Managing Climate and Carbon Risk in Investment Portfolios

February 2018

SOCIETY OF ACTUARIES

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Executive Summary

This research focuses on analyzing and managing climate change and carbon risk in the equity investment portfolios of insurance company and pension fund assets. The following findings and contributions are elaborated in this final report, which should provide useful insights to both industry practitioners and academics for the management of climate-driven investment risks:

1. There is a general lack of attention devoted to climate change and carbon risk from an investment perspective, and existing methods for managing the risk are heavily based on divestment from emission-heavy industries and investment in green instruments. (Section 1)

2. From empirical studies based on historical price data, we find that:

    - Carbon and climate change risks have not been fully recognized and priced by the stock markets in Europe and North America. (Section 2.2.1)
    - Carbon-intensive industries did not deliver sufficient risk-adjusted return in the past decade to be considered indispensable performance enhancers in investment portfolios. (Section 2.2.2)
    - Emission allowances can serve as potential diversifiers in investment portfolios while providing a significant offset to carbon risk exposure. (Section 2.3)

3. Metrics and methodologies are proposed to quantify the carbon and climate change risks for stocks, while models and frameworks are presented for the quantification and stranded asset risk in terms of impact on the stock's investment return. (Section 3)

4. Drawing from findings from this research as well as established methods in existing studies, we propose a framework for constructing an optimal portfolio with effectively mitigated climate change and carbon risk. In addition to a step-by-step guide, an illustrative example is provided to guide the implementation of the framework for practical industry use. (Section 4)

Section 1: Literature Review

Stern (2007) was among the first to study the economic impact of climate change and presented the findings in a 600-page report. This report focused on both the quantitative impacts of climate change risk on the macroeconomy and the cost-benefit analysis of emission reduction. In addition to considering the physical effects of global warming (such as damage to environment, property, human life and resources) by using disaggregated techniques, integrated assessment models (IAMs) were used to quantify the consequences to the economy as a whole, while macroeconomic models were adopted to capture the cost and effects of transitioning to low-carbon energy systems. The marginal cost of continued emissions was compared to the marginal cost of emission abatement and other collaborative evidence to conclude that the benefit of emission control considerably outweighs the associated cost. This study examined the climate change risk at a high level and was not targeted at the impacts of the risk from an investment perspective. However, this reference is important from a historical perspective as it inspired a series of important studies on the topic of climate change risks.

A report by Brath et. al. (2015) for the Canadian Institute of Actuaries is among the few studies carried out by an actuarial organization with a focus on climate change risk and its relevance to actuarial practices. In addition to an introduction to the climate change problem and the associated risks from an insurance business perspective (such as rising sea levels, floods and droughts), the study specifically discusses resource scarcity and sustainability, carbon is viewed as an intersection of climate change risks and global resource limitation. Because resource constraints limit the potential for economic growth, they should be expected to have a pervasive effect on actuarial assumptions about financial, economic and demographic outcomes.

Such key considerations are important factors in our present study. Although it is conducted at a relatively high level and is less specific about the climate change–related investment risk, this study provides a comprehensive review of the existing emission control frameworks, including regulatory policies and treaties. It also highlights a few important issues we will consider for the climate change risks underlying investment portfolios, such as stranded assets in the fossil fuel sector, wide variations in emission levels by countries and sectors, and the geographically uneven effects of climate change.

As a sequel to a survey conducted in 2014, Messervy (2016) has studied the climate risk management practices that are currently deployed by the insurance industry. The study shows that, based on the responses from 148 insurers, 16% have a high rating in managing climate-related risk. This represents an improvement over the 2014 result, yet it still displays a lack of effort in coping with this emerging threat within the industry. While property and casualty (P&C) insurers are most directly and tangibly exposed to climate risk through the businesses written, health insurers also face potentially significant risk from the detrimental climate impact to human health and well-being; however, the latter group shows a general lack of attention to climate risk management. Life insurers and pension funds have relatively little direct exposure to climate risk on the liability side, but they do have material exposure on the asset side by holding long-duration investment portfolios with significant weights in real estate and carbon-intensive industries.

Laplante and Watson (2017) have studied the performance of environmentally conscious indices under the influence of carbon risk. They point out that the global effort of transitioning to lower carbon economies brings both risks and opportunities to financial institutions, where mispricing of the carbon risk is expected to worsen. Environmentally conscious indices are alternative investment vehicles that satisfy the interest of a low carbon economy where green investing is preferred. These indices vary heavily in composition and carbon footprints. The report analyzes five environmentally conscious indices—STOXX Global Climate Change Leaders, S&P/TSX 60 Fossil Fuel Free Carbon Efficient Index, S&P/TSX 60 Carbon Efficient Select, S&P Global Clean Energy and FTSE EO 100—against which the S&P 500 and Dow Jones were chosen as market benchmarks. Over the study period from 2011 to 2016, four of the indices offered both lower carbon intensities and better performance than the market. S&P Global

Clean Energy, the only exception, offered lower returns and a substantially higher carbon intensity than the market. It can be concluded that when managed wisely, it is possible to address the carbon risk of equity portfolios profitably. However, there are no comparative intertemporal studies on these indices to determine the policy effect of major environmental regulations and movements that should, in theory, impact the stock performance of carbon-intensive industries.

In addition to green indices, Ibikunle and Steffen (2015) have studied the performance of green mutual funds compared to those of black mutual funds and conventional mutual funds from 1991 to 2014. (Black mutual funds are heavily invested in fossil energy and natural resources.) Their analysis adopts a single-factor capital asset pricing model and Carhart's four-factor return model to explain each fund's return using market risk premium, return spread between small and large cap firms, return spread between value and growth stocks, and return spread between winners and losers in the past year. Both models were implemented with a data set consisting of 175 green, 259 black and 976 conventional funds. While the green funds underperformed the conventional funds over the full sample period, they displayed no significant performance difference from the black funds on a risk-adjusted basis. In addition, the risk-adjusted return of green funds improved remarkably to catch up with that of the conventional funds and exceeded that of the black funds over the recent period of 2012–2014. Of particular interest to our study is the subperiod analysis of the fund's performance prior to and after 2003, the year in which the European Union Emission Trading Scheme (EU ETS) was initiated. Unfortunately, few valid conclusions can be drawn based on the results as the mean excess return estimates for all funds appeared to be higher for the second period. Nevertheless, the fact that more than two thirds of the green funds in the sample were created after 2013 provides evidence of the market's higher demand for green investments in response to the establishment of emission control protocols.

Condon (2015) has examined the opportunities for investment portfolio decarbonization under the prevailing climate change scheme. Aside from the complex implications of stranded assets and upstream/downstream involvements of the investable firms in fossil fuel production, the author carried out a study using the MSCI World Index. He found that decarbonization of an investment portfolio can be achieved effectively through divestment from four major source sectors of greenhouse gas emissions—utilities (33%), materials (23%), energies (12%) and transportation (11%)—by avoiding the highest carbon emitters from these four industries and replacing them with low carbon footprint firms from other sectors. The author further showed that removing the 10% most carbon-intensive companies from these four sectors is sufficient to achieve a 20% reduction in the carbon emissions of a portfolio based on the MSCI World Index. Nevertheless, the study lacks consideration of the resultant portfolio performance.

Anderson, Bolton and Samama (2016) have proposed an investment portfolio hedging strategy against climate change risk, which is confirmed through a numerical analysis. The authors demonstrate that existing pure-play green indices are not effective hedging instruments against climate change risk. These indices simply invest heavily in the renewable and clean energy market, which ignores the timing of the impacts of risk, especially the policy risk. Instead, the authors favor the divestment approach, where an investment portfolio is decarbonized by removing/underweighting the carbon-intensive stocks from its components and restructured to minimize the tracking error with regard to selected benchmarks. Assuming that carbon risk is currently underpriced by the market, the authors propose the following two algorithms for decarbonizing a portfolio. In the first, the portfolio's constituents are ranked according to their carbon footprints. Then, an optimization problem is solved to minimize the ex ante tracking error (that is, the standard deviation of the differences in the monthly returns between the resultant portfolio and the benchmark) by varying the assets' weights in the portfolio, subject to a carbon exposure constraint. The authors propose two alternative versions of the constraints. The first is total exclusion of the k assets with the worst carbon footprint. In the second, an upper bound Q can be imposed on the weighted average of all assets' carbon footprints. Numerical examples are provided to show that these two alternatives lead to significantly different portfolio compositions but similar tracking errors. The calculation of the tracking error relies on a multifactor risk model similar to the one in Ibikunle and Steffen (2015), although simpler alternatives are available. In summary, this approach is particularly suitable for managing the carbon risks embedded in long-term passive investment portfolios, such as the ones comprising the assets of insurance companies and pensions.

Mercer et al. (2016) published a study on the impacts of climate change risks on investment portfolios, where a scenario-based model is deployed in quantifying such impacts for the period from 2015 to 2020. We provide a quick review of this approach here because it provides valuable insights to our study. First, using an advanced climate modeling technique and based on existing studies, four scenarios relevant to investors are developed, namely Transformation, Coordination, Fragmentation (lower damages) and Fragmentation (higher damages). These scenarios are built on two key components: the emission pathways that depend on the climate control action and the economic damage derived by using integrated assessment models. For example, the Transformation scenario is characterized by an ambitious and strong climate change mitigation action to limit global warming to within 2 degrees Celsius above the preindustrial era; emissions will peak by 2020 and then be reduced by 56% relative to 2010 levels by 2050, by which time fossil fuels will represent less than half of the global energy mix. Next, asset returns are assumed to be driven by four climate change risk factors, namely technology, resource availability, physical climate impacts and policy. A quantitative pathway is then developed for each risk factor and scenario. Last, asset class and sector sensitivities to each of the risk factors are assessed based on current evidence and forward-looking qualitative judgments. These sensitivities are relative measures in 0.25 increments and are assumed to remain static over the modeling period. For example, the emerging market global equity is assumed to have a –0.25 sensitivity to resource availability, while global real estate has a –0.75 sensitivity to physical climate impacts. Within the equity sector, carbon-intensive industries such as oil and gas are assumed to carry highly negative sensitivities ranging from –0.5 to –1. Of particular interest is that hedge funds, private debt and developed markets sovereign bonds have 0 sensitivities to all four climate risk factors. These can be considered and factored into a sustainable portfolio construction methodology that is proposed in our study. The climate impact on return for each asset class is then given by the following equation:

$$\text{Investment return impacts} = \text{Scenario pathways} \times \text{Asset sensitivity}$$

Notice that the model proposed in this study is deterministic and relies on qualitative judgments as inputs, which are the drawbacks in most existing methodologies for managing climate-related investment risk. The results of this study provide insights into investment portfolio management under the potential impacts of climate change risk. Unfortunately, these insights do not extend to any explicit portfolio optimization frameworks explored in our study.

Section 2: Market Analysis of Carbon Risk and Emission-Intensive Sectors

This section presents the empirical analysis of several key aspects of carbon risk embedded in the stock market and carbon emission allowances using historical stock market and European Union allowance (EUA) price data. In particular, the following three topics are explored:

- Whether carbon risk has been recognized and priced in the stock market
- How stock markets perform for traditional carbon-intensive sectors
- The historical performance of emission allowances and its diversification potential as an alternative asset class

2.1 Historical Market Pricing of Carbon Risk

Despite the complex long-term nature of carbon risks, it is of great interest to learn whether carbon risk has historically been recognized and priced by the stock market. The level to which carbon risk has already been accounted for has key implications for the significance of portfolio decarbonization in the current economy.

The most direct driver of carbon risk is the adoption of new emission control policies and protocols governing market participants. Therefore, a market's recognition of carbon risk is reflected in the stock price returns around the launch periods of major emission control schemes; returns that are most pronounced in the carbon-intensive sectors. This calls for an intertemporal analysis of the stock prices of emission-heavy industries by using event study techniques carried out through the following steps:

1. Select stock samples from the carbon-intensive sectors in the markets of interest. Historical prices of the selected stocks are collected for a sufficiently long study period that covers the initiation of the emission control scheme (the event).

2. Since the carbon-intensive sectors are generally affected by oil price movements, a two-factor model is adopted to filter the systematic effects of stock market movements and oil price changes as given by the following equation:

$$r_{i,t} = \beta_0 + \beta_1 r_{M,t} + \beta_1 r_{oil,t} + r_{excess,t}$$

   where $r_{i,t}$ is a stock's return for period t; $r_{M,t}$ is the period-t return of the corresponding market index; and $r_{oil,t}$ is the period-t return of the oil price. $r_{excess,t}$ is the period-t excess return not captured by the two factors (such as market return and oil price return) and hence constitutes the return information to be used for the analysis. The factor model is calibrated to the historical price data by using a calibration period sufficiently distant from the event.

3. A testing period is determined that spans (for example) the year before and the year after the event to accommodate the leakage and diffusion of information, which affects the timing that the market recognizes and reflects the carbon risk in the stock prices. The excess returns for the testing period are estimated from the calibrated two-factor model in the previous step.

4. To perform qualitative analysis, the cumulative excess returns over the testing period are plotted. If carbon risk is recognized and priced, a significant and sudden drop in cumulative excess return should occur around the event point, forming a "cliff" shape. Such drop points are further verified to ensure they do not correspond to other market factors (dividends, stock splits and so on).

5. To perform quantitative analysis, statistical tests are conducted to check whether the average excess returns after the event are lower than those prior to the event, which provides evidence of the market's recognition and pricing of carbon risk.

2.1.1 Historical Pricing of Carbon Risk in European Markets

Launched at the beginning of 2005, the European Union Emission Trading Scheme is the first formal market-based emission control scheme in the world. The establishment of such a regulatory scheme sends a clear message on the downside of carbon risk exposures, which should be priced by the market and reflected as return strains in emission-heavy stocks. For this analysis, 15 stocks from the emission-intensive sectors across the EU region were selected as the sample based on their market capitalizations and emission levels (Table 2.1).

Table 2.1

Selected Samples From the European Market's Emission-Intensive Sectors

Name	Sector	Country	Index/Exchange	Symbol
National Grid Plc	Gas, Water, Multiutilities	Britain	FTSE 100	NG.L
Centrica PLC	Gas, Water, Multiutilities	Britain	FTSE 100	CAN.L
BP plc	Oil & Gas Producers	Britain	FTSE 100	BP.L
Severn Trent Plc	Oil & Gas Producers	Britain	FTSE 100	SVT.L
Royal Dutch Shell Plc	Oil & Gas Producers	Britain	FTSE 100	RDSB.L
Anglo American Plc	Mining	Britain	FTSE 100	AAL.L
Antofagasta Plc	Mining	Britain	FTSE 100	ANTO.L
BHP Billiton Ltd	Mining	Britain	FTSE 100	BLT.L
Total SA	Oil & Gas Producers	France	Euronext Paris	FP.PA
BASF SE	Chemical and Materials	Germany	DAX	BAS.F
E.ON SE	Energy and Utilities	Germany	DAX	EOAN.F
RWE AG	Energy and Utilities	Germany	DAX	RWE.F
ENEL Spa	Energy and Utilities	Italy	FTSE MIB	ENEL.MI
Eni SpA	Oil & Gas Producers	Italy	FTSE MIB	ENI.MI
Statoil	Oil & Gas Producers	Norway	OSEAX	STL.OL

To make the analysis more comprehensive, subsector indices for the European Energy, Utility and Material sectors were also selected, contributing three additional samples to the 15 shown in the table.

The study period ran from January 1, 2004, to July 31, 2017.[1] The calibration period for the factor model ran from January 1, 2007, to July 31, 2017, while the testing period spanned a period from January 1, 2004, to December 31, 2005. Both factors in the two-factor model are significant for the 15 sample stocks at the 5% significance level. (The cumulative excess return plots are shown in Appendix A.) Qualitatively, only five of the 18 samples (NG.L, CAN.L, RDSB.L, ENEL.MI and ENI.MI) display cliff-like patterns in cumulative excess returns around the launch of EU ETS to show evidence of historical carbon risk pricing. In the statistical analysis, only one of the 18 samples (ENEL.MI) passes the hypothesis test, showing that the post-ETS-launch returns are inferior, on average, in reflecting the market's recognition of carbon risk. Therefore, carbon risk has not been fully recognized and priced in the European stock markets in spite of the European Union's pioneering initiatives and efforts in emission reduction and control.

