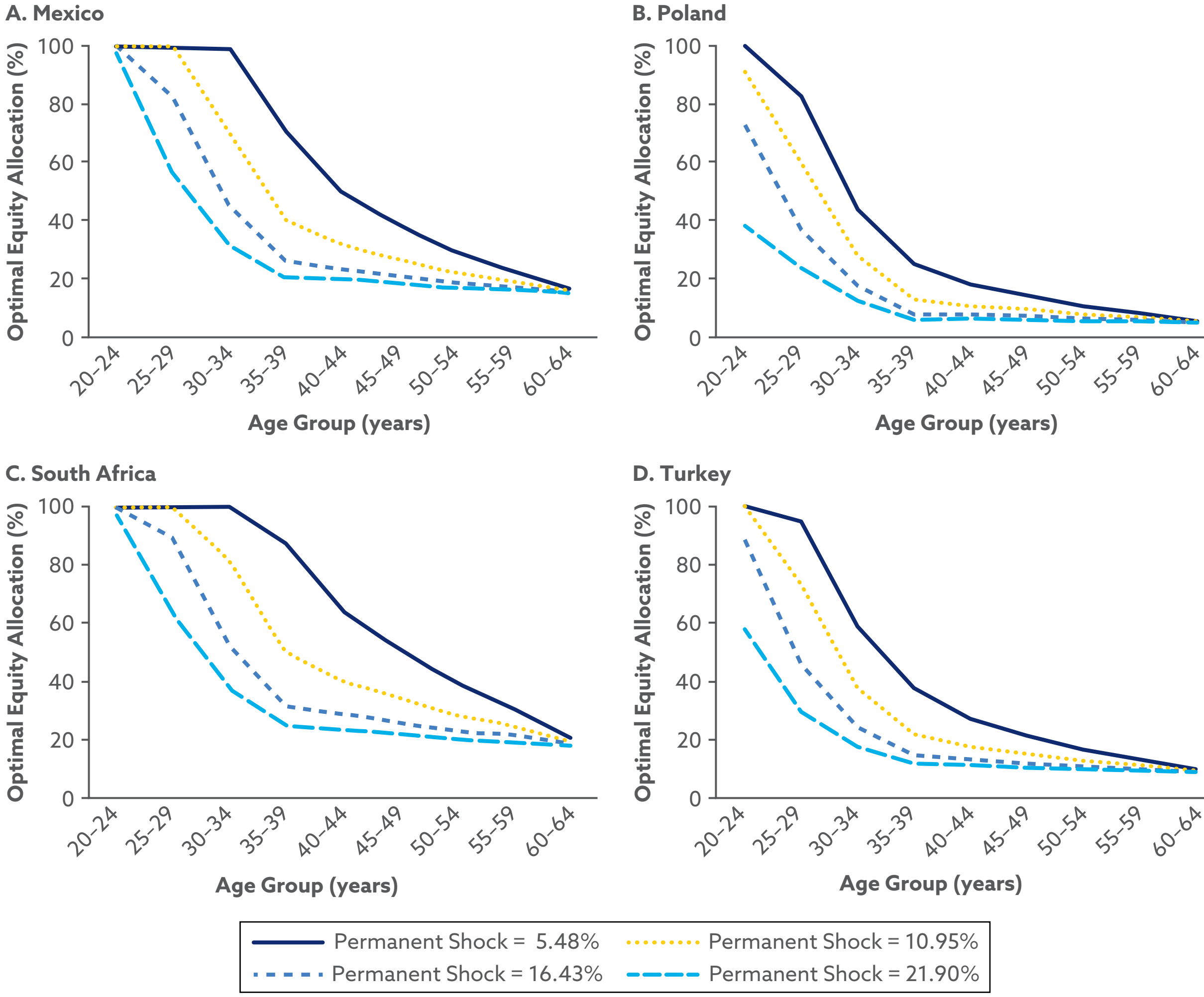
Exhibit 10. Optimal Equity Allocations for Different Risk Aversion Coefficients, by Country



For example, in Mexico and South Africa, the optimal allocation to equities starts decreasing after the 30–34 age group for a 5.48% permanent shock. In contrast, it starts decreasing from the 20–24 age group for a 21.90% permanent shock. In Poland and Turkey, optimal equity allocations are consistently lower across all age groups compared with Mexico and South Africa at the same average sizes of permanent shock.

Alternatively, the equity allocations for the 60–64 age group look similar under different degrees of permanent shocks in the four countries. This similarity arises because financial capital, rather than human capital, becomes the primary determinant of portfolio composition in the oldest age groups.

