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Carbon Emissions, Net-Zero Transition, and Implications for Equity Portfolio Risk

CARBON EMISSIONS, NET-ZERO TRANSITION, AND IMPLICATIONS FOR EQUITY PORTFOLIO RISK

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We quantify the relationship between a company's carbon emissions footprint, its transition to net zero, and the expected distribution of its future stock returns as reflected in listed option prices. Option prices on high carbon emitters reflect their differential risk profile as measured by industry-relative carbon intensity. The strength of the relationship between option-implied risk and emissions changed after the 2016 adoption of the Paris Agreement. The relationship is weaker for companies that have committed to 2°C alignment goals. The undiversifiable nature of this risk is evident in the behavior of equity portfolios with high relative exposure to carbon emissions. Using a factor-based framework, we quantify the bias in the risk forecasts associated with reported carbon emissions exposure. Investors can use this framework to both measure and manage carbon emissions–related risk.

Climate change will affect every industry, region, and company in the global financial sector. In assessing this impact and the associated risk to companies, it is essential to recognize the differing implications based on whether the risk is associated with changes in physical conditions or modifications related to transitioning economies.

As climate change leads to more severe weather events, such as flooding, droughts, and storms, the physical conditions under which companies operate will inevitably change. This physical risk and associated changes will not be homogeneous across regions and industries, and companies will be affected regardless of their contribution to climate change or individual carbon emissions footprint. For example, even a company in an industry with minimal emissions will be affected by physical threats based on its geographical location.

Transition risk is separate and distinct from physical risk. It refers to the consequences businesses and investors face as countries accelerate the adoption and implementation of policies to cut carbon emissions. A company's emissions footprint relates directly to its exposure to this transition risk, with the expectation that those companies with higher emissions have higher exposure to this type of risk. While climate mitigation policies will asymmetrically affect companies based on their operating region or industry, a company's emission profile will determine whether it might benefit or suffer potential losses from the policies.

The public and private pledges to reduce emissions already require drastic cuts in corporate emissions. Henceforth, companies with higher emissions face increased scrutiny, leading to potential reputational risk. Furthermore, the Climate Change 2023 Synthesis Report (IPCC 2023) affirmed that the "current mitigation and adaptation actions and policies are not sufficient" (p. 57) To inflect emissions, public administrations have been tightening regulations. In the EU, for instance, the European Green Deal created an emissions trading system, carbon pricing on imported goods, and captured carbon through carbon sinks, amongst other elements. In this constantly evolving environment, business models relying on carbon emissions are at risk. But are investors considering this risk in their decisions? In other words, are financial markets pricing carbon risk?

We attempt to shed light on this question by evaluating the impact of emissions intensity on security prices in options and equity markets. The risk-based approach used in this chapter is designed to provide practitioners with a framework to evaluate the potential impact of emissions on the investment risk, at both the security and the portfolio level. Following a summary of prior relevant research, we document the extent to which a company's emissions intensity affects its future distribution of returns as predicted by options markets. We then evaluate how emissions intensity affects portfolio risk by quantifying the bias in the portfolio risk forecasts associated with systematic carbon emissions exposure.

Prior Research and Motivation

Research on the impact of emissions on financial markets falls into at least three broad categories. The first includes studies that attempt to measure the presence of a carbon-related risk premium (Bolton and Kacperczyk 2021). Risk premia are ideally estimated over a long period with accurate data on the underlying factor. Given the limited data availability and time period of carbon-related data, however, as well as the rapidly changing dynamics of emissions-related regulation, the results of these studies are questionable. Furthermore, the way transition risk is incorporated into asset prices has distinct phases. Changes in regulation imply the existence of a transition stage, during which prices of assets with low emissions are bid up while prices of assets with high emissions are bid down, in response to changing investor beliefs. The different repricing phases are difficult to identify empirically because individual asset prices may transition at various times and different speeds. In addition, allocating credits to higher-emitting companies in certain countries can result in windfall economic gains and abnormal stock returns. Oestreich and Tsiakas (2015) document the abnormally higher returns of companies that received free carbon emission allowances. Despite these challenges, these studies support the idea that carbon emissions provide power in explaining the cross section of stock returns and motivate emissions as a risk factor in both portfolio construction and performance measurement.

The second strand of research relates to the quality of the carbon-related data and measurement issues. Aswani, Raghunandan, and Rajgopal (2024) argue that reliance on estimates of carbon emissions (in this case, data from Trucost) instead of the actual emissions disclosed by the companies themselves causes the performance differential between high and low emitters. When they narrowed their sample to US companies that disclosed their emissions between 2005 and 2019, Aswani et al. found no relation between actual emissions and stock returns, concluding that the documented "carbon premium" must be driven by biases in the estimates. The second criticism the authors raised is the possibility of a critical missing variable—namely, a potential link amongst high emissions, high productivity, and stock returns that, to the extent it could be demonstrated, would be misconstrued as evidence of a carbon risk premium. This raises the question of whether high carbon emitters' high stock returns simply reflect these companies' greater economic activity and operating efficiency instead of a carbon risk premium. Another aspect of the missing variable critique is the correlation between emissions and other systematic drivers of risk and return. For example, Ardia, Bluteau, Lortie-Cloutier, and Tran (2023) document this systematic difference in factor exposure between high and low emitters. Ardia et al. find a statistically meaningful difference in value and momentum exposure in portfolios formed based on greenhouse gas emissions. In this chapter, we explicitly control for a wide array of such measures so that the impact of emissions intensity can be isolated.

The third strand of research focuses on the relationship between climate-related policy uncertainty and the option prices on issuers' equity securities. These studies, such as Ilhan, Sautner, and Vilkov (2021), have primarily focused on a limited universe of stocks or sectors to demonstrate that prices of short-term (i.e., one-month) options reflect the elevated risk associated with higher-emitting industries or sectors. These studies have not explicitly focused on company-related intensity, so they offer limited insight to practitioners looking to make company-specific investment decisions or seeking to identify opportunities in a particular industry.

This chapter contributes to this existing literature on two dimensions. First, we focus on the risk associated with emissions, similar to the consideration of common risk factors such as momentum, growth, and earnings quality. Focusing on the risk dimension allows investors to quantify the impact of emissions on their risk assessment of a single company and portfolio. Given our focus on the risk implication, we define a company's carbon intensity as the ratio of Scope 1 and 2 emissions to total revenue. Because companies with higher carbon-intensive revenues will likely face more exposure to carbon-related market and regulatory risk, this metric can proxy for a portfolio's exposure to potential climate change–related risks relative to other portfolios or a benchmark. This measure is also applicable across asset classes, and it is a simple and intuitive measure of the emission intensity of a security or portfolio.

Carbon intensity, as we define it, does not use company market capitalization or the size of the investor's position relative to the market, and therefore, it does not capture any measure of investor responsibility. Our measure of carbon intensity is especially relevant for an investor looking to manage the risk implications of emissions in investment portfolios rather than taking an activist position with respect to the emissions of their investment. Thus, the decision to accept positive or negative exposure to this risk factor will be based on the investor's view—whether that investor believes in a carbon risk premium or believes that the market has underestimated the risk associated with higher emissions. The higher the emission-related risk, the greater the necessity to actively measure and manage this risk exposure.

The second dimension this chapter contributes to existing literature is the focus on the incremental risk of carbon emissions in the context of other common risk factors used by financial practitioners to quantify the risk exposures. Most institutional investors in equity markets use a factor-based risk model, and we explicitly measure the incremental impact of increased carbon exposure in such a risk model. If traditional risk factors adequately capture the impact of emissions on portfolio risk, investors do not need to explicitly measure and monitor emissions-related exposure. In contrast, if emissions-related exposure is incremental to risk as measured using traditional risk models, investors could gain a clear benefit to managing this risk exposure.

In this chapter, we evaluate the impact of emissions on the risk profile of individual securities using data from options markets. Options data provide a unique perspective to measure investor expectations of the future risk of higher emitters and quantify how that risk has changed over time.