2.1.2 Historical Pricing of Carbon Risk in North American Markets

A similar intertemporal analysis can be conducted for the North American market, which is of more interest for this research project. Unlike the analysis for the European market, the emission policy event of interest is the signing of

[1] All study periods used in the analysis in Section 2 were subject to data availability and quality considerations. Much longer study periods are desirable for more reliable conclusions.

the Paris Agreement in April 2016, which is relatively recent. The Paris Agreement sets forth terms in greenhouse gas emission controls and mitigation within the United Nations Framework Convention on Climate Change (UNFCCC) and is signed by 196 countries. Market pricing of carbon risk should be reflected in periods around this policy event. For this analysis, 15 stocks from the emission-intensive sectors of the U.S. and Canadian markets were selected as the sample based on their historical emission levels (Table 2.2).

Table 2.2
Selected Samples From North American Markets' Emission-Intensive Sectors

Name	Sector	Country	Index/Exchange	Symbol
Exxon Mobil Corporation	Energy	U.S.	SP500	XOM
Chevron	Energy	U.S.	SP500	CVX
ConocoPhillips	Energy	U.S.	SP500	COP
Occidental Petroleum	Energy	U.S.	SP500	OXY
Air Products and Chemicals	Materials	U.S.	SP500	APD
Dow Chemical	Materials	U.S.	SP500	DOW
Duke Energy	Utilities	U.S.	SP500	DUK
American Electric Power Companies	Utilities	U.S.	SP500	AEP
Southern Company	Utilities	U.S.	SP500	SO
Exelon Corporation	Utilities	U.S.	SP500	EXC
Suncor Energy	Energy	Canada	SPTSXComposite	SU
Canadian Natural Resources Limited	Energy	Canada	SPTSXComposite	CNQ
Transcanada Corporation	Energy	Canada	SPTSXComposite	TRP
Husky Energy	Energy	Canada	SPTSXComposite	HSE
Imperial Oil	Energy	Canada	SPTSXComposite	IMO

To make the analysis more comprehensive, indices for the Energy, Utility, and Material sectors from the SP500 and SPTSX composite indices were also selected, contributing six additional samples to the 15 shown in the table.

The study period ran from August 1, 2007, to July 31, 2017. The calibration period for the two-factor model ran from August 1, 2007, to December 31, 2013, while the testing period spanned the months from April 1, 2015, to March 31, 2017. Market return remains a significant factor for all samples at the 5% significance level, while oil return is a significant factor for most (16 of 21) of the samples. (The cumulative excess return plots are shown in Appendix B.) Qualitatively, only six of the 21 samples (XOM, SO, SU.TO, HSE.TO, IMO.TO and SP500 Energy Index) display cliff-like patterns in cumulative excess returns around the signing of the Paris Agreement to provide evidence of historical carbon risk pricing. In the statistical analysis, none of the 21 samples show any statistical difference in the average returns for periods prior to and after the event. Therefore, carbon risk has not been fully recognized and priced in the North American stock markets.

In summary, *the intertemporal analysis in this section shows that carbon risk has not yet been fully recognized and priced by the stock markets in either Europe or North America,* which calls for a reduction of carbon risk exposures in long-term investment portfolios with the expectation that the risk will be recognized and priced in the future.

2.2 Stock Performance of Carbon-Intensive Sectors

This section studies the performance of carbon-intensive sectors relative to other stock market sectors. It explores whether these sectors outperform the others on a risk-adjusted basis and should be considered indispensable components of the portfolio. The motivation is that emission-heavy industries carry consistently higher carbon footprints and carbon risk exposure, though the precise timing of such risk in the future is difficult to predict. A reduction in portfolio carbon risk exposure can be achieved effectively now by limiting investment weights in the carbon-intensive sectors, which requires justification by examining the risk-return profiles of these forgone sectors. The analysis is cross-sectoral, meaning risk-adjusted returns are empirically estimated from historical data using measures such as the Sharpe ratio and the Treynor ratio.

2.2.1 Cross-Sectoral Analysis in European Markets

The European stock market consists of a wide range of exchanges and indices within the EU region. In this analysis, the performances of sectors are measured using the 14 STOXX-Europe sector exchange traded funds (ETFs), which are funds designed to track the performance of indices comprising companies from the various market sectors. The carbon-intensive sectors include the oil and gas, utilities, and materials industries. The STOXX Europe 600 UCITS ETF - which tracks the performance of an index of the 600 largest companies from European developed countries - is used as the benchmark index in the calculation of sector performance measures. The fund value data were collected from January 1, 2007, to July 31, 2017, from which the performance metrics are calculated and summarized in Tables 2.3 and 2.4. The relative rankings are shown in square brackets for ease of comparison.

Table 2.3

Sharpe Ratios of European Sector and Benchmark Indices

Sector	10-Yr SR	5-Yr SR	3-Yr SR	Avg 5-Yr Rolling SR
Financial	0.294 [6]	1.331 [1]	0.881 [3]	0.668 [6]
Technology	0.282 [7]	1.244 [3]	1.022 [2]	0.589 [8]
Insurance	0.307 [5]	1.277 [2]	0.791 [6]	0.678 [5]
Health Care	0.627 [3]	0.937 [7]	0.520 [9]	1.160 [2]
Food & Beverage	0.751 [1]	0.889 [9]	0.864 [5]	1.179 [1]
Personal & Households	0.683 [2]	1.107 [5]	1.086 [1]	1.094 [3]
Real Estate	0.143 [11]	0.773 [10]	0.500 [10]	0.631 [7]
Industrial Goods	0.380 [4]	1.005 [6]	0.776 [7]	0.706 [4]
Telecommunications	0.278 [8]	0.622 [11]	0.310 [11]	0.514 [10]
Resources	0.137 [12]	0.270 [14]	0.236 [12]	0.077 [15]
Oil & Gas	0.076 [14]	0.141 [15]	0.021 [15]	0.194 [13]
Utilities	0.002 [15]	0.574 [12]	0.131 [14]	0.131 [14]
Construction & Materials	0.227 [9]	1.183 [4]	0.875 [4]	0.503 [11]
Retail	0.108 [13]	0.442 [13]	0.186 [13]	0.486 [12]
Benchmark Index	0.222 [10]	0.892 [8]	0.533 [8]	0.554 [9]

Table 2.4

Treynor Ratios of European Sector and Benchmark Indices

Sector	10-Yr TR	5-Yr TR	3-Yr TR	Avg 5-Yr Rolling TR
Financial	0.130 [7]	0.318 [2]	0.201 [5]	0.915 [4]
Technology	0.135 [6]	0.331 [1]	0.251 [2]	0.678 [9]
Insurance	0.145 [5]	0.316 [3]	0.183 [6]	0.692 [8]
Health Care	0.326 [2]	0.249 [6]	0.132 [8]	13.029 [1]
Food & Beverage	0.381 [1]	0.241 [7]	0.219 [3]	0.878 [5]
Personal & Households	0.311 [3]	0.281 [5]	0.258 [1]	1.521 [2]
Real Estate	0.080 [10]	0.209 [9]	0.132 [9]	–0.028 [15]
Industrial Goods	0.171 [4]	0.238 [8]	0.173 [7]	0.922 [3]
Telecommunications	0.127 [8]	0.156 [11]	0.073 [12]	0.772 [7]
Resources	0.072 [11]	0.090 [14]	0.076 [11]	0.247 [12]
Oil & Gas	0.035 [14]	0.039 [15]	0.006 [15]	0.356 [11]
Utilities	0.001 [15]	0.151 [12]	0.033 [14]	0.153 [13]
Construction & Materials	0.109 [9]	0.298 [4]	0.202 [4]	0.523 [10]
Retail	0.049 [13]	0.108 [13]	0.044 [13]	0.777 [6]
Benchmark Index	0.056 [12]	0.167 [10]	0.114 [10]	0.112 [14]

The carbon-intensive industries underperformed most of the other sectors on a risk-adjusted basis. In particular, the oil and gas and the utilities sectors are often ranked near the bottom of sector performance. This conclusion is also evident from the plots of the five-year rolling Sharpe and Treynor ratios (shown in Appendix C). It is interesting to note that the risk metrics vary greatly over time, which is particularly pronounced for the Treynor ratio as the beta estimates displayed high instabilities from 2013 to 2014.

2.2.2 Cross-Sectoral Analysis in North American Markets

A similar cross-sectoral analysis is conducted for the North American markets, separating out the United States and Canada. Sector performances for the U.S. market are measured by using the S&P 500 sector indices, which comprise companies from the various market sectors in the S&P 500 according to the Global Industry Classification Standards (GICS). The carbon-intensive sectors include the energy, utilities, and material industries. The S&P 500 index is used as the benchmark index in the calculation of sector performance measures. The index value data were collected from July 31, 2007, to July 31, 2017, from which the performance metrics are calculated and summarized in Table 2.5 and 2.6. The relative rankings are shown in square brackets for ease of comparison.

Table 2.5

Sharpe Ratios of U.S. Sector and Benchmark Indices

Sector	10-Yr SR	5-Yr SR	3-Yr SR	Avg 5-Yr Rolling SR
Energy	0.123 [10]	0.018 [10]	–0.496 [10]	0.331 [10]
Utilities	0.313 [7]	0.682 [8]	0.789 [7]	0.597 [8]
Material	0.309 [8]	0.806 [7]	0.344 [9]	0.552 [9]
Consumer Discretionary	0.649 [4]	1.573 [1]	1.102 [2]	1.301 [1]
Consumer Staples	0.707 [2]	1.056 [6]	0.961 [3]	1.142 [3]
Financial	0.192 [9]	1.377 [4]	0.925 [4]	0.668 [7]
Health Care	0.712 [1]	1.473 [2]	0.835 [6]	1.282 [2]
Information Technology	0.672 [3]	1.432 [3]	1.279 [1]	0.987 [4]
Real Estate	0.328 [6]	0.582 [9]	0.531 [8]	0.743 [6]
Benchmark Index	0.430 [5]	1.315 [5]	0.867 [5]	0.920 [5]

Table 2.6

Treynor Ratios of U.S. Sector and Benchmark Indices

Sector	10-Yr TR	5-Yr TR	3-Yr TR	Avg 5-Yr Rolling TR
Energy	0.036 [10]	0.004 [10]	–0.111 [10]	0.082 [10]
Utilities	0.107 [6]	0.214 [5]	0.279 [1]	0.177 [7]
Material	0.086 [8]	0.141 [8]	0.065 [9]	0.122 [9]
Consumer Discretionary	0.173 [4]	0.254 [2]	0.189 [4]	0.283 [2]
Consumer Staples	0.208 [1]	0.199 [6]	0.194 [3]	0.277 [3]
Financial	0.055 [9]	0.227 [4]	0.164 [5]	0.138 [8]
Health Care	0.208 [2]	0.260 [1]	0.157 [6]	0.292 [1]
Information Technology	0.182 [3]	0.237 [3]	0.220 [2]	0.216 [4]
Real Estate	0.104 [7]	0.132 [9]	0.129 [8]	0.192 [5]
Benchmark Index	0.108 [5]	0.194 [7]	0.135 [7]	0.180 [6]

The carbon-intensive industries underperformed most of the other sectors for the U.S market based on the majority of the metrics. In particular, both the energy and material sectors are ranked at the bottom of sector performance. This conclusion is also evident from the plots of the five-year rolling Sharpe and Treynor ratios (shown in Figures D.1 and D.2 in Appendix D). The rolling metrics for the three U.S. carbon-intensive sector indices remain below the benchmark and other indices for most of the study period.

Sector performances for the Canadian market are measured using the S&P TSX sector indices, which comprise companies from the various market sectors in the S&P TSX Composite according to the GICS. Carbon-intensive sectors are the energy, utilities and material industries. The S&P TSX Composite index is used as the benchmark index in the calculation of sector performance measures. The index value data were collected from July 31, 2007, to July 31, 2017, from which the performance metrics are calculated and summarized in Tables 2.7 and 2.8. The relative rankings are shown in square brackets for ease of comparison.

Table 2.7

Sharpe Ratios of Canadian Sector and Benchmark Indices

Sector	10-Yr SR	5-Yr SR	3-Yr SR	Avg 5-Yr Rrolling SR
Energy	–0.101 [12]	–0.189 [12]	–0.551 [12]	–0.081 [11]
Utilities	0.117 [10]	0.217 [9]	0.454 [5]	0.209 [10]
Material	0.077 [11]	–0.087 [11]	–0.025 [10]	–0.133 [12]
Consumer Discretionary	0.387 [4]	1.728 [3]	0.903 [4]	1.153 [2]
Consumer Staples	0.922 [1]	1.841 [1]	1.349 [1]	1.682 [1]
Financial	0.262 [7]	1.137 [5]	0.335 [8]	0.622 [8]
Health Care	0.326 [6]	0.170 [10]	–0.239 [11]	1.093 [3]
Information Technology	0.410 [3]	1.755 [2]	1.212 [2]	0.692 [7]
Real Estate	0.222 [8]	0.508 [8]	0.442 [6]	0.854 [5]
Telecom	0.358 [5]	1.020 [6]	1.201 [3]	0.820 [6]
Industrial	0.460 [2]	1.263 [4]	0.433 [7]	0.947 [4]
Index	0.122 [9]	0.593 [7]	–0.006 [9]	0.344 [9]

Table 2.8

Treynor Ratios of Canadian Sector and Benchmark Indices

Sector	10-Yr TR	5-Yr TR	3-Yr TR	Avg 5-Yr Rolling TR
Energy	–0.026 [12]	–0.033 [12]	–0.106 [12]	–0.015 [11]
Utilities	0.043 [9]	0.050 [10]	0.112 [5]	0.059 [9]
Material	0.025 [11]	–0.022 [11]	–0.008 [10]	–0.028 [12]
Consumer Discretionary	0.120 [6]	0.338 [3]	0.197 [4]	0.251 [4]
Consumer Staples	0.390 [1]	0.532 [1]	0.429 [1]	0.557 [1]
Financial	0.074 [7]	0.192 [6]	0.062 [8]	0.127 [8]
Health Care	0.177 [2]	0.060 [9]	–0.093 [11]	0.482 [2]
Information Technology	0.160 [3]	0.506 [2]	0.324 [3]	0.213 [6]
Real Estate	0.072 [8]	0.117 [7]	0.110 [6]	0.218 [5]
Telecom	0.146 [4]	0.305 [4]	0.393 [2]	0.294 [3]
Industrial	0.126 [5]	0.229 [5]	0.084 [7]	0.204 [7]
Index	0.028 [10]	0.081 [8]	–0.001 [9]	0.057 [10]

Similar to the results for the U.S. markets, the three carbon-intensive sectors heavily underperformed the benchmark and other sectors on a risk-adjusted basis. The energy and material sectors are associated with negative Sharpe and Treynor ratios across different time horizons, making them the least favorable investments on the list. Further evidence of this is demonstrated by the five-year rolling Sharpe and Treynor ratio values (shown in Figures D.3 and D.4 in Appendix D). The rolling metrics for the three Canadian carbon-intensive sector indices remain below the benchmark and other indices for most of the study period.

In conclusion, emission-heavy sectors underperformed other industry sectors and market benchmark indices historically on a risk-adjusted basis in both Europe and North America. This leads to the conclusion that they are not indispensable performance enhancers in investment portfolios. This result implies that the expected forgone portfolio return in the decarbonization process is likely to be minimal, and new optimal portfolios can be constructed with reduced carbon risk exposures.