Exhibit 11. Optimal Equity Allocations for Different Sizes of Permanent Shocks, by Country

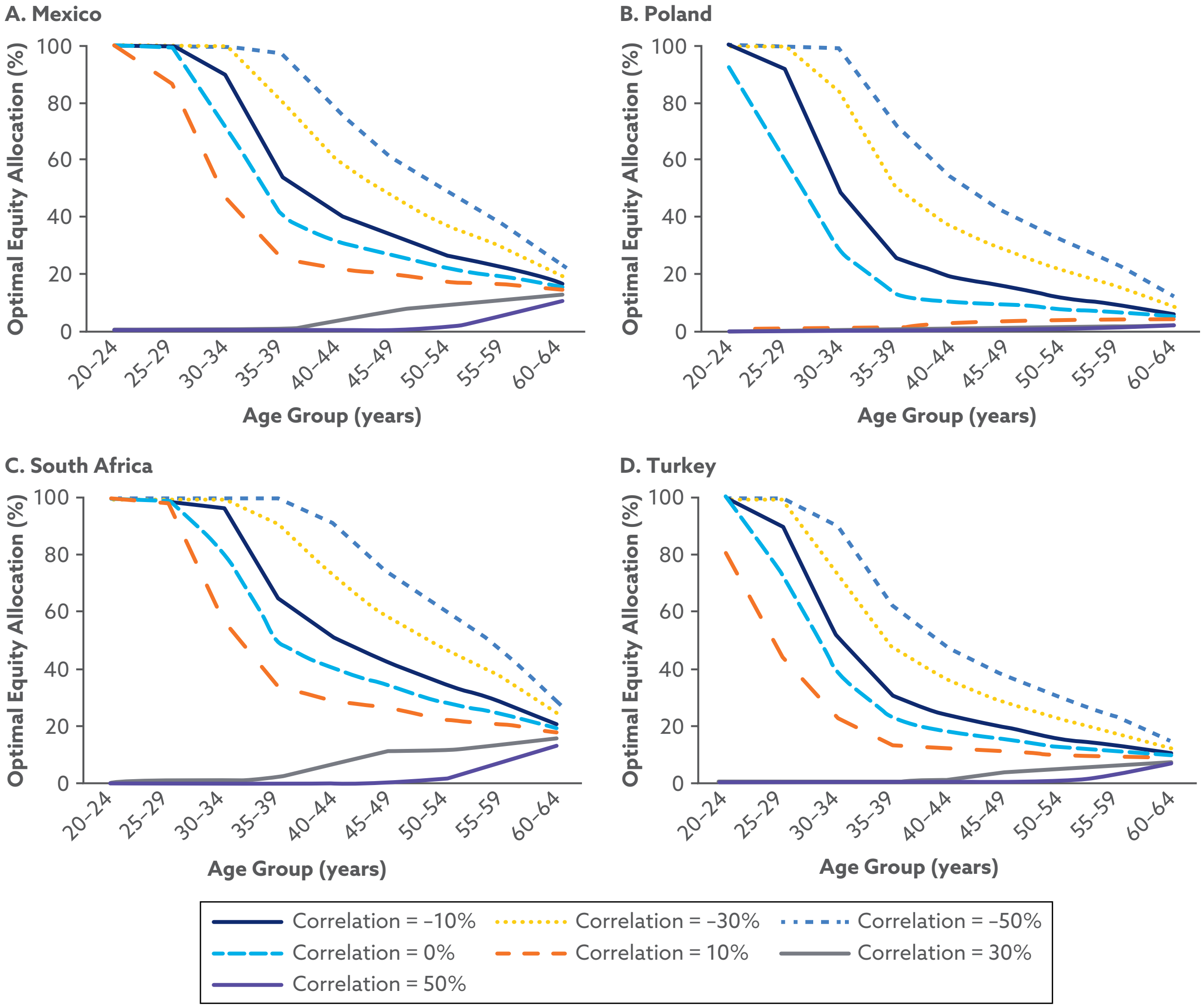


Correlation between Human Capital and Stock Returns

Up to this point in the life-cycle funds' portfolio optimization, human capital is assumed to be stochastic but uncorrelated with stock returns. The final sensitivity analysis examines optimal equity allocations when human capital is both stochastic and correlated with stock returns. **Exhibit 12** reports portfolio distributions for various negative and positive correlation coefficients (–50%, –30%, –10%, 0 [baseline], 10%, 30%, and 50%) in Mexico, Poland, South Africa, and Turkey. As the correlation between human capital and stock returns becomes more negative, stock allocations increase across all age groups.

This result aligns with classical portfolio optimization principles, where a negative correlation between assets provides diversification benefits, leading to a higher optimal stock ratio.

Exhibit 12. Optimal Equity Allocations for Different Correlation Coefficients, by Country