The adoption of the Paris Agreement, a legally binding international treaty on climate change, presents an opportunity to measure the change in investor expectations associated with the economic costs of carbon emissions. Adopted by 195 parties at the UN Climate Change Conference (COP21) in Paris, France on 12 December 2015, the treaty took effect on 4 November 2016. This change in the regulatory environment likely impacted the perceived operating risk faced by high emitters, and as such, one would expect a shift in their perceived risk profile.

Adopting the treaty also raised awareness amongst investors about the potential risks associated with high carbon emissions. Although others have documented the impact at an industry or regional level (see Ilhan, Sautner, and Vilkov 2021), to date there have been no studies on the impact at a company-specific level. We supplement our analysis by evaluating the effects of a company's committed climate transition pathway on the relationship between options prices and emissions.

Having demonstrated that carbon is priced at the individual security level, we evaluate whether this risk can be diversified away in a portfolio context. To the extent that carbon risk is idiosyncratic to a company's business strategy and geographical operating footprint, this risk may not be material in a portfolio context. By building portfolios with companies that have explicit exposure to carbon intensity but are neutral to other risk factors, we demonstrate that these portfolios have systematically higher risk than expected.

Data Description

The data used in this chapter represent a combination of carbon data and financial data. The carbon intensity data for individual companies are drawn from Trucost. The financial data are drawn from Barra's Global Total Market Equity Model for Long-Term Investors (GEMLT). Our study is based exclusively on data from companies listed on US exchanges.

The choice of Trucost as the source of carbon emissions and net-zero emission commitments was based on our desire to use a sole source with the most extensive coverage. The data reflect a combination of the actual company-reported data and estimated data from a broad universe of companies. This approach allows us to use the most extensive universe to measure the impact of emissions on risk and evaluate the effect of the combination of Scope 1 and 2 emissions.[1] The data are produced annually, and we used the reported carbon measure for all the months of the corresponding year in our analysis.

We calculate carbon intensity for each company using the ratio of emissions to revenues at each point in time. This metric is one of the more commonly used measures of carbon intensity because it scales a company's emissions by a measure of its contemporaneous output and is also the recommended metric of the Task Force on Climate-Related Financial Disclosures (TCFD 2021). Both revenues and emissions have high levels of autocorrelation, so the lag associated with reporting carbon data does not significantly impact the calculated intensity measure. This measure is also widely used as a statistic to estimate the carbon intensity of a portfolio, computed as a portfolio's weighted average carbon intensity (WACI). Because of the focus on revenues, as opposed to market capitalization, we can use this measure to estimate the carbon intensity of both equity and fixed-income portfolios.

Carbon intensity data measured using this metric are susceptible to outliers for companies with little to no revenue, so we make standard adjustments to ease interpretation of results. For example, our carbon intensity measure is Winsorized to the 5th and 95th percentiles and standardized every month.

[1]Scope 1 emissions are direct emissions from owned or controlled sources. Scope 2 emissions are indirect emissions from the generation of purchased energy.

Exhibit 1. Selected Industry-Level Carbon Intensities

Industry	Industry Average	Residuals Average	Residuals Std. Dev.	10%	25%	50%	75%	90%
Thrifts	−1.69	−0.10	0.57	−0.72	−0.48	−0.18	0.30	0.61
Insurance	−1.40	−0.06	0.45	−0.59	−0.37	−0.10	0.21	0.51
Regional banks	−1.35	−0.06	0.47	−0.56	−0.36	−0.11	0.15	0.54
Capital markets	−0.87	−0.08	0.49	−0.74	−0.36	−0.04	0.25	0.46
Diversified financials	−0.68	−0.07	0.47	−0.56	−0.32	−0.03	0.19	0.45
Oil exploration	1.29	0.06	0.48	−0.42	−0.20	0.04	0.36	0.67
Utility	1.35	0.03	0.67	−0.79	−0.38	0.16	0.44	0.74
Oil and gas	1.38	0.06	0.79	−0.81	−0.48	0.13	0.64	1.00
Airlines	1.51	0.17	0.61	−0.64	−0.29	0.21	0.55	0.87
Diversified metals	1.51	0.23	0.61	−0.45	−0.23	0.27	0.63	1.06

To control for the impact of industries on carbon intensity, we estimate a residual carbon intensity metric by adjusting each stock's carbon intensity for the average intensity in its industry.[2] As shown in **Exhibit 1**, the average intensity of industries differs widely, so it is impossible to appropriately compare a company's emissions intensity absent such an adjustment. In this framework, a company is a low emitter only if it has low emissions relative to others in its industry peer group. We define the residual measure as company-specific carbon intensity (CSCI) to reflect a company's carbon intensity relative to others in its industry grouping at each point in time. Because of the industry-relative comparison, the emissions footprint of those companies in high-emission industries can be compared with those in low-emission industries.

The CSCI framework also acknowledges the fact that production process and production inputs per dollar revenue differ across industries. Because the adjustment is industry relative, however, we assume the processes are similar across industry. Therefore, if two companies in the same industry have the same revenue, the one with the more significant carbon emissions will have the higher intensity.

Exhibit 2 illustrates CSCI for companies in the energy equipment and services industry and the diversified financials industry. Each company's industry membership is based on its risk model exposure. In the GEMLT framework, industry exposure is not constrained to be a binary indicator variable.

[2]Specifically, intensity is the residual from a regression model where the dependent variables represent each company's industry exposure. Industries are based on Barra's GEMLT industries, and companies are permitted to have exposure to more than one industry. For robustness, we replicated the analysis presented in this chapter using simple indicator variables for industry exposures with substantially similar results.

Exhibit 2. Industry Carbon Intensity and CSCI, Focus on Energy and Diversified Financials

Rank, Industry	Company	Company Carbon Intensity	Industry Carbon Intensity	GEMLT Industry Exposure	CSCI
Bottom 5, Energy Equipment & Services	KLX Energy Services Holdings, Inc.	0.08	0.72	1.50	−1.01
	Expro Group Holdings N.V.	−0.09	0.72	1.23	−0.98
	RPC, Inc.	0.05	0.72	1.35	−0.92
	Oceaneering International, Inc.	0.22	0.72	1.46	−0.83
	Newpark Resources, Inc.	0.02	0.72	1.15	−0.81
Bottom 5, Diversified Financials	Payoneer Global Inc.	−2.19	−0.71	1.04	−1.44
	PagSeguro Digital Ltd. Class A	−2.26	−0.71	1.20	−1.40
	Block, Inc. Class A	−2.07	−0.71	1.54	−0.97
	Visa Inc. Class A	−1.35	−0.71	0.66	−0.88
	Mastercard Incorporated Class A	−1.28	−0.71	0.65	−0.82
Top 5, Diversified Financials	Acacia Research Corporation	0.08	−0.71	0.56	0.48
	Toast, Inc. Class A	−0.53	−0.71	1.44	0.51
	Upstart Holdings, Inc.	−0.56	−0.71	1.61	0.59
	OneMain Holdings, Inc.	−0.74	−0.71	1.88	0.60
	Affirm Holdings, Inc. Class A	−0.53	−0.71	1.85	0.79
Top 5, Energy Equipment & Services	Helmerich & Payne, Inc.	1.88	0.72	1.17	1.03
	Noble Corporation PLC Class A	2.02	0.72	0.93	1.34
	Tidewater Inc.	2.40	0.72	1.30	1.46
	SEACOR Marine Holdings Inc.	2.33	0.72	0.97	1.63
	Bristow Group Inc.	2.32	0.72	0.77	1.77

As expected, the carbon intensity of the energy equipment and services industry is positive, whereas that of the diversified financials industry is negative by a similar magnitude. After accounting for industries, however, the CSCI measure is comparable for the top and bottom five emitters across these two industries. As illustrated with the two industries in Exhibit 2, this adjustment makes it possible to compare the emissions footprint of companies across industries.