2.3 Portfolio Diversification Potential of Carbon Emission Allowances

This section presents an empirical study of the returns of emission allowances relative to those of major stock indices and the oil price index, with a focus on their correlations. This allows us to form a perspective on the diversification potential of emission allowances as an alternative investment class. The allowance price data used in the analysis consists of the daily settlement prices of the December 2017 EUA futures from September 1, 2010, to July 31, 2017. This period covers part of Phase 2 of the EU ETS and Phase 3 to date. Both are open trading phases under which the allowance is nonmaturing and hence appropriate as a long-term investment asset class. The use of futures data is common in existing studies on emission allowances due to the higher volumes and liquidity in the futures market. Oil price returns are calculated from the Brent oil index. Historical data for selected stock market indices were collected for the same study period. Due to the lack of a common benchmark for the indices, emission allowances and oil price, the risk-adjusted returns are measured using return risk ratio (RRR) calculated as

$$RRR = \frac{E(r)}{\sigma(r)}$$

where r denotes the asset's annualized return. Results are summarized in Table 2.9, with the relative rankings shown in square brackets for ease of comparison.

Table 2.9

Historical Return Risk Ratios for Emission Allowance and Selected Major Stock Indices

Sector/Asset	5-Yr RRR	3-Yr RRR	1-Yr RRR	Avg 5-Yr Rolling RRR
EUA	0.096 [8]	0.017 [8]	0.829 [8]	–0.110 [8]
Dow Jones	1.058 [3]	1.016 [2]	3.011 [1]	0.924 [3]
S&P 500	1.117 [2]	0.887 [3]	2.125 [3]	1.073 [2]
NASDAQ Composite	1.341 [1]	1.188 [1]	2.843 [2]	1.213 [1]
Euronext 100	0.736 [5]	0.572 [5]	1.596 [5]	0.612 [5]
S&P TSX composite	0.575 [6]	0.036 [7]	0.587 [9]	0.353 [7]
FTSE	0.515 [7]	0.337 [6]	1.243 [7]	0.365 [6]
DAX	0.862 [4]	0.667 [4]	1.828 [4]	0.795 [4]
Brent oil	–0.338 [9]	–0.438 [9]	1.314 [6]	–0.467 [9]

Over the seven-year study period, the emission allowances outperformed the oil index but underperformed all selected stock market indices. This is consistent with the observations from the historical five-year rolling return risk ratios in Figure 2.1, which also shows a slow but steady improvement in risk-adjusted allowance returns since 2016. In addition, the emission allowances display low correlations in returns to all seven selected major stock indices as well as the oil price index (Table 2.10). This indicates a high diversification potential of emission allowance as an alternative asset class to be included in investment portfolios, although the precise diversification benefit must be quantified in the portfolio optimization practice.

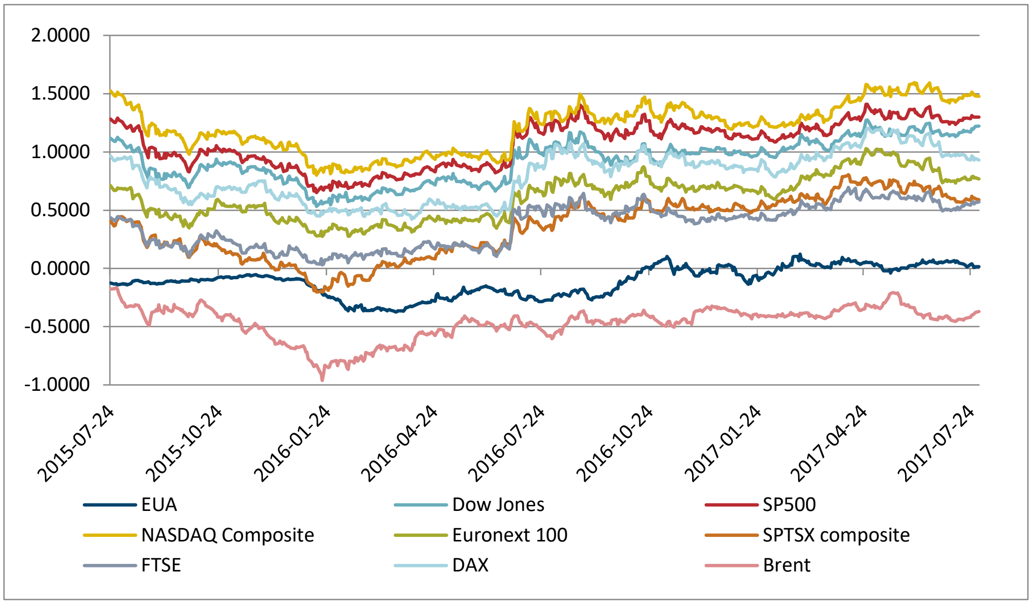
Table 2.10

Historical Return Correlations Between Emission Allowance and Selected Major Stock Indices

Sector/Asset	Linear Correlation	Spearman's Rho
Dow Jones	0.1316	0.1276
S&P 500	0.1321	0.1359
NASDAQ Composite	0.1275	0.1193
Euronext 100	0.1409	0.1326
S&P TSX composite	0.1388	0.1551
FTSE	0.1243	0.1195
DAX	0.1320	0.1262
Brent oil	0.1760	0.1774

Figure 2.1

Five-Year Rolling Return Risk Ratios for Emission Allowances and Selected Indices



In conclusion, emission allowances underperform the major stock market indices historically but have displayed slowly improving return risk ratios over time since 2016. *The EUAs have low return correlations with the indices and hence can be incorporated into investment portfolios for their diversification potential.*

Section 3: Measuring and Quantifying Climate Change Risk

This section presents the key considerations, frameworks and models for the quantification and measurement of climate change risk in the context of investment portfolio management. More specifically, the following three aspects are addressed:

- Measuring carbon risk
- Measuring climate change risk under the scenario-based model
- Measuring stranded asset risk

3.1 Measuring Carbon Risk Exposure

The carbon risk faced by a company is best measured by its carbon footprint, which is simply the annual total Scope 1 and 2 emissions calculated following the Greenhouse Gas Protocol.[2] The protocol establishes a set of generally accepted standards in calculating an entity's greenhouse gas (GHG) emissions and divides the emissions into three scopes:

- Scope 1, also referred to as *direct GHG*, includes emissions from sources that are owned or controlled by the organization. These include stationary combustion from the combustion of fossil fuels for comfort heating or other industrial applications; mobile combustion from the combustion of fossil fuels used in the operation of vehicles or other forms of mobile transportation; process emissions released during the manufacturing process in specific industry sectors; and fugitive emissions that are an unintentional release of GHG from sources such as refrigerant systems and natural gas distribution.
- Scope 2, also referred to as *energy indirect GHG*, includes emissions from the consumption of purchased electricity, steam or other sources of energy (such as chilled water) generated upstream from the organization.
- Scope 3, also referred to as *other indirect GHG*, includes emissions that are a consequence of an organization's operations but are not directly owned or controlled by the organization. This is the most difficult to estimate and is usually excluded from the CDP voluntary emission reports used in this research.

For the purpose of investment portfolio risk management, the total annual emissions usually need to be normalized, leading to the term *carbon intensity*. In most existing studies, this is defined as the annual emissions divided by annual sales revenue, effectively measuring the "density" of emissions corresponding to the company's scale of business. This measure for carbon risk is easy to interpret under the prevailing climate control schemes, since a higher carbon intensity indicates that the company creates more pollution to generate a unit of revenue.

As we are mainly concerned about carbon risk embedded in stocks, we may also consider normalizing the emission by the company's annual net profit, which is directly claimable by the shareholders and thus contributes to the stock performance. The drawback for this approach is that negative profit results in negative carbon intensity, so this metric is only defined for positive profits.

We denote the carbon intensities corresponding to the two definitions above by I_R and I_P, respectively. The equations are as follows:

$$I_R = \frac{AE}{RV}$$

[2] More information found at http://www.ghgprotocol.org.

$$I_P = \frac{AE}{P}\ for\ P > 0, Undefined\ for\ P < 0$$

where AE, RV and P represent the company's annual emission, annual revenue and annual net profit, respectively. In practice, with sufficient emission and financial data, the values assigned to the parameters in these formulas are replaced by their expected values estimated using the historical results. In this case, I_P has a much wider scope of application; it is unlikely that the stock for a company with negative average profits is entering the investment asset universe for portfolio optimization in the first place.

Each of the two carbon intensity measures, I_R and I_P, have their own advantages. I_R has higher stability as a company's revenue tends to be more stable than its net profits across years and hence may be considered a more reliable metric. It is also an accepted measure in the field of carbon-neutral investing. However, I_P is a more interpretable measure of carbon risk for stock investments, since in corporate finance theory, net profits are claimable by the company's shareholders and thus contribute directly to stock returns. Aside from the drawback of I_P having a narrower definition in its scope of application (caused by possibly negative profits), the choice between the two measures essentially represents a trade-off between high stability and ease of interpretation.

Using the 2013 CDP emission reports and the relevant financial statement data, the 2013 carbon footprints of a few North American companies are shown in Table 3.1 for illustrative purposes.

Table 3.1
2013 Carbon Footprint of Selected Companies

Company	Total Emissions (Tons)	Intensity (I_R)	Intensity (I_P)
Exxon Mobil Corporation	146,000,000	0.347	4.481
UPS	12,538,847	0.226	2.868
AT&T Inc.	8,843,067	0.069	0.480
eBay Inc.	240,326	0.029	0.084
Suncor Energy Inc.	20,840,798	0.526	5.329
General Motors Company	7,986,135	0.051	1.494
Intel Corporation	3,125,807	0.059	0.325
Walt Disney Company	1,766,380	0.039	0.288
Goldman Sachs Group Inc.	291,374	0.007	0.036
PepsiCo, Inc.	5,783,274	0.087	0.858
Boeing Company	1,574,000	0.018	0.343
Canadian National Railway Company	5,243,252	0.496	2.007

Note: All carbon intensity values are recorded as one in a thousand.

The portfolio carbon footprint is calculated as a weighted average of the constituents' carbon footprints. In practice, carbon footprints are best used as a relative measure. For example, in most simple portfolio decarbonization methods, the constituent stocks are ranked according to their carbon intensities, where the stocks belonging to the highest basket of intensities are excluded from the asset universe of consideration. Alternatively, a maximum can be placed on the portfolio carbon intensity, while the determination of such a bound requires a subjective assessment.

To properly account for the carbon risk reduction caused by holding emission allowances in an investment portfolio, some additional adjustments are required. Carbon intensities are by nature a flowing ("income statement") metric, whereas the carbon offset embedded in emission allowances constitutes a value ("balance sheet") metric. A precise translation between the two is unlikely, if not impossible, to be reached using structured algebraic techniques. As a simplified approach, a multiplier can be applied to the carbon offset value of emission allowances (currently 1 metric ton per EUA contract) to map it to the intensity domain. That is,

$$I_{Allowance} = \theta K$$

where K represents the carbon offset value in each allowance, and θ is the subjectively determined multiplier. The portfolio carbon risk exposure is then calculated as a weighted average of the constituents' carbon intensities, including any emission allowances in the portfolio.

3.2 Measuring Climate Change Risk

Although carbon intensity offers a direct measure of the carbon risk exposures of investments, the overall climate change risk is more comprehensive in nature and is better measured by using more modular approaches. The scenario-based framework proposed by Mercer et al. (2016) is most appropriate for such a purpose, and we have adapted it to quantify climate change risk. First, future climate change risk is driven by four factors:

Technology (T): the rate of progress and investment in the development of technology to support the low-carbon economy. It can be interpreted as a measure of future low-carbon investment flows under different climate scenarios. Traditional energy sectors are most influenced by this factor as the low-emission energies start to excel in both efficiency and cost.

Resource availability (R): the impact of chronic weather patterns and related physical changes induced by climate change. This factor identifies how changes to the physical environment might affect an investment's reliance on the use of resources that are at risk of becoming scarcer or, in rare cases, more abundant. Sectors such as agriculture and materials are most influenced by this factor.

Physical impact (I): the impact of climate change on the physical environment, caused largely by shifts in extreme weather incidence/severity. This is a more familiar factor to the public. Examples include rising sea levels, coastal flooding and wildfires. Such a risk driver is systematic and affects many industries, including the real estate and insurance sectors.

Policy (P): this is the major factor on which most of our previous discussions are based. It refers to developments in climate policy to reduce carbon emissions. However, as a risk driver, it is now a comprehensive term that includes the government's coordinated effort in items we have not focused on previously, such as building codes to improve energy efficiency and land use regulations to restrict deforestry.

To capture stochasticity, the pathway of each factor is generated under different scenarios. This scenario-based framework can easily be implemented in the existing modeling platforms of financial institutions, insurance companies and pension plans. The Mercer framework adopts four different climate change scenarios over the projection horizon of 2015 to 2050, which are (from lowest to highest severity): Transformation, Coordination, Fragmentation (lower damages) and Fragmentation (higher damages). A more detailed description and assumptions characterizing the scenarios are given in Table E.1 in Appendix E, which is a direct excerpt from the Mercer report.

The most difficult task in measuring climate risk is obtaining the factor values under the scenarios, which relies on highly complex integrated assessment models. Examples of such models include the Climate Framework for Uncertainty, Negotiation and Distribution (FUND); Dynamic Integrated Climate-Economy (DICE), and World Induced Technical Change Hybrid (WITCH). Although a few considerations in generating the scenario paths are listed in the Mercer report, the key process and example in factor paths simulation are unavailable due to their proprietary nature. In this study, we will make our best effort to generate reasonable factor values using available methodologies. Fortunately, although none of the available IAM models directly produces the paths for the four factors, different economic impact metrics may be obtained from the model outputs to serve as proxies for the factor values. It is also worth emphasizing that the dependence between factors is not explicitly captured by existing IAMs, which is a major drawback worthy of further consideration.

The level of climate change risk for each stock or asset class is given by its sensitivity to each of the four factors. Such sensitivity values are assigned subjectively as relative metrics ranging from –1 to 1. As a simple example of this process, we consider the stock of a major oil producer, which is expected to carry material negative sensitivities to all four risk drivers for several reasons:

- Green technologies (T) and fuels make the traditional energy sector less competitive, for which we assign a sensitivity of –0.5.
- Physical impacts (I) and damages to reserve exploitation sites cause business disruption, for which we assign a sensitivity of –0.5.
- Resource scarcity (R) reduces the availability of reserve sources, for which we assign a sensitivity of –0.75.
- Emission control policies (P) most directly affect the revenue and profit margin of oil and gas producers, for which we assign a sensitivity of –1.

The sensitivity assignment can be done at both strategic asset allocation and security selection levels, and it should vary by regions of business operations due to the geographically uneven impact of climate change. External references, such as the Actuaries' Climate Index (ACI)[3] and Actuaries' Climate Risk Index (ACRI), should be used in making the decisions. The incorporation of results from the ACI and ACRI is straightforward because the sensitivity measure is relative and unitless. Some examples of sensitivities assigned to sectors are given in Table 3.2.

Table 3.2
Examples of Sector-Level Factor Sensitivities

Industry Sector	T	R	I	P
Green Energy	0.5	–0.25	–0.25	1
Traditional Energy	–0.5	–0.75	–0.5	–1
Utilities	–0.25	–0.75	–0.5	–0.75
Materials	0.25	–0.75	–0.25	–0.75
Consumer Discretionary	0	0	0	–0.25
Consumer Staples	0	–0.25	0	0
Industrial	0	0	–0.75	–0.5
Health Care	0	–0.25	0	0
Real Estate	0	–0.25	–1.0	0
Telecommunications	0	0	–0.25	0
Financials	0	–0.25	–0.25	0
Information Technology	0.25	0	0	0

For a given climate change scenario, the climate change risk exposure of each asset is calculated by the summed product of the asset's sensitivities and the factor values. We denote the sensitivities and factor values by λ and f, respectively, with proper subscripts to map to the factors (T, R, I or P). Thus, an asset's climate change risk exposure (CRE) is given by the following equation:

$$CRE = \lambda_T f_T + \lambda_R f_R + \lambda_I f_I + \lambda_P f_P$$

For simplicity, we assume that the sensitivities remain constant over the projection horizon of interest. Therefore, for each path of factor values in a given scenario, we obtain a path of climate change risk exposures, which are key inputs in determining the impact on the asset's investment return.