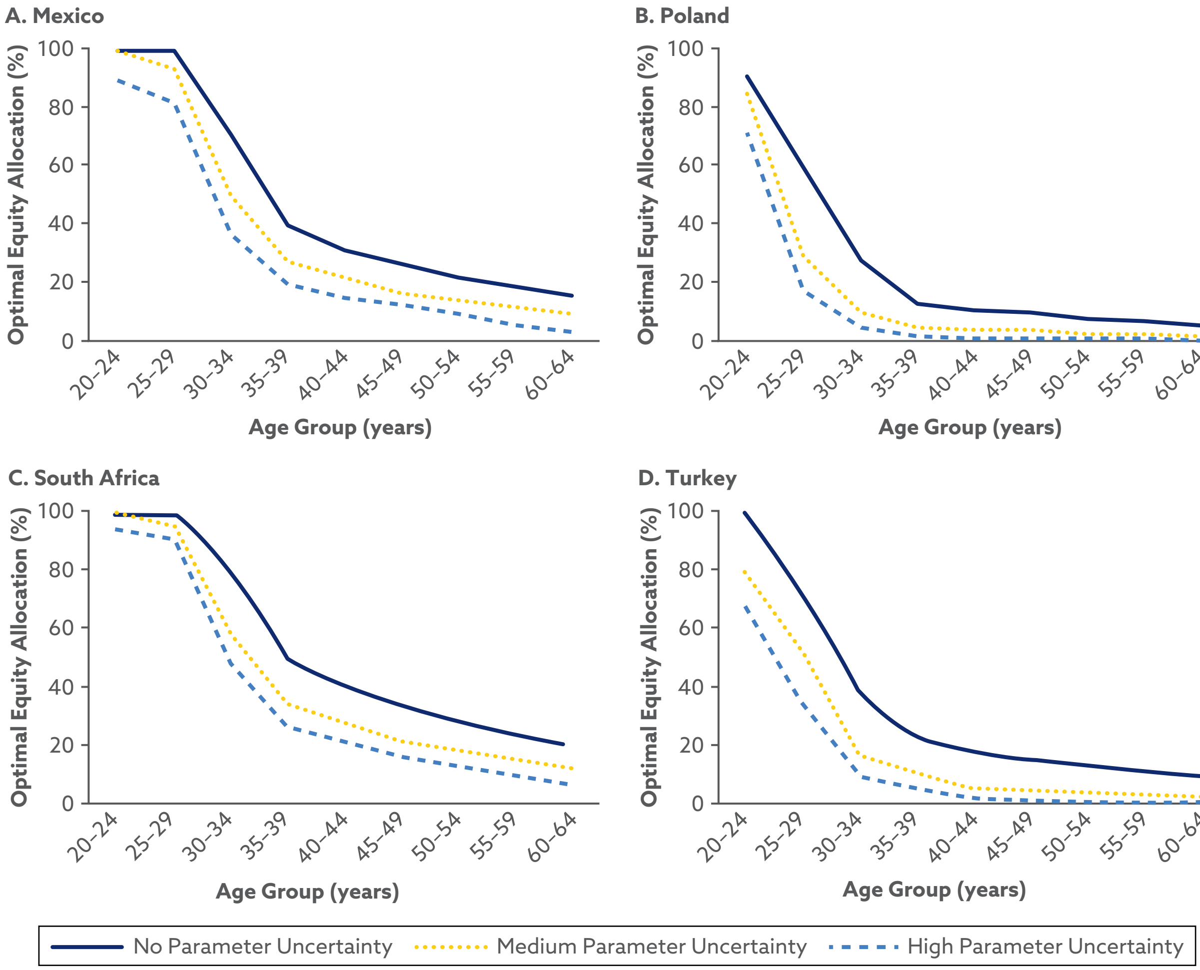


Conversely, as the correlation becomes more positive, optimal equity allocations decrease, within the range of a 10% to 30% positive correlation. From a 30% correlation upward, portfolio distributions exhibit increasing stock allocations with age across all countries, representing a notable departure from typical life-cycle funds (in which equity allocations decrease with age). This finding is in line with Campbell and Viceira (2002) and Cocco, Gomes, and Maenhout (2005), who indicate that beyond a certain level of positive correlation between human capital and stock returns, it is preferable for life-cycle funds to allocate low-risk assets—bonds—to young investors while favoring more risky assets for older ones.

Optimal Portfolio Allocations under Stochastic Human Capital and Parameter Uncertainty

In this part of the analysis, parameter uncertainty is integrated into the modeling of optimal equity allocations with stochastic human capital.[9] **Exhibit 13** shows the optimal equity allocations with stochastic human capital and two levels of parameter uncertainty—medium and high—based on the methodology outlined in Section 4.

Exhibit 13. Optimal Equity Allocations with Risky Human Capital and Parameter Uncertainty, by Country



[9]This analysis aims to examine the impact of parameter uncertainty in a straightforward manner in EM countries without employing advanced methodologies such as those proposed by Hansen and Sargent (2001) and Pástor and Stambaugh (2012). Hansen and Sargent's approach incorporates parameter uncertainty directly into the utility function, whereas Pástor and Stambaugh's study uses MCMC methodology to model parameter uncertainty.

As illustrated, parameter uncertainty consistently lowers optimal equity allocations compared with the no-parameter uncertainty scenario across all age groups. This effect is particularly pronounced in countries with higher stock market volatility, such as Poland and Turkey, where even medium parameter uncertainty leads to significantly more conservative equity allocations. In countries with moderate stock market volatility, such as Mexico and South Africa, equity allocations remain comparatively higher, even under high parameter uncertainty. These findings highlight the importance of parameter uncertainty in EM countries, where stock market volatility is higher compared with the United States and other developed markets.

6. Conclusion and Recommendations

A significant transition from DB plans to DC plans has occurred during the past two decades. This trend highlights the importance of default fund choices, because many participants adopt the default investment option in DC pension plans and tend to remain in that fund afterward (Madrian and Shea 2001). Although life-cycle funds have become one of the most popular choices for default investment options in developed countries, these funds should be modeled differently in EM countries to account for differences in demographic structures and financial market conditions.

Using demographic and financial data from several sources in Mexico, Poland, South Africa, and Turkey, this study examined how life-cycle funds can be modeled for EM countries by incorporating risky human capital and parameter uncertainty. The key findings are as follows:

1. The patterns of labor income growth for an individual over time, as well as capital market assumptions, significantly affect the portfolio allocation of life-cycle funds.
2. The optimal investment strategy of life-cycle funds is highly sensitive to the level of risk aversion, permanent shocks to labor income, and correlation between human capital and stocks. In particular, when the correlation between human capital and stock returns reaches a certain positive threshold, life-cycle funds may prioritize allocating low-risk assets, such as bonds, to younger investors while shifting toward stocks for older investors.
3. Contribution rates and discount rates have a relatively limited effect on the asset allocation of life-cycle funds.
4. Parameter uncertainty leads to notable reductions in allocations to stocks in countries with high stock market volatility.