In **Exhibit 3**, we show the distribution of the CSCI measure over time. The distribution is stable and consistent with standardizing the exposure to make it comparable across periods. The standard deviation is also stable because of the Winsorization process used to manage carbon intensity outliers. Note that the distribution, although stable over time, is not symmetric. Even on an industry-adjusted basis, a few companies are enormous emitters.

Data on options are from OptionMetrics' IvyDB US database. All analyses related to options are based only on equity securities in the US market because of data availability. We estimate the option implied volatility skew as the difference between an out-of-money option (defined by having a delta of 0.10) and a near-the-money option (defined by having a delta of 0.50). Using both calls and puts allows us to evaluate risk on an asymmetric basis and differentiate between the forecasted risk associated with left skew using put options and right skew using call options. We consider both options with 30 days to maturity (one month) and options with 365 days to maturity (one year).

In **Exhibit 4**, we summarize data related to the option skew. The table shows the distribution of the four measures of volatility skew computed from the underlying option prices. As has been well documented for equity options, the average values of implied volatility are higher for the left skew than for

Exhibit 3. Standard Deviation of CSCI

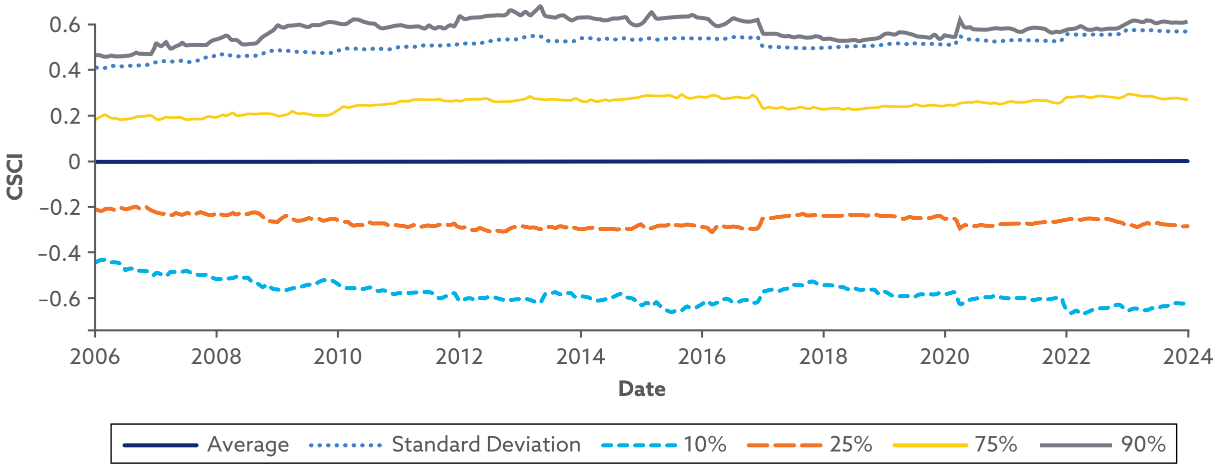


Exhibit 4. Summary Statistics for Option Skew

Implied Volatility Skew						
	No. of Obs.	Average	Std. Dev.	0.25	0.5	0.75
365 days left skew	300,952	0.14	0.17	0.07	0.10	0.16
30 days left skew	300,952	0.33	0.41	0.10	0.20	0.42
30 days right skew	300,952	0.13	0.32	0.01	0.08	0.22
365 days right skew	300,952	0.00	0.09	−0.03	−0.01	0.02
Standardized Scores						
	No. of Obs.	Average	Std. Dev.	25%	50%	75%
365 days left skew	300,951	−0.00	1.00	−0.67	−0.24	0.61
30 days left skew	300,951	−0.00	1.00	−0.76	−0.29	0.62
30 days right skew	300,951	0.00	1.00	−0.73	−0.25	0.62
365 days right skew	300,951	0.00	1.00	−0.65	−0.21	0.60

the right skew. We then standardized the skew to have a mean of zero and a standard deviation of 1 before inputting into the following regression analysis.[3] The summary statistics for the standardized data are shown in the lower half of Exhibit 4. Standardizing the skew makes it appropriate to compare the economic importance of regression statistics across different skew measures.

Exhibit 5 summarizes the financial data used in this chapter. Also shown are the factors used to control for systematic factor-related risk. We selected these factors, sourced from Barra's GEMLT for the universe of securities used in the study,[4] because of their widespread use in the risk measurement of equity portfolios. These risk factor exposures are associated with the specific date they each became available. This approach allows us to avoid the perennial look-ahead bias associated with financial data. Because global accounting reports follow different periodicity, we can use the contemporaneous exposure available for each security without imposing an arbitrary fixed period to account for reporting-related lags. We standardized all factor data by period so that the coefficient estimates directly reflect the economic significance of each variable.

[3]The use of standardized dependent variables is particularly important because we are pooling data from different time periods in our analysis, with the underlying assumption that the variance of the error term is constant over time.

[4]Although these factors are specific to the Barra GEMLT, most commercial risk models used by practitioners incorporate similar factors. The use of these factors and the accompanying risk forecast should be viewed as neither endorsement nor criticism of this particular risk model.

Exhibit 5. Summary Statistics for Financial Factors and CSCI

	No. of Obs.	Average	Std. Dev.	25%	50%	75%
CSCI	300,951	−0.00	0.52	−0.26	0.01	0.25
Beta	300,951	0.00	1.00	−0.71	−0.06	0.65
Book-to-price ratio	300,951	−0.00	1.00	−0.76	−0.21	0.60
Dividend yield	300,951	−0.00	1.00	−0.91	−0.27	0.97
Earnings quality	300,951	0.00	1.00	−0.67	−0.10	0.58
Earnings variability	300,951	0.00	1.00	−0.80	−0.26	0.62
Earnings yield	300,951	0.00	1.00	−0.52	0.05	0.60
Growth	300,951	−0.00	1.00	−0.57	−0.03	0.54
Investment quality	300,951	−0.00	1.00	−0.57	0.19	0.68
Leverage	300,951	0.00	1.00	−0.79	−0.12	0.67
Liquidity	300,951	−0.00	1.00	−0.64	−0.04	0.62
Long-term reversal	300,951	0.00	1.00	−0.62	−0.04	0.59
Mid cap	300,951	0.00	1.00	−0.98	0.38	0.89
Momentum	300,951	−0.00	1.00	−0.59	0.06	0.64
Profitability	300,951	−0.00	1.00	−0.68	−0.11	0.62
Residual volatility	300,951	0.00	1.00	−0.75	−0.19	0.59
Size	300,951	0.00	1.00	−0.72	−0.08	0.64

The scope of this chapter is to quantify the impact of carbon emissions on risk, so we decided to be overly broad in the variable selection process. The variables used, listed in Exhibit 5, reflect a combination of risk-related variables, valuation factors, profitability factors, and technical (i.e., historical return) factors.[5] From an econometric standpoint, this approach reflects the decision to potentially overspecify the model instead of being susceptible to an omitted variable bias. The potential overspecification can reduce the statistical power of the tests.

Finally, **Exhibit 6** shows the correlation between the financial risk measures and the CSCI measure. In general, the CSCI variable has a low correlation with economic variables. The low correlation indicates that other variables cannot be used as proxies to capture carbon-related effects.

[5]This list reflects the complete list of risk factors used in the Barra GEMLT risk model.

Exhibit 6. Correlation of CSCI and Financial Variables

	CSCI
Beta	**−0.11**
Book-to-price ratio	0.07
Dividend yield	0.13
Earnings quality	0.11
Earnings variability	0.01
Earnings yield	0.03
Growth	−0.10
Investment quality	0.04
Leverage	0.13
Liquidity	−0.01
Long-term reversal	0.01
Mid cap	0.07
Momentum	0.02
Profitability	−0.08
Residual volatility	−0.04
Size	0.07

Methodology and Results

We separately examined carbon intensity as a risk factor in the options market and the equity market.