[3] More information found at http://actuariesclimateindex.org/home/

3.3 Modeling Stranded Asset Risk

The term *stranded assets* refers to a broad class of assets that may not deliver the expected returns due to regulatory, technological and other socioeconomic reasons related to the climate change risk. The best example is fossil fuel reserves, following the assumption that most existing reserves cannot be fully exploited at the current technology level due to the emission reduction goals made in established climate control schemes. In practice, many fossil fuel (such as coal, oil and gas) reserves cannot be deployed anymore due to regulatory emission caps or heavy taxation. Therefore, capital invested today in future oil, gas and coal production is at risk of being stranded, leading to significantly lower than expected returns.

The quantification of such a risk, which is referred to as a stranded asset risk (SAR), is difficult due to its long-term nature and uncertainties about future climate policy changes. For a given fossil fuel reserve, an estimated quantification can be made using the following equation:

$$SAR = (M)(LGS)(PS)$$

where *M* is the current market value of the asset (the fuel reserve); *PS* is the probability that the asset will be stranded; and *LGS* is the percentage loss in market value if the asset is stranded in the future. *M* can be determined with a reasonable degree of accuracy based on market information, whereas *LGS* and *PS* can be estimated using models based on assumed policy parameters and normative inputs.

In terms of *PS*, the probability of the asset being stranded over any given period is heavily policy-driven. To model this variable, let *E* represent the exploitable level of the fuel reserve. There exists a threshold level *C*, where the asset is considered stranded if $E > C$. In the case of a rule-based emission control scheme, the regulator imposes an emission cap on each company, from which the threshold can be derived. In the case of a market-based emission control scheme (such as the EU ETS), the threshold corresponds to the maximum reserve exploitation level beyond which the marginal cost of emission allowance or carbon tax exceeds the profits from the exploitation. So the probability that the asset will be stranded in a given period is:

$$\boldsymbol{PS = Pr(E > C) = E[1_{E>C}]}$$

In terms of *LGS*, the percentage value lost given the asset being identified as stranded is the difference between the reserve level and the threshold, less any recoverables *R* (sale of excess installations and exploitation equipments, transformed use of resources and so on), all expressed in terms of percentage of the asset's market value. This can be calculated using the following equation:

$$\boldsymbol{LGS = \frac{E - C}{E} - \frac{R}{M}}$$

The quantification of SAR requires a diligent and comprehensive analysis of the asset of interest as well as a deep understanding of the economics of the industry. The next step is transcribing the stranded asset risk into a perspective of the company's stock return. This can be achieved by examining the composition of the company's asset portfolio:

$$\boldsymbol{\Delta r = \frac{A - SAR - D}{A - D} - 1}$$

Here *r* represents the change in stock return triggered by the asset being stranded, absent all other factors, and *A* and *D* are the values of the company's total assets and debt, respectively. These are preferably market-consistent valuations, although the book values can be used to obtain an approximation.

This framework for estimating stranded asset risk can be extended to a multiperiod case, which is more relevant in practice. In addition, the risk variables can be modeled using different approaches as deemed appropriate (such as deterministic or stochastic, parametric or nonparametric). An example is provided in Appendix H.

Section 4: Investment Portfolio Optimization Under Climate Change Risk

This section presents the investment portfolio optimization framework with mitigated exposures to climate change risk. The framework uses the results and conclusions from the previous sections as well as some well-established results in the existing literature. We use a representative portfolio with a predefined asset universe to illustrate the implementation of the algorithm for an insurer or a pension fund (referred to as Company X in this report). To simplify the explanation, we consider only equity portfolios, but other security classes such as bonds and commodities can easily be incorporated into the framework.

4.1 Background of Portfolio Optimization

The framework presented is based on the mean-variance portfolio optimization theory. Given a selected universe of *n* risky assets (stocks) and a target portfolio return, we aim to minimize the portfolio variance. The problem is formulated as follows:

$$\min w^T \Omega\, w$$

$$s.t.\ \ w^T \mu = \mu_T$$

$$w^T 1_n = 1$$

where

- *w* is the *n* by 1 portfolio weight matrix containing the dollar weights allocated to each stock in the portfolio. For simplicity, we assume no leverage or short selling. Hence each entry in *w* is between 0 and 1 inclusive, with a column sum of 1.
- Ω is the *n* by *n* covariance matrix for the stock returns.
- μ is the *n* by 1 mean vector for the stock returns.
- μ_T is the target portfolio return set by the insurer or pension plan.
- 1_n is the *n* by 1 vector of ones.

This problem is equivalent to maximizing the expected utility from the portfolio investments for a risk-averse entity (investor or institution). A general analytical solution to this problem also exists, and it yields an efficient frontier described by a hyperbola when the assets are not perfectly (positive or negative) correlated. If we define

$$a = \mu^T \Omega^{-1} \mu \qquad b = \mu^T \Omega^{-1} 1_n$$

$$c = \mu^T \Omega^{-1} 1_n \qquad d = \mathrm{ac} - b^2$$

$$\Phi = \frac{1}{d}(a\Omega^{-1} 1_n - b\Omega^{-1}\mu)$$

$$\Theta = \frac{1}{d}(c\Omega^{-1}\mu - b\Omega^{-1} 1_n)$$

then, the optimal solution is given by

$$w^* = \Phi + \Theta\mu_T$$

with the efficient frontier given by

$$\sigma_P = \sqrt{\frac{c}{d}\left(\mu_P - \frac{b}{c}\right)^2 + \frac{1}{c}}$$

where σ_P and μ_P denote the volatility and the expected value of portfolio return, respectively.

Unfortunately such a solution is not possible as other more complex constraints are added to the problem, which is often the case in practice since the insurer or pension plan is subject to regulations and internal risk management guidelines, posing additional constraints to the portfolio holdings. However, the Markowitz (1959) framework sets the foundation of the investment portfolio optimization algorithms currently adopted by financial institutions, insurers and pension funds.

(Source and background reference: Fahmy, H., The Foundations of Finance Theory: A Mathematical Approach.)

4.2 Portfolio Optimization Framework with Climate Change Risk Management

Overall, the optimization algorithm implements portfolio-level climate change risk management through two channels:

1. Introducing additional constraints to the existing optimization problem that aims to reduce the portfolio level carbon risk exposures

2. Quantifying the expected changes in the returns of various assets and securities in response to climate change under different scenarios and reflecting them in the parameters of the existing optimization problem

These two channels work in synergy, so not only is the resultant portfolio immune to the highly unpredictable impacts from carbon risk, but it also takes advantage of any foreseeable upside potential climate change may bring to certain asset classes. To the best of our knowledge, this comprehensive approach has not yet been leveraged in existing literature in the area of investment management under climate change.

4.2.1 Key Modules in the Framework

1. Asset universe selection. A universe of assets is first selected. This is a topside decision that accounts for regulatory constraints as well as internal investment/product risk management policies. For example, speculative derivative investments are usually excluded from the asset universe for insurers and pension plans. The investment portfolio is built by using the assets in this selected universe.

2. Risk-return characterization. For all assets in the selected asset universe, we estimate the mean, variance and complete covariance structures of the assets' annual returns by using historical price data adjusted for dividends and stock splits. The estimated values can then be stored in the mean vector μ and covariance matrix Ω as defined earlier in section 4.1.

3. Strategic asset allocation. A sector allocation is performed to determine the relative investment weights in the major asset classes and major stock market sectors. The target portfolio return is factored into consideration in this step. Strategic asset allocation introduces constraints in equality or inequality forms to the portfolio optimization problem. For example,

- Sum of investment weights in financial sector = 10%
- Sum of investment weights in health sector > 5%

A strategic asset allocation must serve the main investment propositions of the portfolio. For insurers and pension funds, the asset portfolio backs up relatively long-term liabilities, so a balanced sector allocation aiming for long-term growth is appropriate.

4. Carbon risk management. Following the methods presented in Section 3.1, two steps are involved in this module:

- Estimating the carbon footprints of the assets. For stock portfolios, the preferred intensity measure is the profit-based I_P. For emission allowance contracts, we determine the relevant parameters: the multiplier θ and the emission offset value K.
- Devising carbon risk management strategies, which may include but is not limited to the following:
  a) Tactical asset allocation, in which we adjust the strategic asset allocations to restrict weights in the carbon-intensive sectors.
  b) Divestment, in which we exclude the top emitters (such as the top 10% in terms of carbon intensity) from the asset universe. This is a common approach in existing portfolio decarbonization strategies.
  c) Portfolio exposure control, in which we set a cap for portfolio carbon intensity (for example, 0.5) and introduce it to the optimization problem as an inequality constraint. An alternative is making the portfolio carbon-neutral (carbon intensity = 0), which constitutes an equality constraint.

5. Stranded asset management. Following the method presented in Section 3.3, we identify stocks associated with stranded assets based on prevailing information and environmental regulations. We quantify the SAR in terms of impacts to stock returns and reflect the results in the mean vector μ of the asset universe. Most potential stranded assets reside in the energy and material sectors.

6. Scenario-based climate change risk management. Using the framework presented in Section 3.2, we quantify climate change risks for each asset class (or, if resources permit, each individual asset) in the asset universe in terms of impacts to returns. We then reflect the results in the mean vector μ of the asset universe. Notice that the framework in Section 3.2 is based on the Mercer et al. (2016) approach. The actual scenarios and risk factors used in this module should be based on the preferred integrated assessment model and climate risk drivers with adjustments and inputs from available subject area experts or resources. The basic components are as follows:

- We set a proper projection horizon that covers the period of interest, which can be based on the term of the liabilities.
- We select an integrated assessment model for climate economics. The models vary in complexity and ease of implementation. Suggested candidates include the WITCH and DICE models. If resources permit, a combination of IAMs can also be used.
- We formulate climate change scenarios reflecting different levels of coordinated climate control effort and the resultant global warming effects. The scenarios should be associated with different parameter inputs in the chosen set of IAMs.
- We assign probabilities of occurrence to each scenario.
- We choose climate change risk factors whose paths can be generated by the selected set of IAMs. In cases where the risk factor variable is not a direct output of the IAM, proxies can be used as necessary.
- We assign risk driver sensitivities to each asset class, which ranges in the interval [–1, 1] in increments of 0.25.

- Under each scenario, we generate paths of risk factor values by using the selected set of IAM and appropriate proxies. Transformations are used as necessary to map the factor values to unitless relative values.
- Under each scenario, we calculate the paths of climate change risk exposure for each asset class by taking the summed product of its sensitivities and the corresponding factor value paths. Then we take the values corresponding to the ends of the periods of interest and calculate the difference (that is, the change in exposures).
- We translate the change in climate risk exposures to return impacts by proper mapping or transformation. Next we take the expected values of the impacts using the probability of occurrence previously determined for each scenario. We reflect the results in the mean vector μ of the asset universe along with subjective inputs.
- To perform tactical asset allocation, we adjust the strategic asset allocations based on the sectors' relative expected performances under climate change risk from the scenario-driven results.

This module requires a significant amount of normative inputs in forming the scenarios, mappings and transformations to obtain the desired outputs, which will reflect the company's expertise and effort in managing climate change risk. Linear transformations may be used for simplicity, though more complex methods should be considered if possible to capture the nonlinear evolutions of climate change risk.

7. We formulate the new portfolio optimization problem as follows:

$$\min w^T \Omega\, w$$

$$s.t. w^T \mu = \mu_T$$

$$w^T 1_n = 1$$

$$Aw = a$$

$$Bw < b$$

where

- *A* is a *k* by *n* matrix, and *a* is an *n* by 1 vector. They collectively define the *k* equality constraints determined in Modules 3 and 4.
- *B* is an *m* by *n* matrix, and *b* is an *m* by 1 vector. They collectively define the *m* inequality constraints determined in Modules 3 and 4.

Such a vector/matrix-based mathematical representation of the problem is easy to implement in many common platforms. It does not introduce any technical contributions in the portfolio decarbonization and optimization process. It is also important to note that Modules 1 through 3 - asset universe selection, risk-return characterization and strategic allocation - are common practices in the traditional mean-variance portfolio optimization framework adopted by most financial institutions and pension funds. They are not specific modules of climate change risk management for investment portfolios and are included in the framework for completeness.

4.2.2 Example: Optimal Portfolio Under Climate Change Risk

This section presents a hypothetical example to illustrate the investment portfolio optimization framework introduced in Section 4.2. We take the role of a representative pension fund for illustration purposes only; this fund is not based on the status of any actual entity in the industry.

General Assumptions and Specifications

- The portfolio is built from only publicly traded U.S. and Canadian stocks.
- A relatively small but diverse universe of stocks are used.
- *The target return of the portfolio is 15% per annum*, and the goal is to minimize portfolio risk.
- No identifiable stranded assets underlie the stocks in the selected universe at the current time.
- The beginning of the period of interest for the investment portfolio is set to 2018.
- Climate change risk will not pose significant changes to the dependencies between asset returns.

Asset Universe Selection

The asset universe consists of 35 publicly traded stocks. The emission allowance (represented by the December 2017 EUA futures) also enters the portfolio during the optimization process. Table 4.1 provides a complete list of the stocks in the universe as well as their market sectors.

Table 4.1
Asset Universe for the Representative Pension Fund

Company	Stock Symbol	Sector	Country
eBay Inc.	EBAY	Consumer Discretionary	U.S.
Walt Disney Company	DIS	Consumer Discretionary	U.S.
General Electric Company	GE	Consumer Discretionary	U.S.
Time Warner Inc.	TWX	Consumer Discretionary	U.S.
Starbucks Corporation	SBUX	Consumer Discretionary	U.S.
PepsiCo, Inc.	PEP	Consumer Staples	U.S.
Coca-Cola	KO	Consumer Staples	U.S.
Walmart, Inc.	WMT	Consumer Staples	U.S.
General Mills	GIS	Consumer Staples	U.S.
Proctor & Gamble	PG	Consumer Staples	U.S.
Exxon Mobil Corporation	XOM	Energy	U.S.
Suncor Energy Inc.	SU.TO	Energy	Canada
Duke Energy Corporation	DUK	Energy	U.S.
Chevron	CVX	Energy	U.S.
ConocoPhillips	COP	Energy	U.S.
Goldman Sachs Group, Inc.	GS	Financial	U.S.
Morgan Stanley	MS	Financial	U.S.
Bank of Montreal	BMO.TO	Financial	Canada
JPMorgan Chase & Co.	JPM	Financial	U.S.
Citigroup Inc.	C	Financial	U.S.
Manulife Financial Corp.	MFC.TO	Financial	Canada
Colgate-Palmolive	CL	Health Care	U.S.
Johnson & Johnson	JNJ	Health Care	U.S.
United Parcel Service	UPS	Industrials	U.S.
Boeing Company	BA	Industrials	U.S.
Canadian National Railway Company	CNR.TO	Industrials	Canada
Oracle Corporation	ORCL	Information Technology	U.S.
Intel Corporation	INTC	Information Technology	U.S.
Google Inc.	GOOGL	Information Technology	U.S.
Microsoft	MSFT	Information Technology	U.S.
Dow Chemical Company	DOW	Materials	U.S.
Simon Property Group	SPG	Real Estate	U.S.
AT&T Inc.	T	Telecom	U.S.
Rogers Communications Inc.	RCI-B.TO	Telecom	U.S.

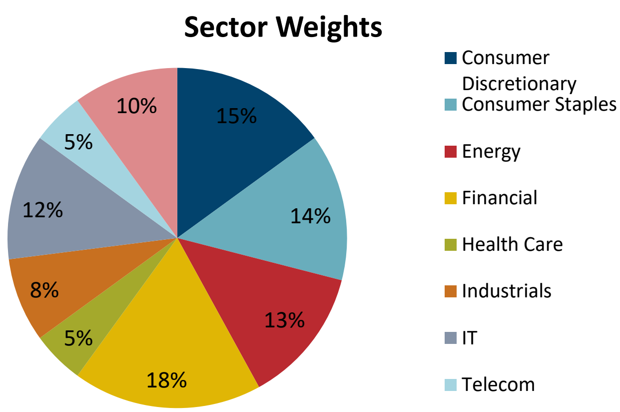
Mean-Variance Characterization

The mean and covariance structure of the stock returns and allowance future returns are estimated empirically using their historical daily price data for the period from January 2012 to August 2017. All estimates are annualized and summarized in Table F.1 in Appendix F.