These findings highlight the necessity of tailoring life-cycle fund design in EM countries to reflect their distinct demographic and financial characteristics. In this respect, the following recommendations may offer useful perspectives for pension fund managers, policymakers, and investors in EM countries:

- **Country-specific and sector-specific labor income patterns:** Pension fund managers and policymakers should focus on designing life-cycle funds tailored to the labor income profiles of specific countries and sectors rather than adopting the US approach of target-date fund models. In addition to the shape of the labor income profile, the volatility of human capital and its correlation with stock returns should also be examined closely for different sectors in EM countries.

The findings from this study particularly highlight the importance of stochastic and positively correlated human capital in the design of life-cycle funds. For example, an employee in the construction sector with investments heavily tied to construction stocks faces a strong positive correlation between human capital and stock returns, requiring a different asset allocation than in typical US models.

In this respect, micro-level data on earnings patterns, income variability, and market correlations become essential for capturing sectoral differences. Incorporating such data into the investment design process enables the creation of life-cycle funds that align with the diverse risk profiles and income dynamics of different sectors, ensuring more tailored and effective outcomes for EM investors.

- **Addressing parameter uncertainty in EM countries:** Emerging markets are characterized by higher stock market volatility compared with the United States and other developed economies, resulting in greater uncertainty in the distribution of asset returns. Combined with risky human capital and its correlation with stock market performance, this variability often results in a lower optimal equity allocation compared with developed markets.

  In this context, pension funds should consider adopting scenario-based modeling or Bayesian frameworks to effectively account for this uncertainty in EM countries. Such approaches can help align asset-allocation strategies with the specific risks of EM financial markets, making life-cycle funds better tailored to the needs of investors in these markets.

- **Policy support for cost-effective and efficient default options:** Governments should establish regulatory frameworks that encourage the creation of life-cycle funds optimized for local market conditions, ensuring both transparency and affordability. Some EM countries still adopt conservative funds as default options in their pension systems (OECD 2020). Moreover, a lack of trust in and understanding of financial markets often results in limited exposure to equities, even when that asset class is optimal for long-term wealth maximization, particularly in the youngest age groups.

  To address these dynamics, policymakers and fund managers should prioritize initiatives to improve financial literacy among pension plan participants. By fostering greater trust and information in life-cycle funds, such measures can promote long-term pension savings and more effective implementation of life-cycle investment strategies.

REFERENCES

Ayres, Ian, and Barry J. Nalebuff. 2008. "Life-Cycle Investing and Leverage: Buying Stock on Margin Can Reduce Retirement Risk." NBER Working Paper 14094. https://ssrn.com/abstract=1149340.

Azar, Samih A. 2006. "Measuring Relative Risk Aversion." *Applied Financial Economics Letters* 2 (5): 341–45. doi:10.1080/17446540600690151.

Bagliano, Fabio C., Carolina Fugazza, and Giovanna Nicodano. 2014. "Optimal Life-Cycle Portfolios for Heterogeneous Workers." *Review of Finance* 18 (6): 2283–323. doi:10.1093/rof/rft046.

Bagliano, Fabio C., Carolina Fugazza, and Giovanna Nicodano. 2019. "Life-Cycle Portfolios, Unemployment and Human Capital Loss." *Journal of Macroeconomics* 60: 325–40. doi:10.1016/j.jmacro.2019.03.006.

Bailey, Jeffrey V., and Kurt D. Winkelmann. 2021. *Defined Contribution Plans: Challenges and Opportunities for Plan Sponsors*. Charlottesville, VA: CFA Institute Research Foundation. https://rpc.cfainstitute.org/research/foundation/2021/defined-contribution-plans.

Barberis, Nicholas. 2000. "Investing for the Long Run When Returns Are Predictable." *Journal of Finance* 55 (1): 225–64. doi:10.1111/0022-1082.00205.

Benartzi, Shlomo, and Richard H. Thaler. 2007. "Heuristics and Biases in Retirement Savings Behavior." *Journal of Economic Perspectives* 21 (3): 81–104. doi:10.1257/jep.21.3.81.

Benzoni, Luca, Pierre Collin-Dufresne, and Robert S. Goldstein. 2007. "Portfolio Choice over the Life-Cycle When the Stock and Labor Markets Are Cointegrated." *Journal of Finance* 62 (5): 2123–67. doi:10.1111/j.1540-6261.2007.01271.x.

Bodie, Zvi, Dennis McLeavey, and Laurence B. Siegel, eds. 2007. *The Future of Life-Cycle Saving and Investing*. Charlottesville, VA: CFA Institute Research Foundation.

Bodie, Zvi, Robert C. Merton, and William F. Samuelson. 1992. "Labor Supply Flexibility and Portfolio Choice in a Life Cycle Model." *Journal of Economic Dynamics & Control* 16 (3–4): 427–49. doi:10.1016/0165-1889(92)90044-F.