Carbon Pricing in the Options Market

We evaluate the relationship between the carbon intensity measure and option skew in terms of left skew and right skew for both one-month and one-year options. We examined this separately before and after the implementation of the Paris Agreement in November 2016. The pre-2016 period uses data from February 2006 to November 2016, and the post-2016 period reflects the data through January 2024. **Exhibit 7** summarizes the regression results for the four option skew metrics.

The results represent a pooled regression using each month's CSCI variable, financial variables, and fixed effects for each month. The left skew measurement pre- and post-2016 have similar explanatory power, with R-squares of 0.23 for

Exhibit 7. Impact of Emissions on Option Skew

	Left Skew: 365 days				Left Skew: 30 days				Right Skew: 30 days				Right Skew: -365 days			
	Pre 2016		Post 2016		Pre 2016		Post 2016		Pre 2016		Post 2016		Pre 2016		Post 2016	
CSCI	−0.04**	*−6.59*	0.00	*1.06*	−0.02**	*−4.14*	0.02**	*4.13*	−0.02**	*−4.16*	0.01	*1.83*	−0.03**	*−5.21*	−0.01**	*−2.43*
Beta	0.13**	*36.36*	0.02**	*9.34*	0.03**	*9.62*	−0.00	*−0.62*	−0.13**	*−39.47*	−0.02**	*−8.87*	−0.23**	*−65.86*	−0.11**	*−45.66*
Book-to-price ratio	0.09**	*19.18*	0.10**	*36.19*	0.08**	*18.04*	0.07**	*25.13*	0.04**	*9.07*	0.08**	*26.37*	0.01	*1.40*	0.07**	*24.83*
Dividend yield	0.05**	*12.78*	0.07**	*26.41*	0.07**	*20.89*	0.04**	*17.63*	0.07**	*22.65*	0.04**	*17.20*	0.09**	*24.78*	0.08**	*32.19*
Earnings quality	−0.03**	*−9.70*	0.01**	*4.06*	−0.01**	*−4.56*	0.01**	*3.38*	0.02**	*8.33*	0.02**	*8.07*	0.03**	*9.57*	0.00	*0.14*
Earnings variability	0.08**	*20.76*	0.04**	*13.80*	0.07**	*18.85*	0.06**	*20.85*	0.12**	*31.15*	0.03**	*10.42*	0.06**	*16.04*	0.03**	*9.86*
Earnings yield	−0.07**	*−20.54*	−0.02**	*−5.43*	−0.08**	*−22.90*	−0.01**	*−5.24*	−0.02**	*−6.37*	0.00	*0.91*	−0.01**	*−2.92*	−0.04**	*−14.06*
Growth	−0.03**	*−6.84*	−0.00	*−1.76*	−0.03**	*−8.09*	−0.01**	*−5.18*	−0.03**	*−7.68*	−0.00	*−0.60*	−0.04**	*−10.95*	0.00	*0.70*
Investment quality	0.04**	*13.01*	−0.04**	*−14.50*	0.04**	*11.90*	−0.05**	*−22.08*	0.01**	*2.76*	−0.03**	*−11.31*	−0.02**	*−6.10*	−0.05**	*−19.54*
Leverage	0.07**	*22.91*	0.08**	*34.12*	0.03**	*9.07*	0.06**	*25.11*	0.01**	*3.59*	0.05**	*20.17*	−0.01**	*−4.81*	0.02**	*8.61*
Liquidity	0.03**	*9.17*	−0.09**	*−39.80*	−0.14**	*−42.26*	−0.09**	*−38.11*	−0.16**	*−50.89*	−0.07**	*−29.05*	−0.20**	*−59.58*	−0.10**	*−40.86*
Long-term reversal	0.08**	*23.24*	0.03**	*14.18*	0.08**	*27.13*	0.04**	*18.29*	0.05**	*17.48*	−0.00	*−1.23*	−0.02**	*−5.91*	0.01**	*2.97*
Mid cap	−0.03**	*−8.26*	−0.11**	*−32.00*	0.03**	*9.07*	−0.11**	*−32.55*	0.01**	*2.43*	−0.07**	*−20.29*	−0.01**	*−3.90*	−0.01	*−1.55*
Momentum	0.01**	*3.18*	0.05**	*20.02*	−0.01**	*−3.97*	0.04**	*17.83*	−0.19**	*−62.09*	−0.09**	*−38.40*	0.00	*0.74*	−0.04**	*−16.09*
Profitability	−0.02**	*−5.52*	0.00	*1.40*	−0.03**	*−8.74*	−0.01**	*−4.02*	−0.02**	*−6.14*	−0.00	*−0.09*	−0.02**	*−5.51*	−0.02**	*−9.27*
Residual volatility	0.07**	*19.68*	−0.09**	*−32.60*	0.07**	*19.33*	−0.07**	*−25.24*	−0.01**	*−2.83*	−0.05**	*−17.69*	−0.11**	*−32.20*	−0.13**	*−46.98*
Size	−0.07**	*−18.86*	−0.25**	*−72.34*	−0.38**	*−109.60*	−0.34**	*−104.26*	−0.40**	*−119.71*	−0.27**	*−79.39*	−0.32**	*−91.81*	−0.27**	*−77.13*
No. of Obs.	102,803		198,148		102,803		198,148		102,803		198,148		102,803		198,148	
R^2	12%		16%		23%		23%		27%		17%		21%		14%	

Note: **\|t-stat\| > 2.

one-month options and *R*-squares of 0.12 and 0.16 for the one-year horizon. The results indicate a change in the perception of downside risk associated with CSCI after the passage of the climate treaty.

Before the agreement, carbon intensity was statistically significantly negatively related to downside risk over one-month and one-year horizons. A negative relationship between emissions and left skew indicates that companies with lower emissions have higher downside risk, reflecting a greater chance of a left-tail event. After the agreement's passage, the relationship changes sign: Higher emitters have significantly more downside risk, although no relationship exists at the longer one-year horizon.

This finding is consistent with the notion that after the Paris Agreement took effect, the stock prices of high emitters adjusted to reflect the potential downside scenarios. The coefficient on the CSCI variable can be compared with the coefficients of the other variables because of the standardization process used in the analysis. Over a one-month horizon, as reflected in the 30-day left skew post-2016, the impact of a 1-standard-deviation increase in emissions exposure is 0.0155. This impact is similar in economic magnitude to that of the earnings yield factor, with similar statistical significance indicated by their respective *t*-statistics.

The right skew represents the "upside" opportunity, and with increased regulation, we would expect higher-carbon-intensity companies to have less opportunity. We show the results for the right skew also in Exhibit 7. As expected, the coefficient on carbon intensity is significantly negative before and after 2016 using 365-day option prices. The negative coefficient is 0.0293 in the first period and declines to 0.0093 in the second, with less statistical significance. In the case of right-tail skewness, the passage of agreement appears to have decreased the importance of emission intensity.

Since the Paris Agreement, it has become increasingly common to analyze companies' approaches to managing their carbon emissions relative to the target of reducing emissions by 45% by 2030, with the goal of reaching net zero by 2050. Companies' emissions commitments to net zero are characterized by a temperature reduction goal and a base year—for example, 2°C by 2030. Comprehensive data on companies' commitments have been available since 2019, and we use this data to further evaluate the relationship between option implied volatility skew and emissions. Carbon emissions reflect the company's point-in-time behavior. In contrast, a commitment to a particular net-zero pathway demonstrates the company's overall emission-related goal and provides a clear signal of the company's intent. We expect emissions intensity to matter less for companies with more ambitious commitments.