Strategic Asset Allocation

The pension fund's strategic allocation takes a balanced approach and is summarized in Figure 4.1. Due to the limited number of stocks in the Utilities, Material and Real Estate sectors in the asset universe, they are combined in the "Other" category.

Figure 4.1 Initial Strategic Asset Allocation (SAA) of the Portfolio



Carbon Risk Management

The carbon footprint intensities of the stocks in the asset universe are calculated based on the 2013–2014 emission and financial data. The results are summarized in Table 4.2.

Table 4.2
Carbon Footprints and Intensities of the Stocks in Asset Universe

Company	Total Emission (Tons)	Intensity (I_R)	Intensity (I_P)
eBay Inc.	240,326	0.029	0.084
Walt Disney Company	1,766,380	0.039	0.288
General Electric Company	4,875,000	0.043	0.373
Time Warner Inc.	217,787	0.008	0.059
Starbucks Corporation	1,032,616	0.063	0.499
PepsiCo, Inc.	5,783,274	0.087	0.858
Coca-Cola	3,690,003	0.079	0.430
Walmart, Inc.	21,186,234	0.044	1.322
General Mills	996,400	0.056	0.546
Proctor & Gamble	5,827,000	0.078	0.500
Exxon Mobil Corporation	146,000,000	0.347	4.481
Suncor Energy Inc.	20,840,798	0.526	5.329
Duke Energy Corporation	123,430,000	5.424	46.315
Chevron	62,408,539	0.283	2.913
ConocoPhillips	25,809,000	0.470	2.819

Goldman Sachs Group Inc.	291,374	0.007	0.036
Morgan Stanley	344,504	0.009	0.117
Bank of Montreal	107,786	0.007	0.025
JPMorgan Chase & Co.	1,303,091	0.014	0.060
Citigroup Inc.	1,029,257	0.014	0.075
Manulife Financial Corp.	409,400	0.022	0.131
Colgate Palmolive	667,635	0.038	0.298
Johnson & Johnson	1,183,256	0.017	0.086
United Parcel Service	12,538,847	0.226	2.868
Boeing Company	1,574,000	0.018	0.343
Canadian National Railway Company	5,243,252	0.496	2.007
Oracle Corporation	457,254	0.012	0.042
Intel Corporation	3,125,807	0.059	0.325
Google Inc.	1,187,175	0.021	0.093
Microsoft	1,255,935	0.016	0.057
Dow Chemical Company	35,832,000	0.628	7.485
Simon Property Group	517,860	0.114	0.392
AT&T Inc.	8,843,067	0.069	0.480
Rogers Communications Inc.	198,689	0.016	0.119
American Electric Power Company, Inc.	121,927,400	8.220	82.356

Note: All carbon intensity values are recorded as one in a thousand.

For illustration purposes, we separate the optimization results using the revenue-based (***I_R***) and profit-based (***I_P***) carbon intensities. The carbon intensity parameters for the emission allowance (EUA contract) are set as follows:

1. K = –1 (representing 1 metric ton of emission offset per contract) and $\boldsymbol{\theta = 0.07}$ when the profit-based intensity is used.
2. K = –1 (representing 1 metric ton of emission offset per contract) and $\boldsymbol{\theta = 0.01}$ when the revenue-based intensity is used.

The $\boldsymbol{\theta}$ parameter takes different values for I_R and I_P to form a fair base of comparison in the later analysis. It is also crucial to note that, by nature, I_P is many times larger than I_R since the revenue always exceeds the net profit. In this case, on average, the revenues are 8 times the profits across the asset universe. We use a conservative multiple of 7.

For carbon risk mitigation, we follow these steps:

1. We change the allocation to the Energy sector from 13% to no greater than 7%. Any extra allocation room is added to the Other sector, which now includes the EUA futures.
2. The portfolio carbon risk is capped at 0.0001 for both measures of carbon intensity.

Stranded Asset Management

As stated earlier, we assume no identifiable stranded asset currently underlying the stocks.

Scenario-Based Climate Change Risk Management

We set the projection timeline to range from 2005 to 2100. The period of interest for our investment portfolio spans a 53-year period from 2018 to 2070. Due to the proprietary nature of the Mercer scenario-based climate risk model, we are unable to obtain any detailed information in the scenario generators. In this example, we rely on the WITCH climate economic model—which has a built-in, publicly accessible scenario generator—and adapt the processes to our proposed method in Section 3.2, as described here.

We assume three climate risk factors, where Physical Impacts and Resource Scarcity are combined to form the Climate Impact factor. Physical impacts and resource scarcity are closely related in nature. They both involve material physical detriments caused by chronic climate change and global warming in the WITCH model setting, but they are not part of the model output. Instead, they are assumed to be positively proportional to climate change metrics such as temperature rise and increased GHG concentrations. Hence, we obtain the three factors and their proxies in the WITCH model as shown in Table 4.3.

Table 4.3
Selected Climate Change Risk Factors

Company	Description	Proxy 1	Proxy 2
Technology (T)	Same scope as in the Mercer model (see Section 3.2)	Investment in advanced biofuel (USD)	Investment in energy efficiency (USD)
Political (P)	Same scope as in the Mercer model (see Section 3.2)	GHG abatement (ton CO_2/yr)	None
Climate Impact (C)	Includes both Physical Impacts and Resource Scarcity as in the Mercer model (see Section 3.2)	Radiactive forcing (W/m^2)	Global mean temperature change (°C)

Four climate change scenarios, summarized in Table 4.4, are available from the model.

Table 4.4
Formulated Climate Change Scenarios Under the WITCH Model

Scenario	Description
Fragmentation (weak pledges)	A scenario with limited and fragmented action on climate change. Global temperature increases up to 4°C above the preindustrial era.
Coordination (500 ppm)	A scenario with a weak climate control effort until 2020 and a moderate collaborative global climate control effort afterward, aiming at stabilizing the concentration of GHGs at 500 ppm of CO^2eq by 2100.
Transformation (450 ppm, no permit trading)	A scenario with a weak climate control effort until 2020 and a moderate collaborative global climate control effort afterward, aiming at stabilizing the concentration of GHGs at 450 ppm of CO^2eq by 2100.
Transformation (450 ppm, permit trading)	A scenario with a weak climate control effort until 2020 and a moderate collaborative global climate control effort afterward, aiming at stabilizing the concentration of GHGs at 450 ppm of CO^2eq by 2100. An emission trading scheme is adopted after 2020.

We assume that all four scenarios are equally likely to take place.

The factor sensitivities of the stocks are assigned at the sector level, as given in Table 4.5, so stocks in the same sector are assumed to experience the same investment return impacts from climate change risk.

Table 4.5
Factor Sensitivities to Stock Market Sectors

Industry Sector	T	C	P
Consumer Discretionary	0	0	–0.25
Consumer Staples	0	–0.25	0
Energy	–0.5	–0.5	–1
Financials	0	–0.25	0
Health Care	0.25	–0.25	0
Industrial	0	–0.75	–0.5
Information Technology	0.25	0	0
Materials	0.25	–0.25	–0.75
Real Estate	0	–1	0
Telecommunications	0	–0.25	0
Utilities	–0.25	–0.5	–0.75

The factor proxy values undergo a uniformly linear transformation to arrive at a relative scale between 0 and 100 using the following formula:

$$\boldsymbol{f_t = \frac{X_t - X_{min}}{X_{max} - X_{min}}(100)},$$

where $\boldsymbol{X_t}$ is the factor proxy's original value at time point *t*; $\boldsymbol{X_{min}}$ and $\boldsymbol{X_{max}}$ are the proxy's minimum and maximum values, respectively, on the path of projection; and $\boldsymbol{f_t}$ is the final factor value at point *t*. For a factor with two proxies, the proxy values are averaged before entering the formula. The resultant factor paths under each scenario are given in Figure F.1 in Appendix F.

For numerical efficiency, we take the end point factor values of interest in each path (current point and at year 2070). Since the current year (2018) falls between 2015 and 2020 (the two projection points in the WITCH model), we take the average factor values from these two points.

Under each scenario, we calculate the climate change risk exposures of each asset at the endpoints by its summed product of senstivites and factor values, exactly the same approach as in Section 3.2:

$$\boldsymbol{CRE = \lambda_T f_T + \lambda_R f_R + \lambda_C f_C}$$

Then we average the results across the four scenarios to obtain the expected climate change risk exposures for all assets (which we henceforth refer to as "climate change risk exposure," or CRE, although it is actually an expected value). We calculate the difference in the risk exposures between the two endpoints and map the difference to an impact to returns. In this case, we apply the following set of transformation rules:

- If $\boldsymbol{\Delta CRE_i \geq 0}$,

$$\boldsymbol{\Delta r_i} = \left(\frac{\boldsymbol{\Delta CRE_i + 50}}{\boldsymbol{100}}\right)\%$$

- If $\boldsymbol{\Delta CRE_i \in [-20, 0)}$,

$$\boldsymbol{\Delta r_i} = \left(\frac{\boldsymbol{\Delta CRE_i}}{\boldsymbol{100}}\right)\%$$

- If $\boldsymbol{\Delta CRE_i \in [-20, -60)}$,

$$\boldsymbol{\Delta r_i} = \left(\frac{\boldsymbol{\Delta CRE_i - 40}}{\boldsymbol{100}}\right)\%$$

- $\boldsymbol{\Delta CRE_i \in [-60, -100)}$,

$$\boldsymbol{\Delta r_i} = \left(\frac{\boldsymbol{\Delta CRE_i - 80}}{\boldsymbol{100}}\right)\%$$

- If $\boldsymbol{\Delta CRE_i \leq -100}$,

$$\boldsymbol{\Delta r_i} = \left(\frac{\boldsymbol{\Delta CRE_i - 160}}{\boldsymbol{100}}\right)\%$$

where $\boldsymbol{\Delta CRE_i}$ is the difference in CRE between the current point and the endpoint for the period of interest for stock *i*, and $\boldsymbol{\Delta r_i}$ is the change to the stock's expected return as a result of climate change risk. Such a transformation aims at capturing market crowding behaviors: as the risk unfolds and the market becomes familiar with the climate change risk, the demand for the more favorable sectors will increase steadily, adding an additional layer of impacts beyond those captured by the risk factors.

Therefore, we obtain the end result of this module: a mean return view matrix under climate change risk, which is added to the existing mean return vector $\boldsymbol{\mu}$ to formulate a new mean vector that enters the portfolio optimization problem. The resultant sector level exposure difference and vector are given in Table 4.6, which is applied to the individual stocks according to the sector to which each belongs.

Table 4.6

Sector Level Exposure Differences and the Resultant View Vector on Returns

Industry Sector	ΔCRE	Δr
Consumer Discretionary	–8.14	–0.0814%
Consumer Staples	–7.92	–0.0792%

Energy	–115.53	–2.7553%
Financials	–18.80	–0.1880%
Health Care	–7.92	0.2790%
Industrial	–84.48	–1.0448%
Information Technology	10.88	0.6088%
Materials	–50.06	–0.9006%
Real Estate	–75.18	–1.5518%
Telecommunications	–18.80	–0.1880%
Utilities	–90.61	–1.7061%

The views for the Health Care and Industrial sectors include moderate subjective adjustments to reflect their relative risk compared to that of other sectors. In addition, the view for the return of emission allowances is assumed to be 2%. For brevity, we have not shown the complete new mean vector here. We further modify the strategic asset allocation (SAA) based on the results of the view vector. The principle to follow is relaxing the allocation constraints to sectors that are relatively immune to climate change risk, while restricting allocations to sectors that are vulnerable to the risk, with normative inputs. More specifically:

- For sectors with insignificant return impacts, we modify their current allocations to reflect the view (equality).
- For sectors with material negative return impacts, we set caps to their allocations (inequality).
- For sectors with material positive return impacts, we set floors to their allocations (inequality).

This nonetheless changes many of the equality constraints in the original SAA to inequalities. Whether such a practice is desirable is determined on a case-by-case basis, depending on the corporate-level risk management guidelines. In this example, we assume that topside adjustments fully fall under the authority of the investment unit. Incorporating all mitigations in the previous modules, the final changes to SAA are shown in Table 4.7.

Table 4.7

Changes in Topside Strategic Asset Allocation From Climate Change Risk Mitigation

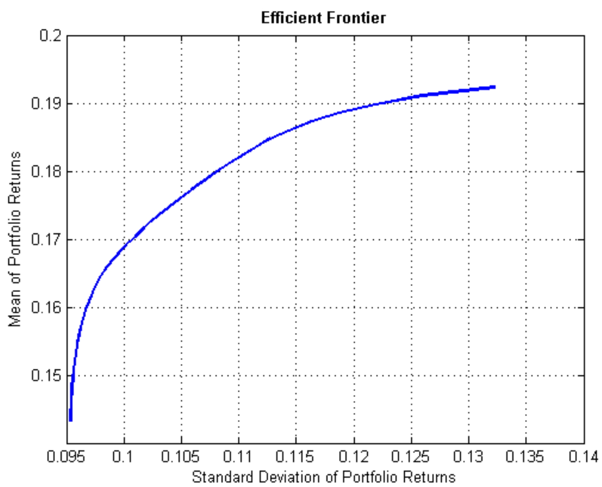
Industry Sector	Original SAA	New SAA
Consumer Discretionary	15%	15%
Consumer Staples	14%	17%
Energy	13%	<5%
Financials	18%	22%
Health Care	5%	>10%
Industrial	8%	<8%
Information Technology	12%	>12%
Materials	In Other sector	<8%
Real Estate	In Other sector	<6%
Telecommunications	5%	>5%
Utilities	In Other sector	<5%

Formulate the New Portfolio Optimization Problem

The new optimization problem is formulated by incorporating all constraints and modifications to constraints in the previous modules, as well as the portfolio target return. The problem is implemented and solved in MATLAB. We present the complete set of results. Figure 4.2 shows the efficient frontier from the original SAA, which is the "existing" optimal portfolio without considering carbon and climate change risk.

Figure 4.2

Efficient Frontier From Initial Strategic Asset Allocation



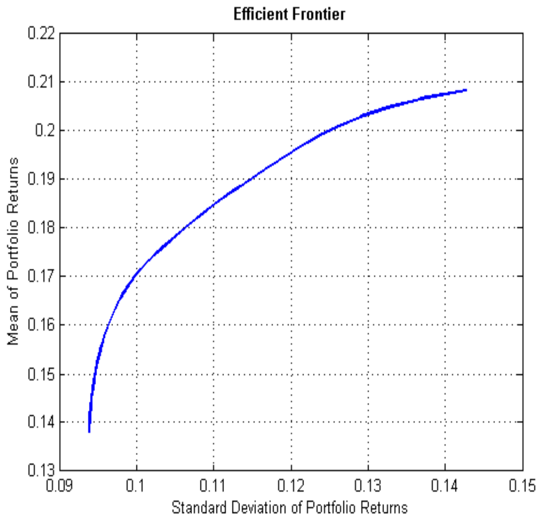
Under the 15% target portfolio return constraint, the minimum variance portfolio is given in Table F.2 in Appendix F. Notice that not all stocks in the asset universe are used in this optimal portfolio. The associated portfolio return volatility is 0.0956. With the mitigations to carbon and climate change risk described in the preceding modules, two new optimal portfolios are constructed based on the I_R and I_P carbon intensity measures, whose compositions are given in Table F.3 in Appendix F. The corresponding efficient frontiers are shown in Figure 4.3.