Campbell, John Y., and Luis M. Viceira. 2002. *Strategic Asset Allocation: Portfolio Choice for Long-Term Investors*. Clarendon Lectures in Economics. Oxford, UK: Oxford University Press. doi:10.1093/0198296940.001.0001.

Carvalho, Carlos M., Hedibert F. Lopes, and Robert E. McCulloch. 2018. "On the Long-Run Volatility of Stocks." *Journal of the American Statistical Association* 113 (523): 1050–69. doi:10.1080/01621459.2017.1407769.

Cocco, João F., Francisco J. Gomes, and Pascal J. Maenhout. 2005. "Consumption and Portfolio Choice over the Life Cycle." *Review of Financial Studies* 18 (2): 491–533. doi:10.1093/rfs/hhi017.

Esch, David N., and Robert O. Michaud. 2014. "The False Promise of Target Date Funds." *Journal of Indexes* 17 (1): 50–59. https://www.etf.com/docs/magazine/2/2014_234.pdf.

Fama, Eugene F., and Kenneth R. French. 1988. "Permanent and Temporary Components of Stock Prices." *Journal of Political Economy* 96 (2): 246–73. doi:10.1086/261535.

Główny Urząd Statystyczny (Central Statistical Office, Poland). 2022. "Structure of Wages and Salaries by Occupation." https://stat.gov.pl/en/topics/labour-market/working-employed-wages-and-salaries-cost-of-labour/structure-of-wages-and-salaries-by-occupation-in-october-2022,17,8.html.

Hansen, Lars Peter, and Thomas J. Sargent. 2001. "Robust Control and Model Uncertainty." *American Economic Review* 91 (2): 60–66. doi:10.1257/aer.91.2.60.

Harvey, Campbell R., John C. Liechty, Merrill W. Liechty, and Peter Müller. 2010. "Portfolio Selection with Higher Moments." *Quantitative Finance* 10 (5): 469–85. doi:10.1080/14697681003756877.

Hoevenaars, Roy P., Roderick D. Molenaar, Peter C. Schotman, and Tom B. Steenkamp. 2014. "Strategic Asset Allocation for Long-Term Investors: Parameter Uncertainty and Prior Information." *Journal of Applied Econometrics* 29 (3): 353–76. doi:10.1002/jae.2331.

Ibbotson, Roger G., Moshe A. Milevsky, Peng Chen, and Kevin X. Zhu. 2007. *Lifetime Financial Advice: Human Capital, Asset Allocation, and Insurance*. Charlottesville, VA: CFA Institute Research Foundation. https://rpc.cfainstitute.org/research/foundation/2007/lifetime-financial-advice-human-capital-asset-allocation-and-insurance.

Idzorek, Thomas M., and Paul D. Kaplan. 2024. *Lifetime Financial Advice: A Personalized Optimal Multilevel Approach*. Charlottesville, VA: CFA Institute Research Foundation. https://rpc.cfainstitute.org/research/foundation/2024/lifetime-financial-advice-a-personalized-optimal-multilevel-approach.

Lagakos, David, Benjamin Moll, Tommaso Porzio, Nancy Qian, and Todd Schoellman. 2018. "Life Cycle Wage Growth Across Countries." *Journal of Political Economy* 126 (2): 797–849. doi:10.1086/696225.

Lusardi, Annamaria, and Olivia S. Mitchell. 2011. "Financial Literacy Around the World: An Overview." *Journal of Pension Economics and Finance* 10 (4): 497–508. doi:10.1017/S1474747211000448.

Madrian, Brigitte C., and Dennis F. Shea. 2001. "The Power of Suggestion: Inertia in 401(k) Participation and Savings Behaviour." *Quarterly Journal of Economics* 116 (4): 1149–87. doi:10.1162/003355301753265543.

Moallemi, Ciamac C., and Mehmet Sağlam. 2017. "Dynamic Portfolio Choice with Linear Rebalancing Rules." *Journal of Financial and Quantitative Analysis* 52 (3): 1247–78. doi:10.1017/S0022109017000345.

OECD. 2020. *Selecting Default Investment Strategies. OECD Pensions Outlook 2020*. Paris: OECD Publishing.

OECD. 2022. *Global Pension Statistics*. Paris: OECD Publishing.

Pástor, Ľuboš, and Robert F. Stambaugh. 2012. "Are Stocks Really Less Volatile in the Long Run?" *Journal of Finance* 67 (2): 431–78. doi:10.1111/j.1540-6261.2012.01722.x.

Pfau, Wade D. 2010. "An Optimizing Framework for the Glide Paths of Life Cycle Asset Allocation Funds." *Applied Economics Letters* 18 (1): 55–58. doi:10.1080/13504850903425124.

Schotman, Peter C., Rolf Tschernig, and Jan Budek. 2008. "Long Memory and the Term Structure of Risk." *Journal of Financial Econometrics* 6 (4): 459–95. doi:10.1093/jjfinec/nbn010.

Spierdijk, Laura, and Jacob A. Bikker. 2017. "Mean Reversion in Stock Prices: Implications for Long-Term Investors 1." In *Pension Fund Economics and Finance*, edited by Jacob Bikker, 119–139. London: Routledge. doi:10.4324/9781315621739-6.

Statistics South Africa. 2022. "Monthly Earnings in South Africa 2017–2022." https://www.statssa.gov.za/publications/02-11-20/02-11-202022.pdf.