We evaluate this hypothesis by categorizing companies into three groups for the commitment year of 2030: those with a commitment to a 2°C reduction or less (the most ambitious), those with a commitment greater than 2°C, and those with no commitment. We show the CSCI measure for each of these groups

Exhibit 8. CSCI and Emissions Commitments for 2030

	N	Average	Std. Dev.	25%	50%	75%
CSCI, no target	8,542	0.01	0.56	−0.23	0.01	0.22
CSCI, target >2°C	93,152.00	0.06	0.49	−0.19	0.06	0.29
CSCI, target ≤2°C	44,284.00	−0.13	0.61	−0.45	−0.06	0.23

in **Exhibit 8**. The average CSCI for companies committed to 2°C alignment is lowest amongst the categories at −0.13, as is the 25th percentile score at −0.45. However, the average CSCI for companies that announced a transition target above 2°C is higher than for those that have not committed. The standard deviation of the scores is similar amongst the three categories. From the standpoint of carbon intensity, there is little differentiation amongst these three categories.

We then estimate a regression of option skew in which the coefficient on emissions intensity can vary based on the 2030 commitment level over the period of available data. We show the results of the regression in **Exhibit 9**. The most informative comparison is between the companies that have committed to a target of less than 2°C and those with a commitment greater than 2°C. The skew of companies with an announced target of less than 2°C have overall sensitivity to the current emissions. In contrast, those with some commitment show a robust systematic relationship to left skew over one year and one month. The companies with no announced commitment have the highest sensitivity amongst the three categories, especially with respect to the sensitivity to the right skew over a one-year horizon. These results support the notion that the markets look beyond current emissions and to net-zero emissions commitments in assessing future risk as reflected in option prices.

Although this reflects the behavior of markets in the United States for companies that are primarily US based, it is significant evidence that the options market does pay attention to companies' climate behavior. Despite some resolution of uncertainty in the post-2016 period, a systematic relationship remains between implied skew, as priced by options, and emissions. As measured in this chapter, the emissions are on an industry-related basis, so even portfolios managed on an industry or sector-neutral basis can potentially be exposed to this factor. The company-specific risk impact of emissions does not mean it cannot be diversified away, however. To the extent that business strategies and regulatory policies are industry specific, this risk may be irrelevant in a well-diversified portfolio. We next assess this notion by evaluating the performance of an equity portfolio.

Exhibit 9. Impact of Emissions Commitment for 2030 on Option Skew

	Post 2019							
	365 Days Left Skew		30 Days Left Skew		30 Days Right Skew		365 Days Right Skew	
	Beta	*t*-Stat	Beta	*t*-Stat	Beta	*t*-Stat	Beta	*t*-Stat
CSCI, no target	−0.02	*−1.19*	−0.04**	*−2.26*	−0.06**	*−3.21*	−0.07**	*−4.11*
CSCI, target >2°C	0.02**	*3.36*	0.03**	*5.23*	0.02**	*4.02*	0.01	*0.83*
CSCI, target ≤2°C	0.00	*0.01*	0.02**	*2.70*	−0.01	*−0.85*	−0.01	*−1.95*
Beta	0.03**	*10.49*	0.01**	*2.15*	−0.02**	*−6.97*	−0.11**	*−37.96*
Book-to-price ratio	0.10**	*29.61*	0.06**	*18.93*	0.07**	*19.31*	0.06**	*17.82*
Dividend yield	0.06**	*19.82*	0.04**	*12.48*	0.04**	*13.28*	0.07**	*21.10*
Earnings quality	0.01**	*3.69*	0.01**	*3.30*	0.02**	*8.27*	0.00	*0.86*
Earnings variability	0.03**	*8.89*	0.05**	*15.50*	0.02**	*5.59*	0.02**	*5.30*
Earnings yield	−0.00	*−0.51*	0.01**	*2.56*	0.03**	*8.32*	−0.02**	*−6.31*
Growth	−0.02**	*−6.45*	−0.03**	*−9.76*	−0.01**	*−3.28*	−0.00	*−0.82*
Investment quality	−0.03**	*−10.29*	−0.05**	*−17.24*	−0.02**	*−8.61*	−0.05**	*−16.84*
Leverage	0.08**	*28.90*	0.05**	*19.58*	0.04**	*14.09*	0.01**	*4.67*
Liquidity	−0.09**	*−32.55*	−0.07**	*−26.01*	−0.04**	*−14.97*	−0.07**	*−23.31*
Long-term reversal	0.03**	*9.57*	0.04**	*16.95*	−0.00	*−0.67*	0.02**	*8.72*
Mid cap	−0.11**	*−28.32*	−0.13**	*−34.24*	−0.09**	*−21.22*	−0.02**	*−4.79*
Momentum	0.04**	*14.62*	0.04**	*13.22*	−0.09**	*−31.44*	−0.05**	*−16.52*
Profitability	0.00	*0.74*	−0.02**	*−7.04*	−0.01**	*−3.65*	−0.03**	*−7.92*
Residual volatility	−0.10**	*−31.57*	−0.07**	*−23.64*	−0.05**	*−15.46*	−0.11**	*−35.05*
Size	−0.24**	*−59.32*	−0.31**	*−78.11*	−0.24**	*−59.13*	−0.24**	*−57.75*
No. of obs.	145,978		145,978		145,978		145,978	
R^2	16%		22%		15%		12%	

Note: **|t-stat| > 2.

Carbon Intensity in Equity Portfolios

Well-diversified portfolios allow investors to limit their exposure to the idiosyncratic variation associated with a particular company's actions and strategies, which is especially important when company decisions are only loosely related to economic performance. Before the Paris Agreement, most companies had yet to integrate management of carbon emissions into their business strategy. After the treaty's implementation in 2016, however, there is certainly anecdotal evidence to corroborate our statistical analysis that companies and investors pay attention to this dimension. If we assume, for example, that the risk associated with emissions intensity reflects an undiversifiable or systematic risk, then a portfolio exposed to this factor will experience higher-than-expected volatility resulting from the comovement of stocks in the portfolio. To the extent that emissions risk reflects a transition risk exposure, we would expect the returns of companies with similar emissions to have a nonzero correlation.

In this section, we build multiple portfolios with systematically different exposures to carbon intensity (as measured by the portfolio CSCI, which is simply the weighted average CSCI of each stock in the portfolio) and evaluate their performance and risk. The portfolios are constructed to minimize risk, measured by the tracking error relative to the Russell 1000 Index, although incrementally increasing exposure to company-specific carbon intensity. The exposure to CSCI varies from –3 standard deviations to +3 standard deviations. Absolute active exposure is constrained to 0.6% for each security. This set of constraints, combined with the incremental approach to increasing CSCI, allows us to isolate the impact of carbon emissions on the portfolios' risk profile.[6] We compare the portfolio results with the Russell 1000, a common equity benchmark in institutional equity portfolio management. If exposure to carbon reflects a systematic undiversifiable risk, the risk forecasts for portfolios should be biased downward because the risk forecasts are missing the common carbon-related risk. The extent of the bias will be a function of the portfolio's carbon exposure, either positive or negative. A portfolio with negative exposure to carbon as measured by CSCI will have the "greenest" stocks in every industry, and if carbon intensity is systematically priced as a risk factor, the covariance of these stocks will be higher than expected.

In conducting these tests, we build the carbon-related portfolio using GEMLT combined with a quadratic optimization process.[7] The portfolios are constructed to achieve the lowest possible level of tracking error with the Russell 1000, given the desired target exposure to CSCI. The monthly expected tracking error serves as

[6]See the appendix for more details on the risk factors' exposures between 2015 and 2024 (Exhibit A1), the forecasted active risk using GEMLT (Exhibit A2), the *ex post* active risk (Exhibit A3), and the bias statistic (Exhibit A4).