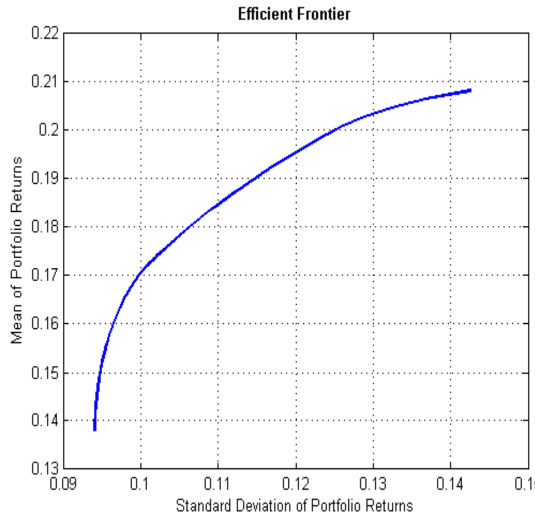
Figure 4.3

Efficient Frontiers for Portfolios with Mitigated Climate Change Risk

Frontier using I_R

Frontier using I_P





The two frontiers are almost identical, although small differences reside in the low-return regions. The volatility of the optimal portfolios are 0.0947 and 0.0948, which are also very close. This demonstrates the robustness of the framework and the validity of the I_P metric in the settings of this example. It is worth pointing out that reducing the required return below the current 15% target should not lead to material variance reduction for the optimal portfolio in this setting.

Since the new efficient frontiers for portfolios with mitigated climate change risk are derived from the algorithm incorporating the mean return view vector, we cannot compare them with the original efficient frontier in Figure 4.2 directly. Instead, we restate the risk-return profile of the original optimal portfolio under the new mean vector. The corresponding portfolio mean and volatility are 14.41% and 0.0956, respectively (the same as before since the covariance matrix remain unchanged). Clearly, this point is below the new efficient frontiers for both intensity metrics.

4.3 Considerations for Insurers and Pension Plans

The portfolio optimization algorithm under climate change risk proposed in the previous section provides a flexible yet tractable framework for the management of climate change and carbon risk in the prevailing dynamic economy. However, we emphasize that the analysis and conclusions drawn in the example in Section 4.2.2 are heavily based on the settings of the representative pension fund only. In addition, this framework has some special practical considerations.

The first key consideration is durations and interest rate risk. Insurers and pension funds have long-term liabilities that must be backed by company assets, including the investment portfolios. This makes interest risk particularly relevant to these groups. Interest rate risk management is a critical component in insurers' and pensioners' existing practices, which can be easily adapted to the scenario-based model for climate change risk in Section 4.2. The quantification of interest rate risk for stock portfolios can be achieved using factor-based models, in which exposures are measured by the portfolio-level (or key rate) durations. In practice, many pension funds measure and manage interest rate risk at the asset class and industry sector level that affects the portfolio construction through top-level constraints in strategic asset allocations. In all situations, interest rate risk must be managed carefully and incorporated into the portfolio optimization framework introduced in this report, whether by assimilating the existing interest risk models or developing new models, to facilitate duration matching of the assets and liabilities.

The second key consideration is geographic differentiation of climate change risk embedded in the stocks. In the example in section 4.2.2, we did not examine the business books of the assets as the resultant portfolio does not have concentrated weights in businesses operating in high-risk regions. Situations may arise where such a geographic differentiation is necessary, when the portfolio has heavy weights in sectors that are prone to physical climate impacts, such as P&C insurers, real estate firms and the farming industry. In these cases, it is necessary to review the core operations and activities of the companies to identify their exposure to climate change across geographic areas and factor their investment returns into the portfolio optimization algorithm.

The third consideration relates to the shift in mortality and illness distributions caused by climate change. Climate change is usually associated with global warming. Aside from the increased frequency and severity of catastrophic weather events and resource scarcities, there are impacts on human health, where certain heat-related diseases are more frequent, altering the mortality and illness distributions at slow paces. The effects of climate change on the liabilities of insurers and pension funds are beyond the scope of this study. However, it is certainly an interesting area to explore, as it may change many of the existing actuarial assumptions underlying the models currently deployed.

The last point of consideration comprises the multiple actuarial practices that the proposed framework can be adjusted to fit. For instance, the modules described in Section 4.2.1 can be used to perform a scenario analysis for existing portfolios under a climate change risk. To do so, we obtain the mean vector and covariance matrix of the assets in the portfolio and start from Module 6 (scenario-based climate change risk management) but focus on a single climate change scenario (such as fragmentation in the example in 4.2.2) by assigning it an occurrence probability of 1. Return impacts of climate change under the scenario are formulated following the steps in the module, leading to a new mean vector and a portfolio return given the existing portfolio weights. Other scopes of application are also possible.

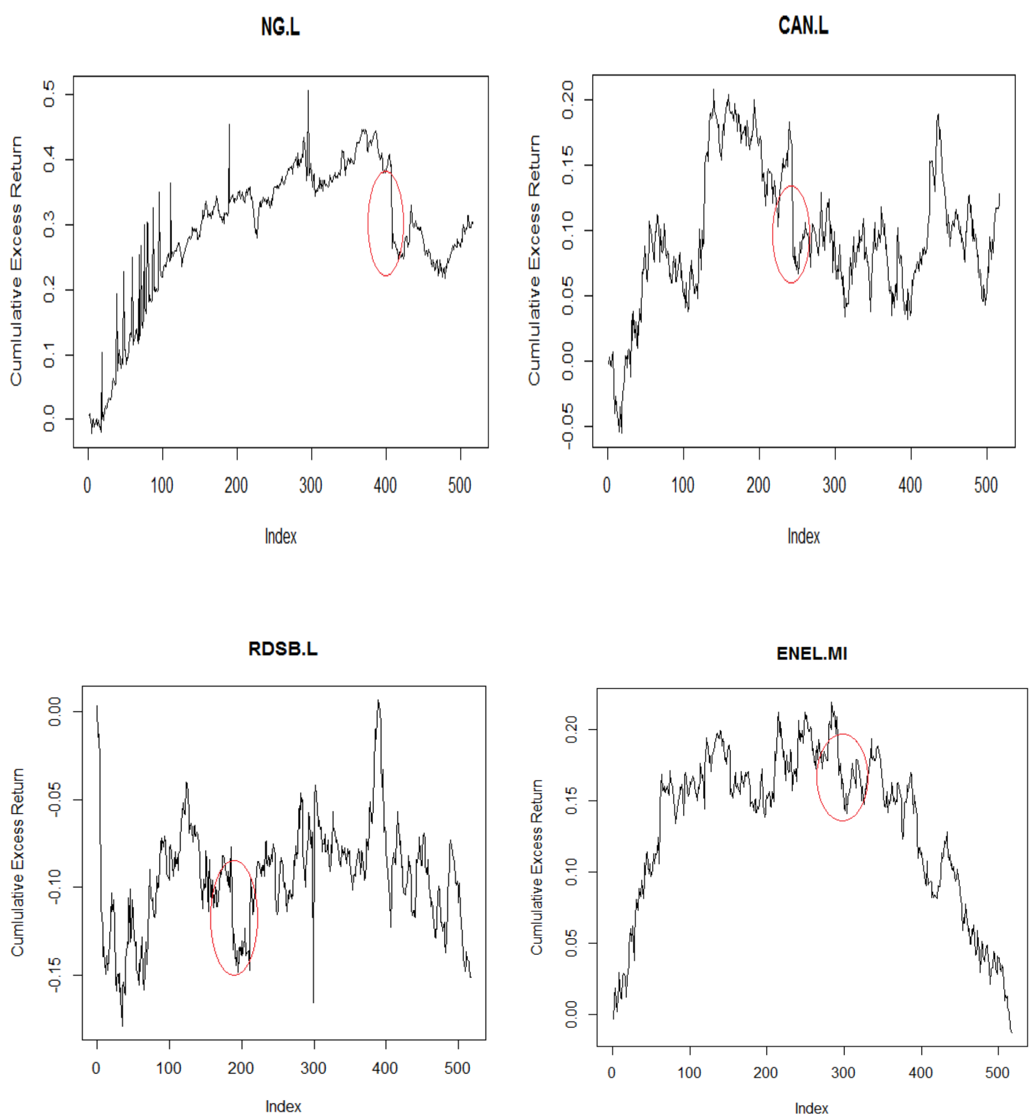
Conclusion

This report has presented a comprehensive analysis of climate change and carbon risk from the perspective of investment portfolio management for insurers and pension plans. We performed an empirical study coupled with other models and methodologies to verify that climate change risk had not been fully recognized and priced by the European and North American markets and that carbon-intensive industries were not critical portfolio performance enhancers on a risk-adjusted basis. Both findings suggest a good potential for constructing optimal portfolios with minimal carbon and climate change risk exposure that should deliver a satisfactory performance in the long run as the risks unfold. While devising measurements and quantification methods for carbon risk, climate change risk, and the resultant stranded asset risks underlying stock investments, we proposed a comprehensive framework for constructing optimal equity investment portfolios with effectively mitigated climate change and carbon risk. A numerical example was also given by using a hypothetical pension fund to demonstrate the portfolio optimization process, under which setting the optimized portfolio was shown to deliver superior expected risk return profiles through the long-term horizon as the climate change risk unfolds. The proposed framework is easy to implement and adapt to the existing modeling platforms of insurers and pensioners, making it a useful valuation tool for the management of investment-related climate change risk in practice.

Appendix A: Market Price of Carbon Risk Cumulative Excess Returns for Selected European Stocks

We look for cliff-like patterns around the middle of the event period (the transition between 2004 and 2005 upon launch of the EU ETS). Three features collectively characterize the pattern: (1) There is a sharp drop in cumulative excess return; (2) it is followed by a period of tranquillity of small adjustments; and (3) *ideally*, it is followed by a period of cumulative excess return that is comparable to or smaller than the predrop period. The horizontal axis indexes the number of days from the start of the plot window.

Figure A.1
Cumulative Excess Return Plots for European Stocks Showing the Pricing of Carbon Risk



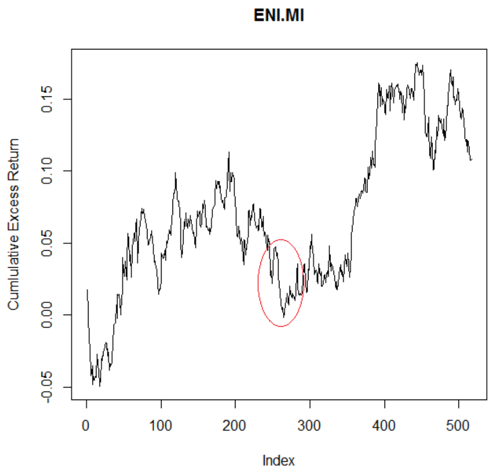
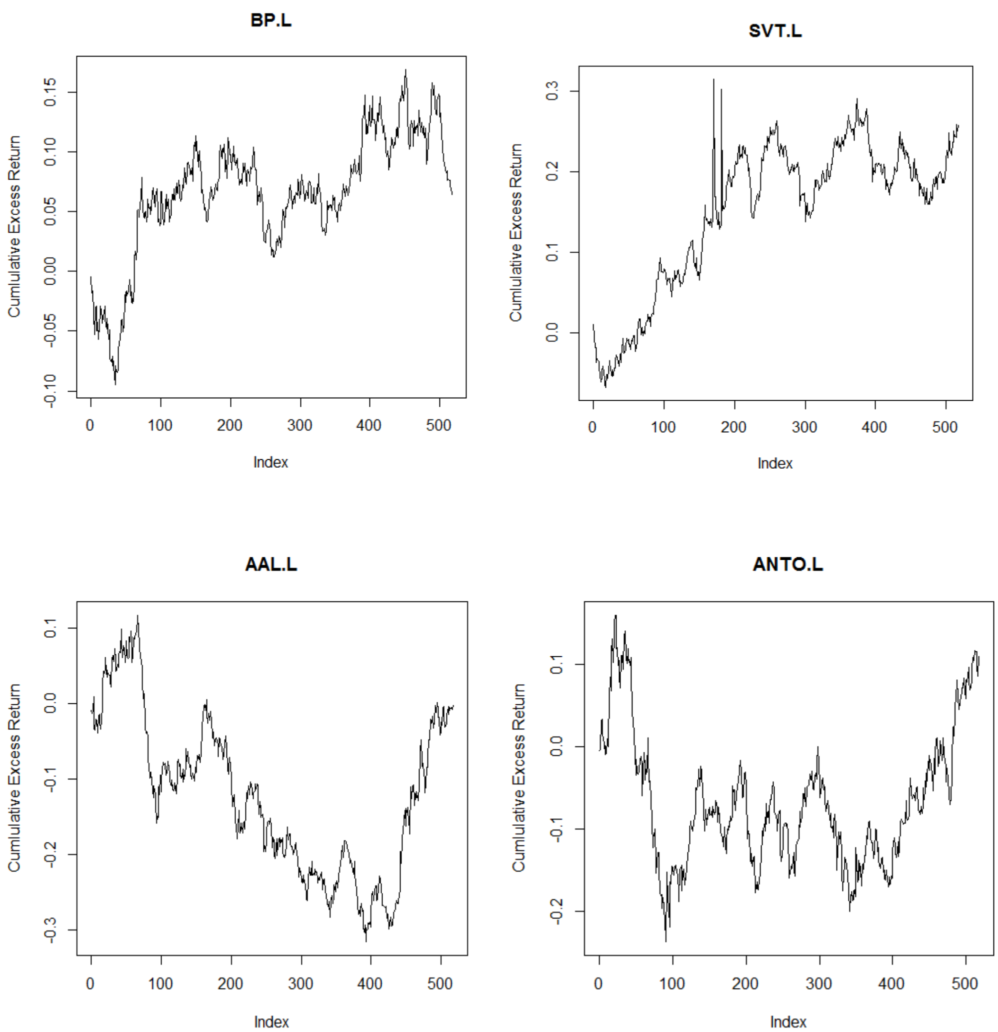
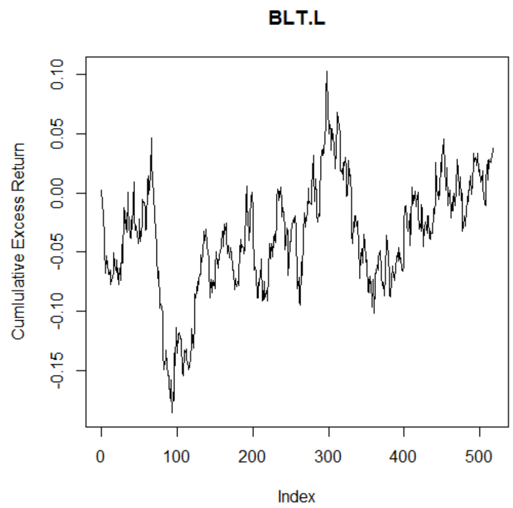
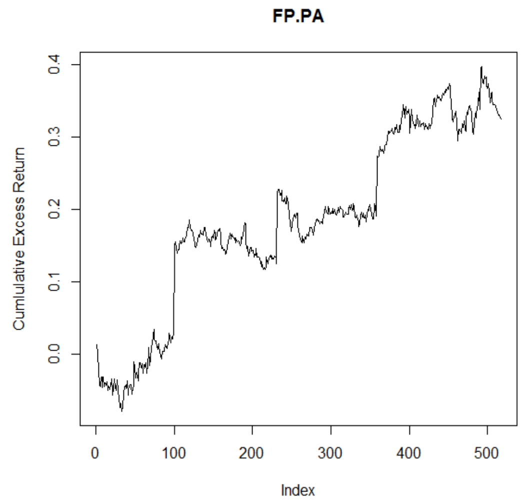