Turkish Statistical Institute (TURKSTAT). 2022. "Earnings Structure Statistics." https://data.tuik.gov.tr/Bulten/Index?p=Structure-of-Earnings-Statistics-2022-49750&dil=2#:~:text=Annual%20average%20gross%20earnings%20was%20144%20thousand%20390%20TRY%20in,366%20TRY%20for%20female%20employees.

Viceira, Luis. 2010. "Pension Fund Design in Developing Economies." In *Evaluating the Financial Performance of Pension Funds*, edited by Richard Hinz, Heinz P. Rudolph, Pablo Antolin, and Juan Yermo. https://scholar.harvard.edu/lviceira/publications/pension-fund-design-developing-economies.

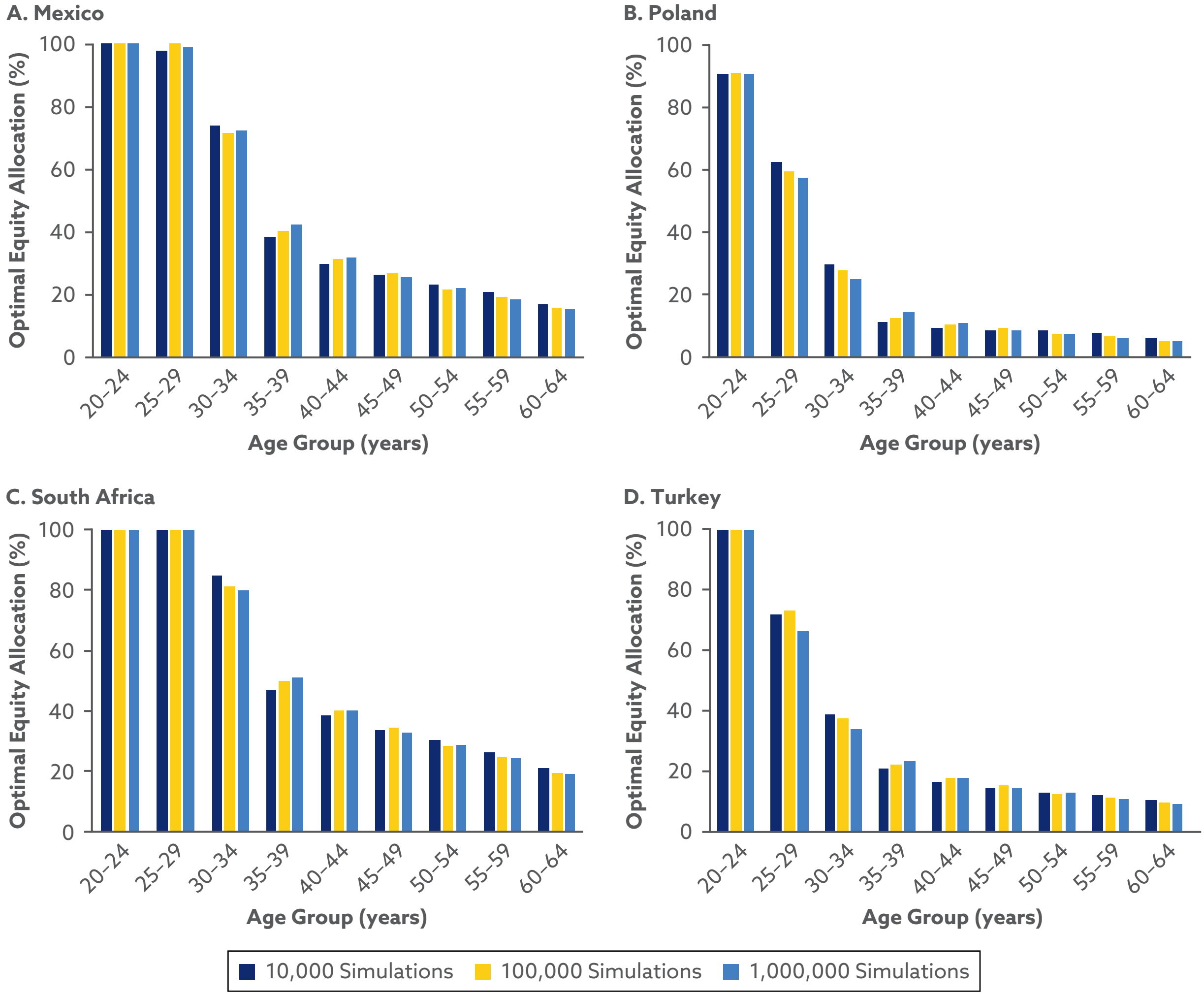
Warren, Geoffrey J. 2019. "Choosing and Using Utility Functions in Forming Portfolios." *Financial Analysts Journal* 75 (3): 39–69. doi:10.1080/0015198X.2019.1618109.

Zellner, Arnold. 1971. "Bayesian and Non-Bayesian Analysis of the Log-Normal Distribution and Log-Normal Regression." *Journal of the American Statistical Association* 66 (334): 327–30. doi:10.1080/01621459.1971.10482263.

APPENDIX A. SIMULATION RESULTS

This appendix presents optimal equity allocations for life-cycle funds modeled with stochastic human capital for different numbers of simulations (10,000, 100,000, and 1,000,000) in Mexico, Poland, South Africa, and Turkey. The optimal equity allocations are similar across different numbers of simulations, with highly consistent results for 100,000, and 1,000,000 runs.