[7]Barra's GEMLT uses the same financial risk factors that we use throughout this study, along with an idiosyncratic risk forecast for each security. To our knowledge, no current risk model directly incorporates the use of carbon or emissions-related risk factors. The results presented on the bias in the risk forecast are consistent with this variable's omission in the portfolio risk estimation. The GEMLT is aligned with an investment horizon of six months. By limiting our sample to US firms, we limit the potential impact of nonsynchronous trading (caused by differing time zones) on correlations and risk estimates.

the forecasted active risk of the portfolio. If the risk forecast is accurate, the ratio of the portfolio excess return (relative to the benchmark) to the forecasted active risk will have a unit standard deviation when measured over multiple periods.

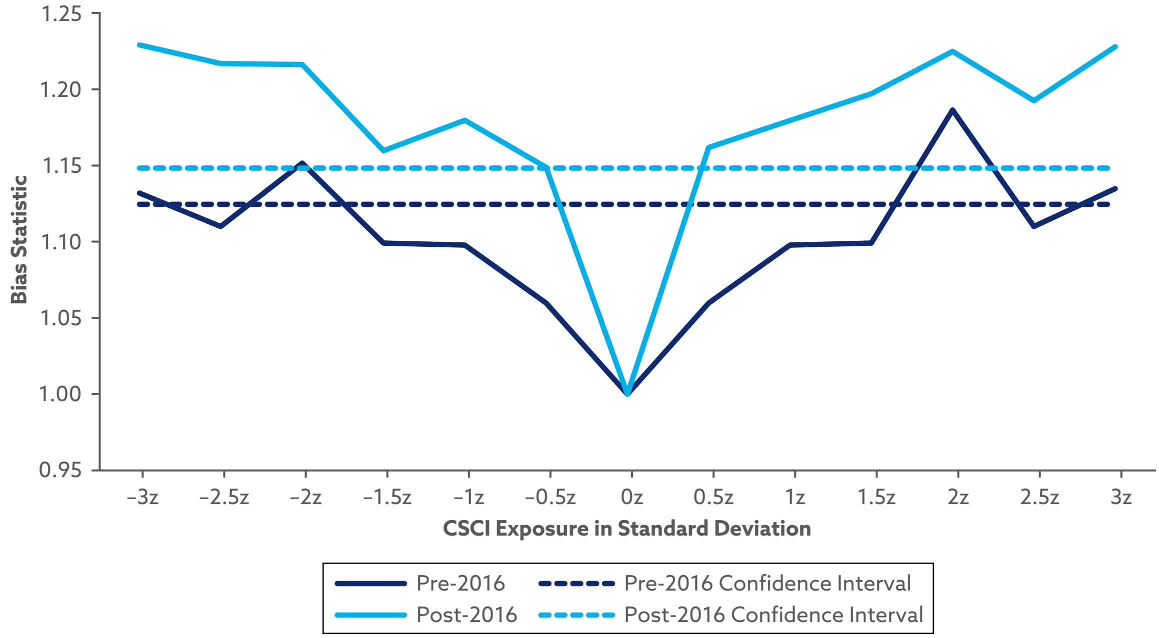
We recognize that risk forecasts are unbiased only over long periods. For example, if measured in periods in which the market is devoid of shocks, the bias statistic will be less than 1. If measured over a period in which the market has been subject to surprises, such as during the COVID-19 pandemic, the bias statistic will be greater than 1. We attempt to address this deficiency by comparing bias statistics of portfolios with varying emissions exposure over the same time period. As such, each portfolio's bias statistic reflects the unique characteristics of the time period. It is possible, however, that high emissions assets were "stranded" and left worthless, which may have been incorporated into asset prices during the period in question. Such a phenomenon could have an impact on our results, but our findings appear to be robust to different time periods.

We reconstruct the portfolio monthly, using the prevailing CSCI exposure and the corresponding risk model. The optimization process aims to identify a set of portfolio weights that minimize tracking error to the benchmark subject to constraints on the targeted CSCI exposure and neutrality to risk factors and industries. Because of the risk factor neutrality, the only potential source of bias in the risk forecast is associated with the CSCI exposure that is explicitly targeted in the optimization. Intuitively, the correlations between stocks with similar CSCI exposure are understated because the risk factor is missing from the covariance matrix. So, by targeting a specific level of CSCI exposure in the portfolio, we are increasing the correlation between the stocks (if the CSCI factor is systematic). The degree of CSCI exposure varies in standard deviation units from –3.00 to +3.00 in increments of 0.50. Note that because of the slight variation in CSCI exposure, using a specific standard deviation target ensures constant portfolio exposure over time.

The test spans February 2006 to January 2024, representing the most extended period over which carbon emissions data are available for a broad universe of equity securities. We measure the forecast bias separately over the pre– and post–Paris Agreement periods. We hypothesize that the latter period will show more significant bias, reflecting a period in which investment professionals have become increasingly climate aware. This latter period is also likely more representative of the environment that investment professionals will face in future years.

Exhibit 10 illustrates the results of the bias test. A portfolio bias statistic greater than 1 indicates a significant risk understatement. This is the case for both periods. The greater the absolute value of CSCI exposure, the greater the bias in the tracking error forecast. The bias statistic follows the V-shaped pattern consistent with risk model misspecification in each period considered. We also show the 95% confidence interval for an unbiased estimate with the appropriate correction for the number of periods used in the estimation in the chart. Notably, the bias is systematically more significant in the post-agreement period, indicating that emissions intensity as measured by CSCI represents

Exhibit 10. Bias Statistic for Forecast Tracking Error vs. CSCI Exposures



a priced factor. As Exhibit 10 shows, the bias is also generally statistically significant, even at modest levels of exposure.

For active equity managers who consider tracking error a critical risk measure, measuring and managing CSCI exposure has become increasingly important since the passage of the Paris Agreement. This importance holds even if the portfolio is not exposed to polluting industries, because the risk factor used here measures exposure on an industry-relative basis. Absent a risk model that explicitly incorporates such a factor, this bias can be approximated by measuring the CSCI of the portfolio relative to the benchmark. The higher the "active" CSCI exposure, the greater the bias. For example, a portfolio with a tracking error of 4% and an active CSCI of 1 standard deviation will have a realized tracking error close to 5% because of the associated bias. This bias could also increase as investors become more aware of high carbon emitters' physical and transition risks.

Conclusion

From these findings, the primary implication for investors is that carbon intensity, specifically measured by the ratio of carbon emissions to revenue, should be treated as a risk factor. The intensity measure used in this chapter has risk implications in terms of economic and statistical significance similar in magnitude to other financial risk factors widely used in the investment industry. Furthermore, using variables related to quality, profitability, or a broad group of other commonly used financial factors does not subsume the power of the carbon intensity variable. Failure to measure and manage this exposure will result in biased estimates of portfolio risk for portfolios exposed to the factor, regardless of whether the exposure is positive or negative.

Although this study focuses on the US equity market, other markets and asset classes can use this framework. We would expect significantly greater bias from this risk factor in regions more susceptible to transition risk or regulatory uncertainty. Although this study used emissions as a risk factor, using companies' net-zero transition commitments could further enhance the equity risk modeling process. Such an approach is similar to using historical and forecast earnings in risk models.

As with most other factors, such as the growth or momentum factor, the return on the carbon intensity factor is uncertain. More importantly, and unlike the other factors, the carbon factor is exposed to regulatory uncertainty and technological innovations. Advances such as carbon capture or the development of alternative energies such as fusion would significantly impact the return and future volatility of the carbon intensity factor, suggesting that this factor could be a substantial source of alpha for those with forecasting ability on this dimension.

Lastly, exposure to carbon intensity should be an active decision incorporated directly into the investment process. Appropriately, investors with different time horizons and risk appetites might make varying decisions based on the results of this study. Some shorter-term investors might see these results as an arbitrage opportunity, choosing to hold stock or option positions that other longer-term investors may avoid. Regardless of the time horizon or risk appetite, investors should consider their portfolio's increased covariance associated with active carbon exposure.

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Appendix

These additional tables highlight the opportunity for the investor to manage their carbon emissions exposure. As illustrated in **Exhibit A1**, we believe it is instructive to see the various statistics by industry to guide improved risk management and portfolio construction. **Exhibits A2** and **A3** highlight that the relationship we described in the chapter is consistent over time, by comparing year-by-year results to the overall results we shared in the chapter.