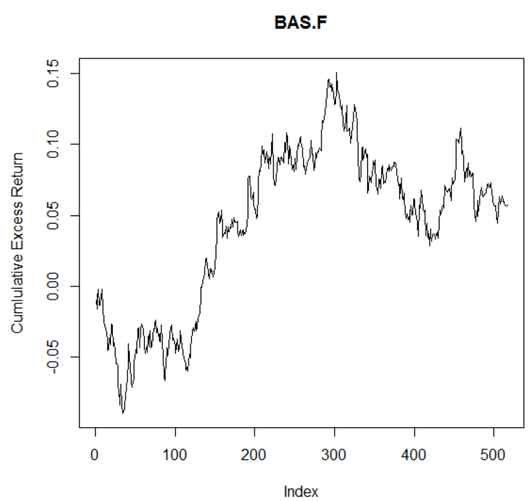
Figure A.1

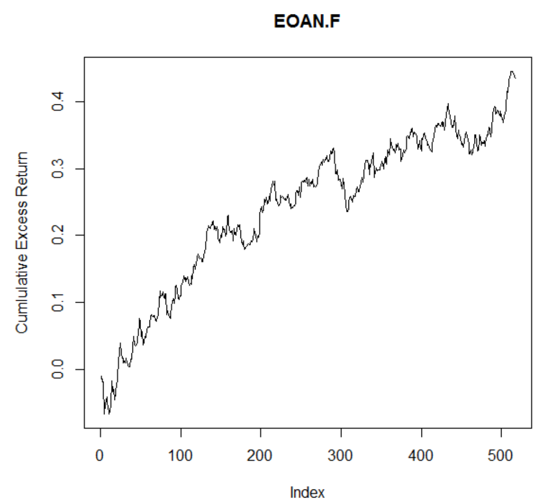
Cumulative Excess Return Plots for European Stocks That Do Not Show the Pricing of Carbon Risk

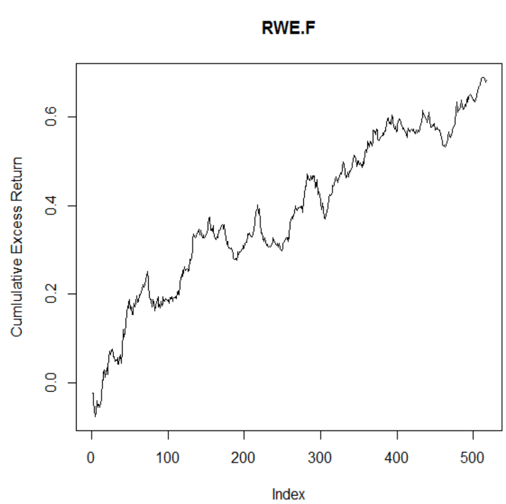


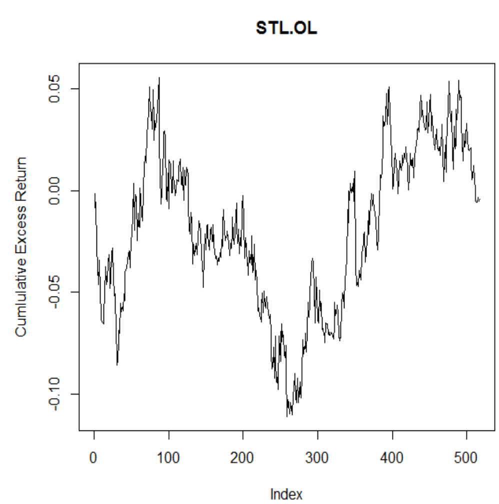

BLT.L
Cumululative Excess Return
-0.15
-0.10
-0.05
0.00
0.05
0.10
0
100
200
300
400
500
Index

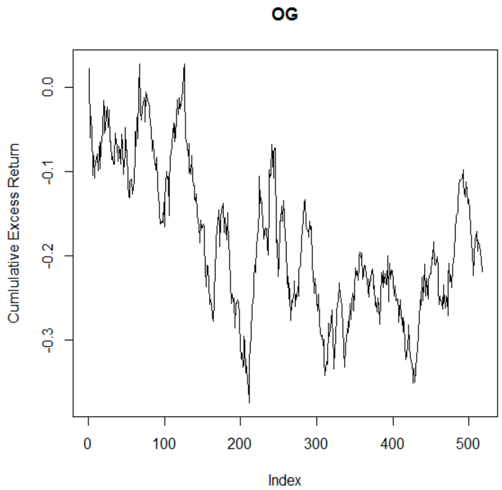

FP.PA
Cumululative Excess Return
0.0
0.1
0.2
0.3
0.4
0
100
200
300
400
500
Index

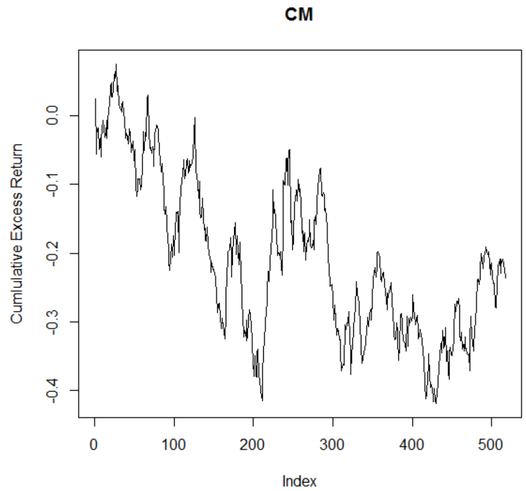

BAS.F
Cumululative Excess Return
-0.05
0.00
0.05
0.10
0.15
0
100
200
300
400
500
Index

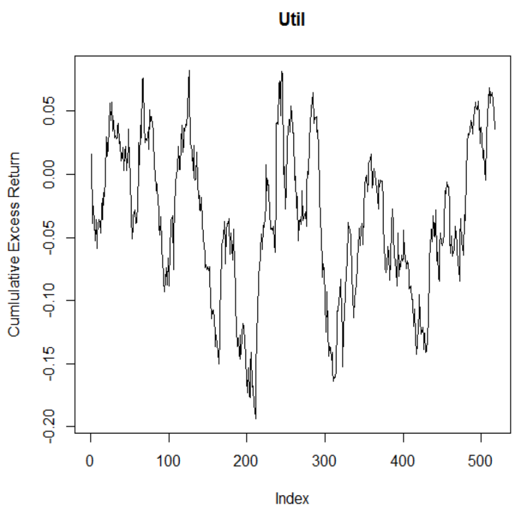

EOAN.F
Cumululative Excess Return
0.0
0.1
0.2
0.3
0.4
0
100
200
300
400
500
Index


RWE.F
Cumululative Excess Return
0.0
0.2
0.4
0.6
0
100
200
300
400
500
Index


STL.OL
Cumululative Excess Return
-0.10
-0.05
0.00
0.05
0
100
200
300
400
500
Index


OG
Cumulative Excess Return
Index
0.0
-0.1
-0.2
-0.3
0
100
200
300
400
500


CM
Cumulative Excess Return
Index
0.0
-0.1
-0.2
-0.3
-0.4
0
100
200
300
400
500

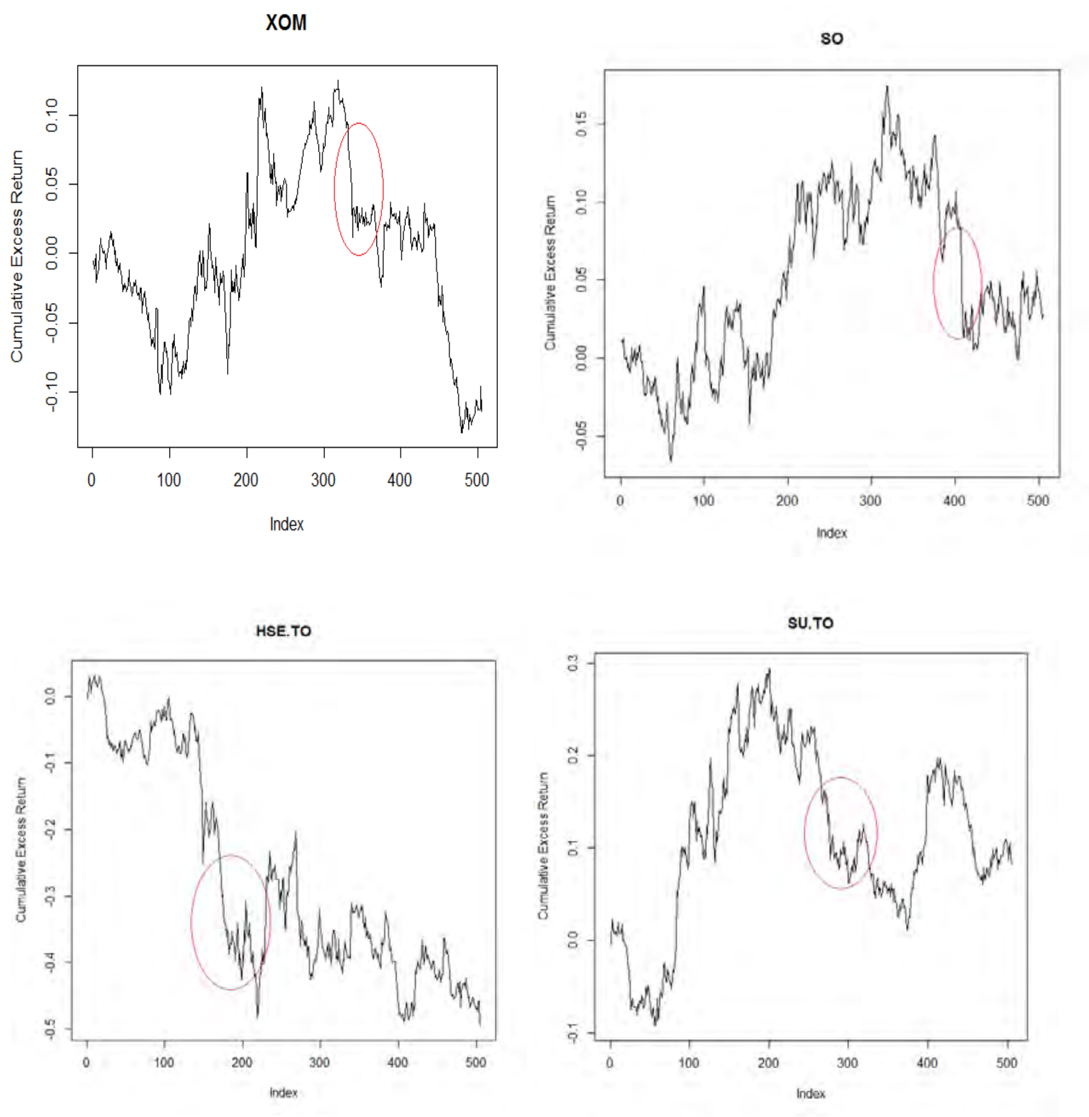

Util
Cumulative Excess Return
Index
0.05
0.00
-0.05
-0.10
-0.15
-0.20
0
100
200
300
400
500

Appendix B: Market Price of Carbon Risk Cumulative Excess Returns for Selected North American Stocks

We look for cliff-like patterns around the middle of the event period (the transition between April 2015 and April 2016 upon signing of the Paris Agreement). Three features collectively characterize the pattern: (1) There is a sharp drop in cumulative excess return; (2) it is followed by a period of tranquillity of small adjustments; and (3) *ideally*, it is followed by a period of cumulative excess return that is comparable to or smaller than the predrop period. The horizontal axis indexes the number of days from the start of the plot window.

Figure B.1

Cumulative Excess Return Plots for North American Stocks Showing the Pricing of Carbon Risk



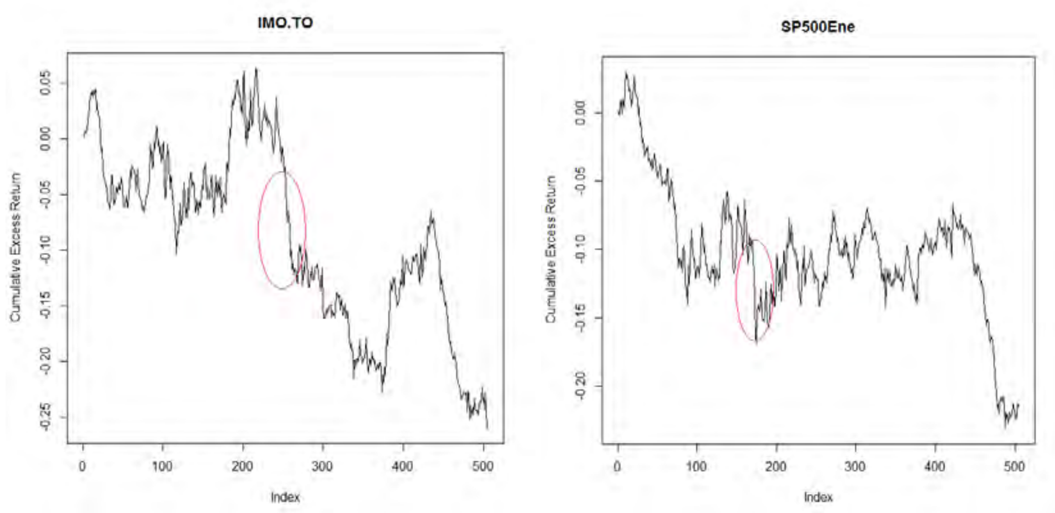
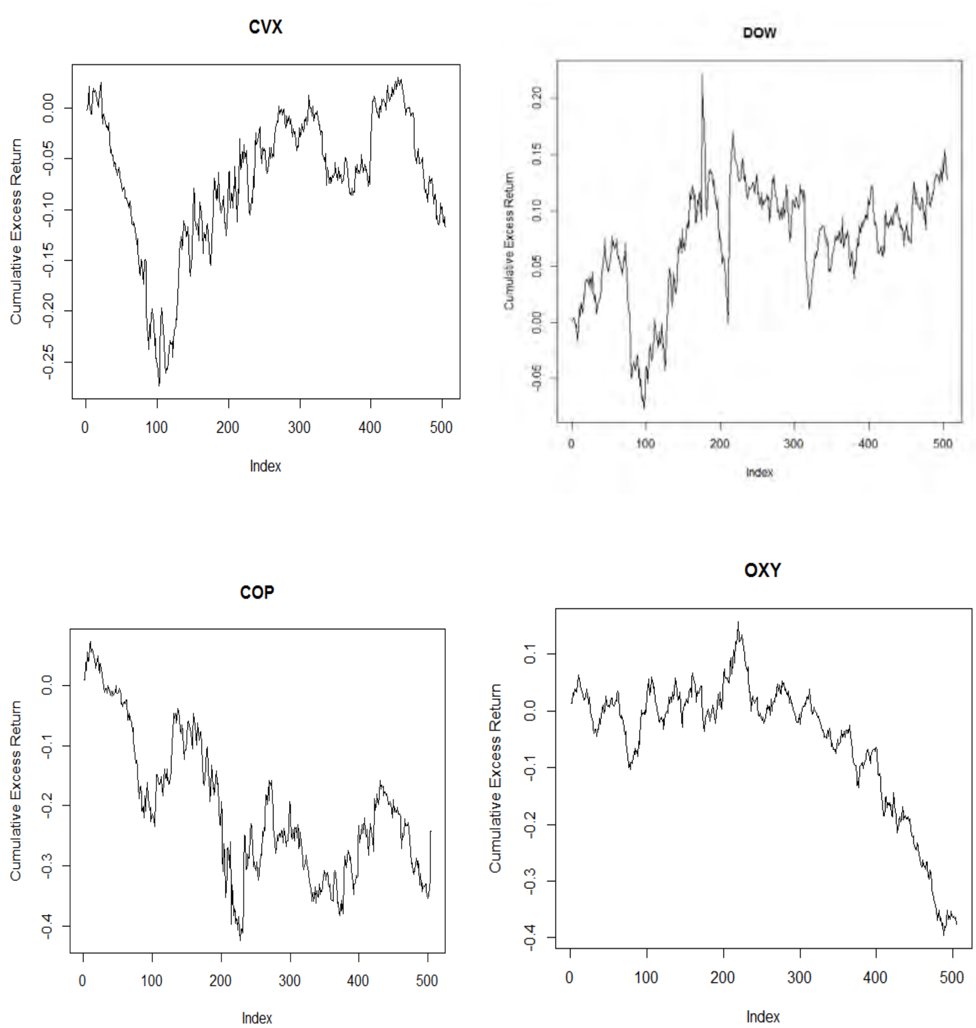
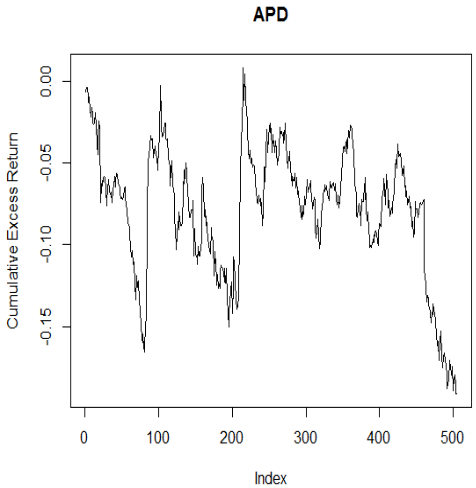
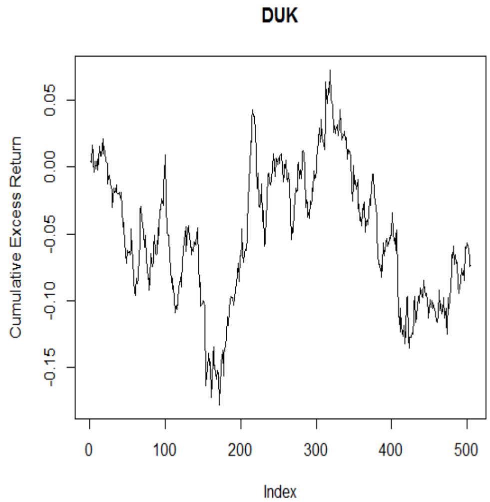