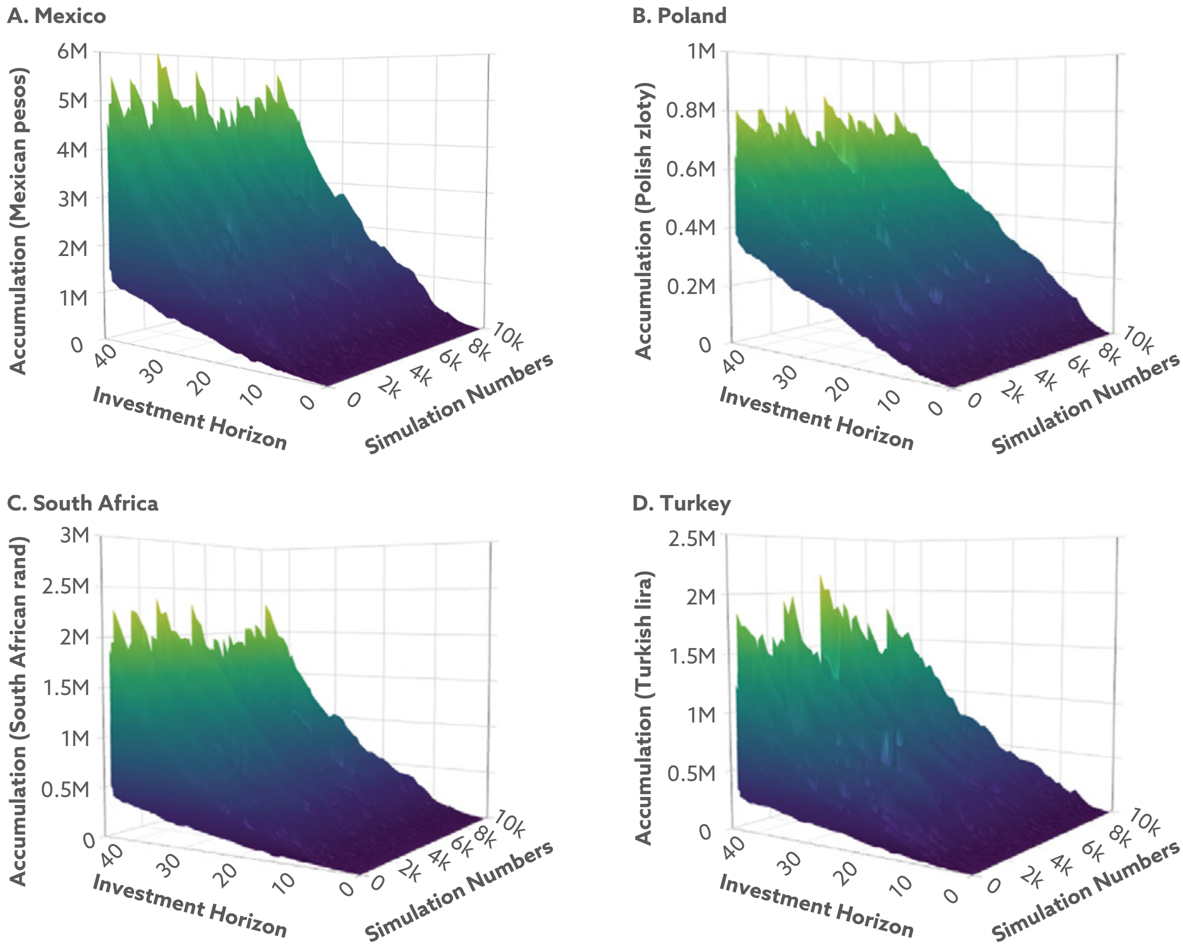
Exhibit A1. Optimal Equity Allocations for Different Numbers of Simulations, by Country



APPENDIX B. SIMULATED WEALTH PATHS

This appendix presents the simulated wealth accumulation paths (up to 10,000 simulations) for life-cycle funds modeled with stochastic human capital over different horizons (up to 45 years) in Mexico, Poland, South Africa, and Turkey. The simulated wealth accumulations are expressed in each country's local currency.