The exhibits are referenced in footnote 8.

Exhibit A1. CSCI, Summary Statistics by Industry

Industry	Industry Avg.	Residuals Avg.	Std. Dev.	10%	25%	50%	75%	90%
THRIFTS	−1.69	−0.10	0.57	−0.72	−0.48	−0.18	0.30	0.61
INSURNCE	−1.40	−0.06	0.45	−0.59	−0.37	−0.10	0.21	0.51
RGNLBNKS	−1.35	−0.06	0.47	−0.56	−0.36	−0.11	0.15	0.54
CAPMRKTS	−0.87	−0.08	0.49	−0.74	−0.36	−0.04	0.25	0.46
DIVFIN	−0.68	−0.07	0.47	−0.56	−0.32	−0.03	0.19	0.45
BANKS	−0.62	0.20	0.50	−0.23	0.00	0.21	0.43	0.72
SOFTWARE	−0.59	−0.05	0.35	−0.42	−0.24	−0.07	0.15	0.32
INTERNET	−0.55	0.00	0.44	−0.32	−0.22	−0.07	0.16	0.56
MEDIA	−0.53	−0.02	0.43	−0.47	−0.27	−0.02	0.25	0.41
HLTHSVC	−0.39	0.04	0.69	−1.05	−0.38	0.29	0.51	0.77
COMMUNIC	−0.26	0.00	0.48	−0.51	−0.24	−0.04	0.30	0.52
TELECOM	−0.11	0.00	0.41	−0.37	−0.23	−0.09	0.26	0.51
HLTHEQP	−0.06	0.00	0.33	−0.34	−0.14	0.07	0.16	0.29
RLESTMNG	−0.05	0.01	0.77	−1.18	−0.57	0.41	0.53	0.72
COMPUTER	−0.04	−0.01	0.59	−0.70	−0.22	0.04	0.35	0.62

(*continued*)

Exhibit A1. CSCI, Summary Statistics by Industry (*continued*)

Industry	Industry Avg.	Residuals Avg.	Std. Dev.	10%	25%	50%	75%	90%
BIOTECH	−0.03	−0.01	0.29	−0.12	−0.01	0.03	0.11	0.17
AEROSPACE	−0.02	0.03	0.40	−0.45	−0.24	0.03	0.26	0.46
CONSDUR	−0.01	0.03	0.52	−0.59	−0.12	0.05	0.25	0.53
PHARMA	−0.01	−0.03	0.34	−0.42	−0.11	0.02	0.13	0.26
COMMSVCS	0.04	0.03	0.84	−0.88	−0.48	−0.13	0.33	1.12
SMICNDEQ	0.07	0.00	0.57	−0.63	−0.36	−0.05	0.41	0.69
RETAIL	0.10	0.01	0.37	−0.52	−0.07	0.10	0.22	0.34
AUTO COMP	0.11	0.03	0.46	−0.40	−0.21	−0.07	0.19	0.68
FOODRETL	0.11	0.03	0.41	−0.46	−0.17	0.06	0.23	0.36
MACHINRY	0.14	0.01	0.48	−0.46	−0.24	−0.04	0.19	0.49
HSHLDPRD	0.15	0.07	0.64	−0.77	−0.25	0.01	0.36	1.00
BLDCNSTR	0.26	−0.03	0.67	−0.76	−0.36	−0.07	0.40	0.79
SEMICOND	0.30	0.02	0.64	−0.91	−0.41	0.17	0.38	0.67
REALEST	0.34	0.03	0.48	−0.29	−0.10	0.01	0.19	0.52
FOODPRD	0.38	0.04	0.62	−0.66	−0.24	0.02	0.25	0.69
ENERGY	0.44	0.04	0.73	−0.64	−0.48	−0.23	0.44	1.09
CONSVCS	0.46	0.00	0.56	−0.56	−0.28	−0.02	0.23	0.70
PRECMETL	0.56	0.19	0.87	−0.35	−0.11	−0.02	0.78	1.94
TRNSPORT	0.72	0.06	0.94	−1.19	−0.42	0.12	0.74	1.21
GOLD	1.00	0.10	0.85	−0.90	−0.78	0.24	0.82	1.07
STEEL	1.10	−0.02	0.61	−0.80	−0.36	−0.05	0.40	0.80
CHEMICAL	1.11	0.01	0.67	−0.80	−0.50	0.00	0.53	0.93
CONSTPP	1.17	0.07	0.58	−0.60	−0.31	0.05	0.47	0.82
INOILGAS	1.20	0.40	0.54	−0.37	−0.01	0.32	0.64	0.93
AGROCHEM	1.22	0.23	0.88	−0.73	−0.51	0.01	0.75	1.70
OILEXPL	1.29	0.06	0.48	−0.42	−0.20	0.04	0.36	0.67
UTILITY	1.35	0.03	0.67	−0.79	−0.38	0.16	0.44	0.74
OILGAS	1.38	0.06	0.79	−0.81	−0.48	0.13	0.64	1.00
AIRLINES	1.51	0.17	0.61	−0.64	−0.29	0.21	0.55	0.87
DIVMETAL	1.51	0.23	0.61	−0.45	−0.23	0.27	0.63	1.06

Exhibit A2. *Ex Ante* Active Risk: GEMLT

	-3z	-2.5z	-2z	-1.5z	-1z	-0.5z	0z	0.5z	1z	1.5z	2z	2.5z	3z
2006	3.11%	3.11%	2.21%	1.39%	0.73%	0.36%	0.00%	0.36%	0.73%	1.39%	2.02%	3.11%	3.11%
2007	3.04%	2.96%	1.57%	1.12%	0.61%	0.30%	0.00%	0.30%	0.61%	1.12%	1.58%	2.96%	3.04%
2008	4.45%	3.49%	2.22%	1.64%	0.90%	0.45%	0.00%	0.45%	0.90%	1.64%	2.12%	3.49%	5.02%
2009	4.88%	3.86%	2.62%	1.97%	1.09%	0.54%	0.00%	0.54%	1.09%	1.97%	2.86%	3.86%	5.55%
2010	2.51%	2.21%	1.52%	1.14%	0.63%	0.31%	0.00%	0.31%	0.63%	1.14%	1.43%	2.21%	2.88%
2011	1.79%	1.59%	1.10%	0.83%	0.46%	0.23%	0.00%	0.23%	0.46%	0.83%	1.10%	1.59%	2.03%
2012	1.84%	1.50%	1.06%	0.80%	0.46%	0.23%	0.00%	0.23%	0.46%	0.80%	1.07%	1.50%	1.89%
2013	1.70%	1.52%	1.07%	0.82%	0.46%	0.23%	0.00%	0.23%	0.46%	0.82%	1.08%	1.52%	1.91%
2014	1.50%	1.35%	0.96%	0.73%	0.41%	0.21%	0.00%	0.21%	0.41%	0.73%	0.96%	1.35%	1.67%
2015	1.54%	1.27%	0.91%	0.69%	0.39%	0.19%	0.00%	0.19%	0.39%	0.69%	0.99%	1.27%	1.57%
2016	1.63%	1.47%	1.05%	0.80%	0.44%	0.22%	0.00%	0.22%	0.44%	0.80%	0.97%	1.47%	1.81%
2017	1.33%	1.21%	0.87%	0.66%	0.37%	0.18%	0.00%	0.18%	0.37%	0.66%	0.88%	1.21%	1.47%
2018	1.39%	1.15%	0.83%	0.64%	0.36%	0.18%	0.00%	0.18%	0.36%	0.64%	0.82%	1.15%	1.39%
2019	1.45%	1.32%	0.95%	0.73%	0.41%	0.20%	0.00%	0.20%	0.41%	0.73%	0.96%	1.32%	1.58%
2020	1.98%	1.66%	1.21%	0.93%	0.52%	0.26%	0.00%	0.26%	0.52%	0.93%	1.29%	1.66%	1.98%
2021	1.77%	1.62%	1.19%	0.91%	0.51%	0.25%	0.00%	0.25%	0.51%	0.91%	1.11%	1.62%	1.92%
2022	1.48%	1.35%	0.99%	0.76%	0.43%	0.21%	0.00%	0.21%	0.43%	0.76%	1.00%	1.35%	1.60%
2023	1.40%	1.28%	0.94%	0.72%	0.40%	0.20%	0.00%	0.20%	0.40%	0.72%	0.94%	1.28%	1.52%
PRE-2016 AVG.	2.54%	2.21%	1.48%	1.09%	0.60%	0.30%	0.00%	0.30%	0.60%	1.09%	1.47%	2.21%	2.77%
POST-2016 AVG.	1.54%	1.37%	1.00%	0.77%	0.43%	0.21%	0.00%	0.21%	0.43%	0.77%	1.00%	1.37%	1.64%