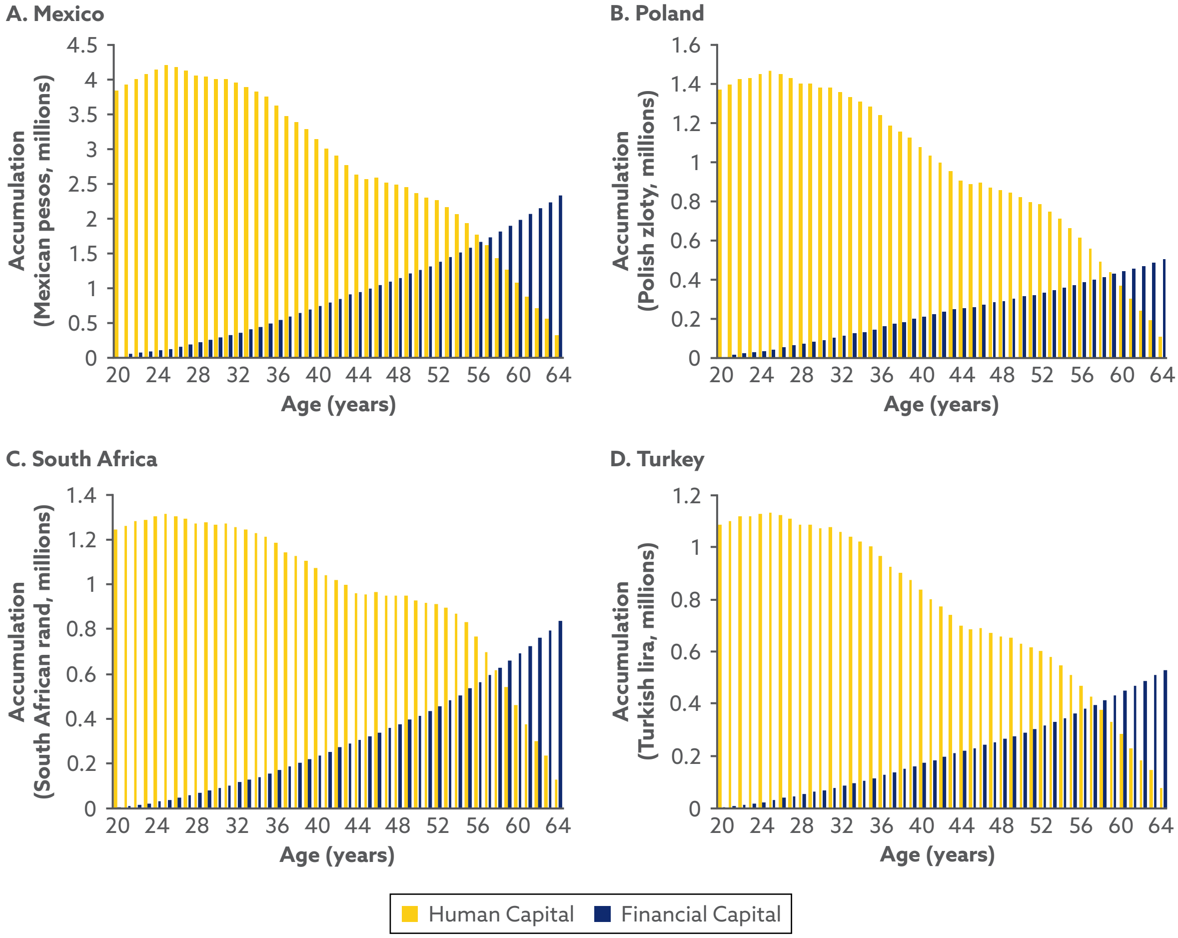
Exhibit B1. Simulated Wealth Accumulations over Different Investment Horizons, by Country



APPENDIX C. EXPECTED ACCUMULATION OF HUMAN CAPITAL AND FINANCIAL CAPITAL

This appendix illustrates the expected accumulation of human capital and financial capital over the life cycle in Mexico, Poland, South Africa, and Turkey. The wealth accumulations are expressed in each country's local currency.

Exhibit C1. Expected Human Capital and Financial Capital Accumulation, by Country



Named Endowments

CFA Institute Research Foundation acknowledges with sincere gratitude the generous contributions of the Named Endowment participants listed below.

Gifts of at least US$100,000 qualify donors for membership in the Named Endowment category, which recognizes in perpetuity the commitment toward unbiased, practitioner-oriented, relevant research that these firms and individuals have expressed through their generous support of CFA Institute Research Foundation.

Ameritech
Anonymous
Robert D. Arnott
Theodore R. Aronson, CFA
Asahi Mutual Life Insurance Company
Batterymarch Financial Management
Boston Company
Boston Partners Asset Management, L.P.
Gary P. Brinson, CFA
Brinson Partners, Inc.
Capital Group International, Inc.
Concord Capital Management
Dai-Ichi Life Insurance Company
Daiwa Securities
Mr. and Mrs. Jeffrey Diermeier
Gifford Fong Associates
John A. Gunn, CFA
Investment Counsel Association of America, Inc.
Jacobs Levy Equity Management
Jon L. Hagler Foundation
Long-Term Credit Bank of Japan, Ltd.
Lynch, Jones & Ryan, LLC
Meiji Mutual Life Insurance Company
Miller Anderson & Sherrerd, LLP
John B. Neff, CFA
Nikko Securities Co., Ltd.
Nippon Life Insurance Company of Japan
Nomura Securities Co., Ltd.
Payden & Rygel
Provident National Bank
Frank K. Reilly, CFA
Salomon Brothers
Sassoon Holdings Pte. Ltd.
Scudder Stevens & Clark
Security Analysts Association of Japan
Shaw Data Securities, Inc.
Sit Investment Associates, Inc.
Standish, Ayer & Wood, Inc.
State Farm Insurance Company
Sumitomo Life America, Inc.
T. Rowe Price Associates, Inc.
Templeton Investment Counsel Inc.
Frank Trainer, CFA
Travelers Insurance Co.
USF&G Companies
Yamaichi Securities Co., Ltd.

Senior Research Fellows

Financial Services Analyst Association

For more on upcoming CFA Institute Research Foundation publications and webcasts, please visit www.cfainstitute.org/research/foundation.

ISBN 978-1-952927-49-2

9 781952 927492 >

CFA Institute Research Foundation

Available online at rpc.cfainstitute.org