Exhibit A3. *Ex Post* Active Risk: Standard Deviation of Monthly Active Returns

	-3z	-2.5z	-2z	-1.5z	-1z	-0.5z	0z	0.5z	1z	1.5z	2z	2.5z	3z
2006	4.13%	4.13%	3.40%	1.91%	0.94%	0.41%	0.00%	0.41%	0.94%	1.91%	3.40%	4.13%	4.13%
2007	2.76%	2.76%	2.20%	1.49%	0.64%	0.31%	0.00%	0.31%	0.64%	1.49%	2.21%	2.76%	2.76%
2008	3.27%	2.87%	1.86%	1.31%	0.67%	0.32%	0.00%	0.32%	0.67%	1.31%	1.86%	2.87%	3.19%
2009	1.57%	1.26%	1.18%	1.03%	0.61%	0.29%	0.00%	0.29%	0.61%	1.03%	1.18%	1.26%	2.83%
2010	1.82%	1.79%	1.63%	1.21%	0.64%	0.32%	0.00%	0.32%	0.64%	1.21%	1.63%	1.79%	2.05%
2011	1.98%	1.76%	1.23%	1.00%	0.60%	0.30%	0.00%	0.30%	0.60%	1.00%	1.23%	1.76%	2.30%
2012	1.86%	1.63%	1.04%	0.71%	0.42%	0.21%	0.00%	0.21%	0.42%	0.71%	1.04%	1.63%	2.18%
2013	1.85%	1.50%	0.96%	0.80%	0.47%	0.23%	0.00%	0.23%	0.47%	0.80%	0.96%	1.50%	2.21%
2014	2.14%	1.93%	1.25%	0.94%	0.52%	0.26%	0.00%	0.26%	0.52%	0.94%	1.25%	1.93%	2.31%
2015	2.57%	2.29%	1.55%	1.14%	0.61%	0.31%	0.00%	0.31%	0.61%	1.14%	1.55%	2.29%	2.83%
2016	1.70%	1.52%	1.05%	0.74%	0.40%	0.20%	0.00%	0.20%	0.40%	0.74%	1.05%	1.52%	1.93%
2017	2.04%	1.84%	1.29%	0.97%	0.52%	0.25%	0.00%	0.25%	0.52%	0.97%	1.29%	1.84%	2.24%
2018	2.17%	1.97%	1.38%	0.98%	0.55%	0.27%	0.00%	0.27%	0.55%	0.98%	1.38%	1.97%	2.33%
2019	1.86%	1.67%	1.15%	0.84%	0.44%	0.21%	0.00%	0.21%	0.44%	0.84%	1.15%	1.67%	2.06%
2020	3.07%	2.79%	1.99%	1.49%	0.80%	0.39%	0.00%	0.39%	0.80%	1.49%	1.99%	2.79%	3.39%
2021	1.41%	1.28%	0.94%	0.74%	0.43%	0.22%	0.00%	0.22%	0.43%	0.74%	0.94%	1.28%	1.54%
2022	1.18%	1.13%	0.92%	0.74%	0.45%	0.23%	0.00%	0.23%	0.45%	0.74%	0.92%	1.13%	1.25%
2023	1.53%	1.42%	1.10%	0.84%	0.49%	0.24%	0.00%	0.24%	0.49%	0.84%	1.10%	1.42%	1.62%
PRE-2016 AVG.	2.33%	2.13%	1.58%	1.12%	0.59%	0.29%	0.00%	0.29%	0.59%	1.12%	1.58%	2.13%	2.61%
POST-2016 AVG.	1.89%	1.73%	1.25%	0.94%	0.52%	0.26%	0.00%	0.26%	0.52%	0.94%	1.25%	1.73%	2.06%

Exhibit A4. Bias Statistic: GEMLT

	-3z	-2.5z	-2z	-1.5z	-1z	-0.5z	0z	0.5z	1z	1.5z	2z	2.5z	3z
2006	1.33	1.33	1.54	1.37	1.30	1.14	1.00	1.14	1.30	1.37	1.68	1.33	1.33
2007	0.91	0.93	1.40	1.33	1.05	1.02	1.00	1.02	1.05	1.33	1.40	0.93	0.91
2008	0.73	0.82	0.84	0.80	0.74	0.71	1.00	0.71	0.74	0.80	0.88	0.82	0.63
2009	0.32	0.33	0.45	0.53	0.56	0.54	1.00	0.54	0.56	0.53	0.41	0.33	0.51
2010	0.73	0.81	1.07	1.06	1.02	1.02	1.00	1.02	1.02	1.06	1.14	0.81	0.71
2011	1.11	1.11	1.12	1.20	1.29	1.28	1.00	1.28	1.29	1.20	1.12	1.11	1.13
2012	1.01	1.08	0.98	0.89	0.93	0.93	1.00	0.93	0.93	0.89	0.97	1.08	1.15
2013	1.09	0.99	0.89	0.98	1.02	1.01	1.00	1.01	1.02	0.98	0.89	0.99	1.16
2014	1.42	1.43	1.31	1.29	1.26	1.27	1.00	1.27	1.26	1.29	1.31	1.43	1.38
2015	1.66	1.79	1.71	1.65	1.57	1.58	1.00	1.58	1.57	1.65	1.57	1.79	1.79
2016	1.04	1.03	1.00	0.93	0.90	0.89	1.00	0.89	0.90	0.93	1.08	1.03	1.06
2017	1.53	1.53	1.48	1.46	1.41	1.38	1.00	1.38	1.41	1.46	1.47	1.53	1.53
2018	1.56	1.71	1.66	1.54	1.53	1.54	1.00	1.54	1.53	1.54	1.68	1.71	1.68
2019	1.29	1.27	1.20	1.15	1.08	1.05	1.00	1.05	1.08	1.15	1.19	1.27	1.30
2020	1.55	1.68	1.64	1.60	1.54	1.50	1.00	1.50	1.54	1.60	1.54	1.68	1.71
2021	0.80	0.79	0.79	0.81	0.84	0.87	1.00	0.87	0.84	0.81	0.85	0.79	0.80
2022	0.80	0.84	0.93	0.97	1.06	1.08	1.00	1.08	1.06	0.97	0.92	0.84	0.78
2023	1.09	1.12	1.17	1.17	1.21	1.20	1.00	1.19	1.21	1.17	1.16	1.12	1.07
PRE-2016 AVG.	1.03	1.06	1.12	1.09	1.06	1.04	1.00	1.04	1.06	1.09	1.13	1.06	1.07
POST-2016 AVG.	1.23	1.27	1.27	1.24	1.24	1.23	1.00	1.23	1.24	1.24	1.26	1.27	1.27

Notes: The bias statistic is computed dividing the active return by the forecasted tracking error as measured by the GEMLT. This calculation creates a monthly bias metric. Computing the standard deviation of this monthly metric over the year creates an annual bias metric.