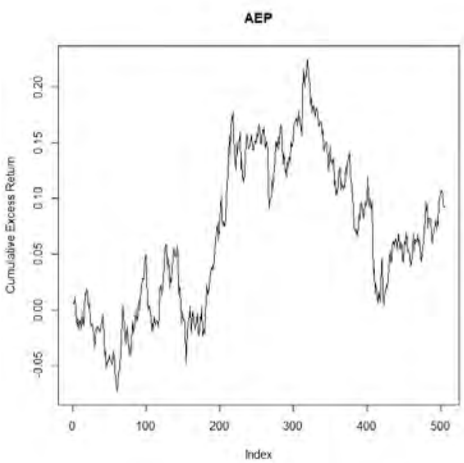
Figure B.2

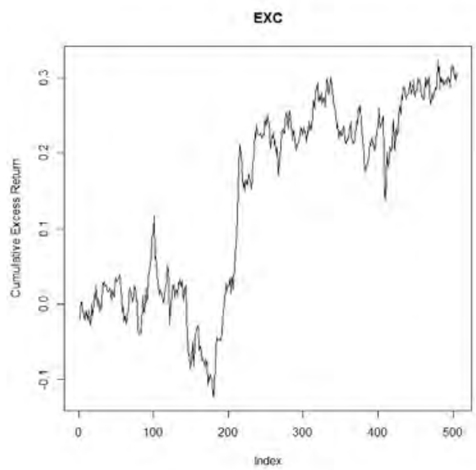
Cumulative Excess Return Plots for North American Stocks That Do Not Show the Pricing of Carbon Risk

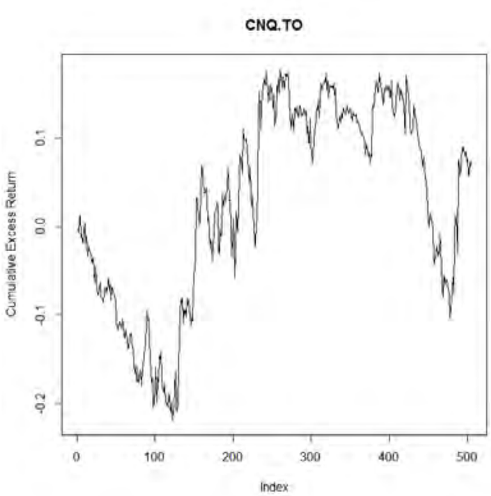


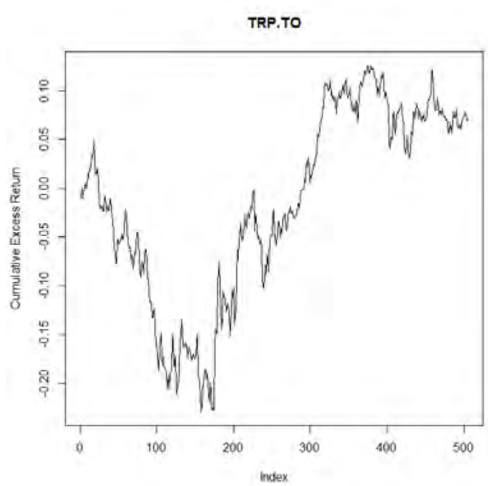

APD
Cumulative Excess Return
0.00
-0.05
-0.10
-0.15
0
100
200
300
400
500
Index

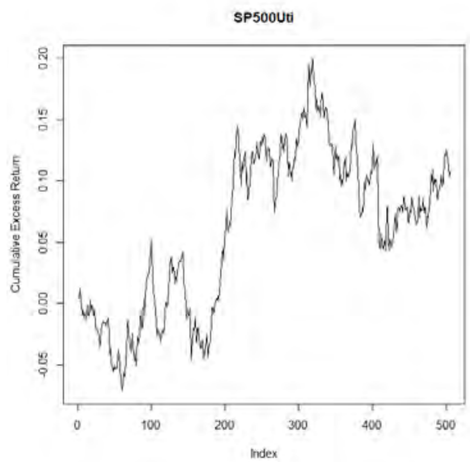

DUK
Cumulative Excess Return
0.05
0.00
-0.05
-0.10
-0.15
0
100
200
300
400
500
Index

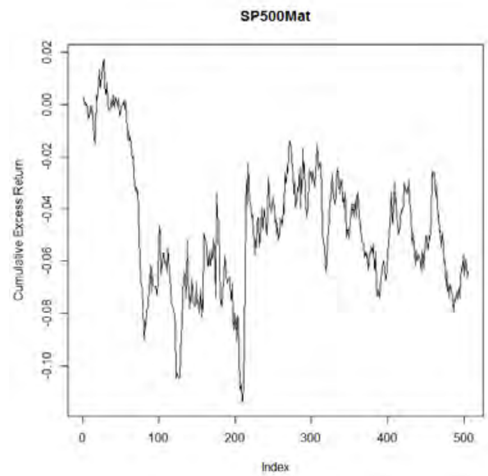

AEP
Cumulative Excess Return
0.20
0.15
0.10
0.05
0.00
-0.05
0
100
200
300
400
500
Index

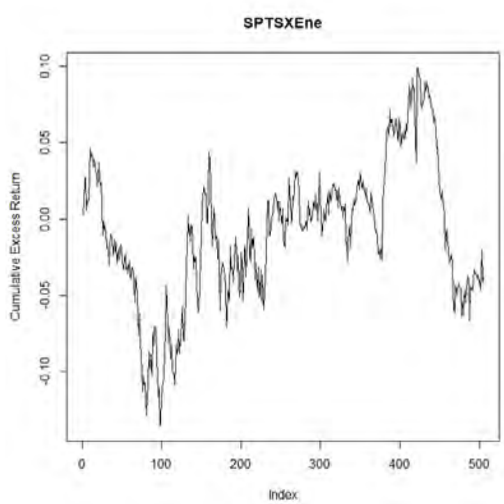

EXC
Cumulative Excess Return
0.3
0.2
0.1
0.0
-0.1
0
100
200
300
400
500
Index

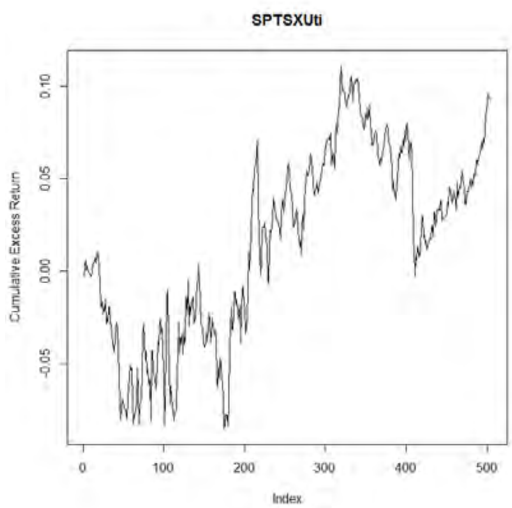

CNQ.TO
Cumulative Excess Return
0.1
0.0
-0.1
-0.2
0
100
200
300
400
500
Index

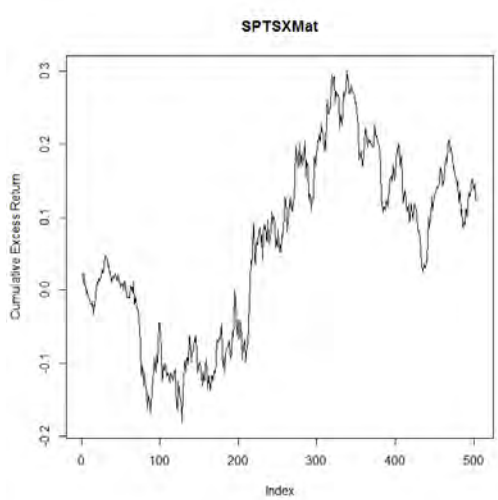

TRP.TO
Cumulative Excess Return
0.10
0.05
0.00
-0.05
-0.10
-0.15
-0.20
0
100
200
300
400
500
Index


SP500Uti
Cumulative Excess Return
Index


SP500Mat
Cumulative Excess Return
Index


SPTSXEne
Cumulative Excess Return
Index


SPTSXUti
Cumulative Excess Return
Index


SPTSXMat
Cumulative Excess Return
Index

Appendix C: Rolling Metrics for European Sector Indices

Figure C.1

Five-Year Rolling Sharpe Ratio for European Sector and Benchmark Indices

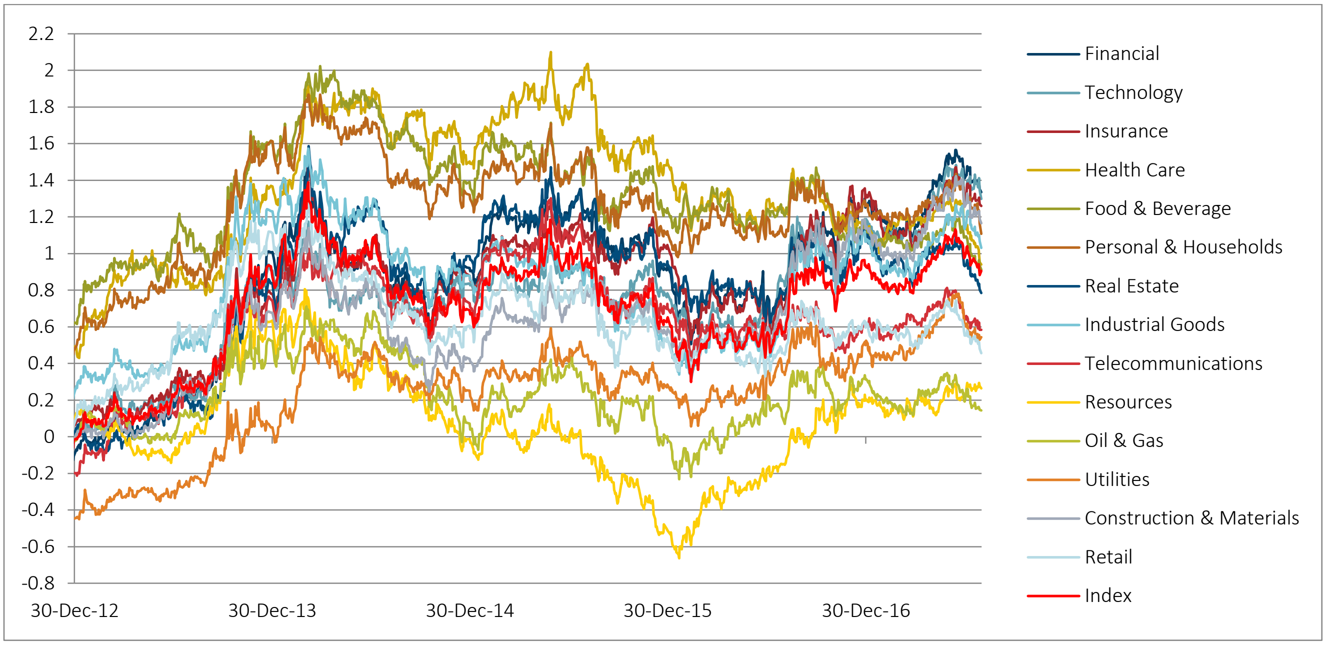
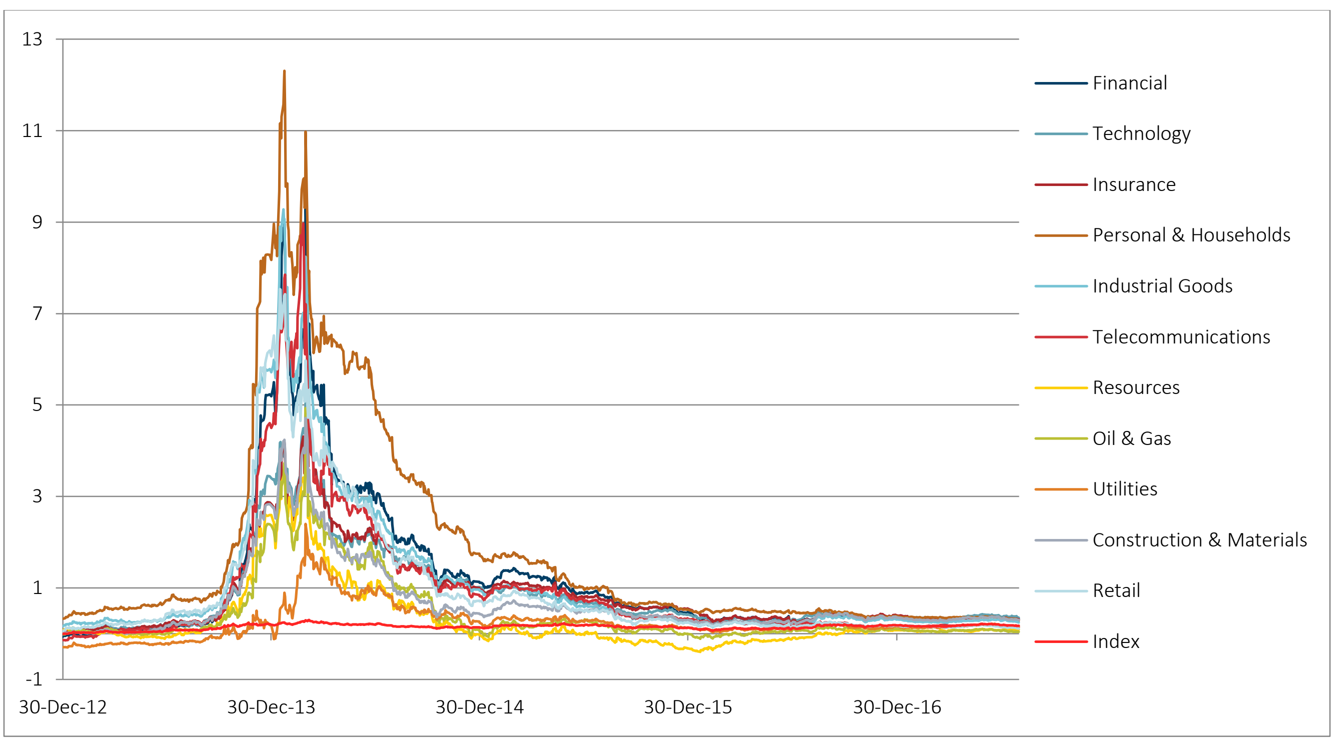


Figure C.2

Five-Year Rolling Treynor Ratio for European Sector Indices (Three of the indices are not shown due to unstable TR values.)



Appendix D: Rolling Metrics for North American Sector Indices

Figure D.1

Five-Year Rolling Sharpe Ratio for U.S. Sector and Benchmark Indices

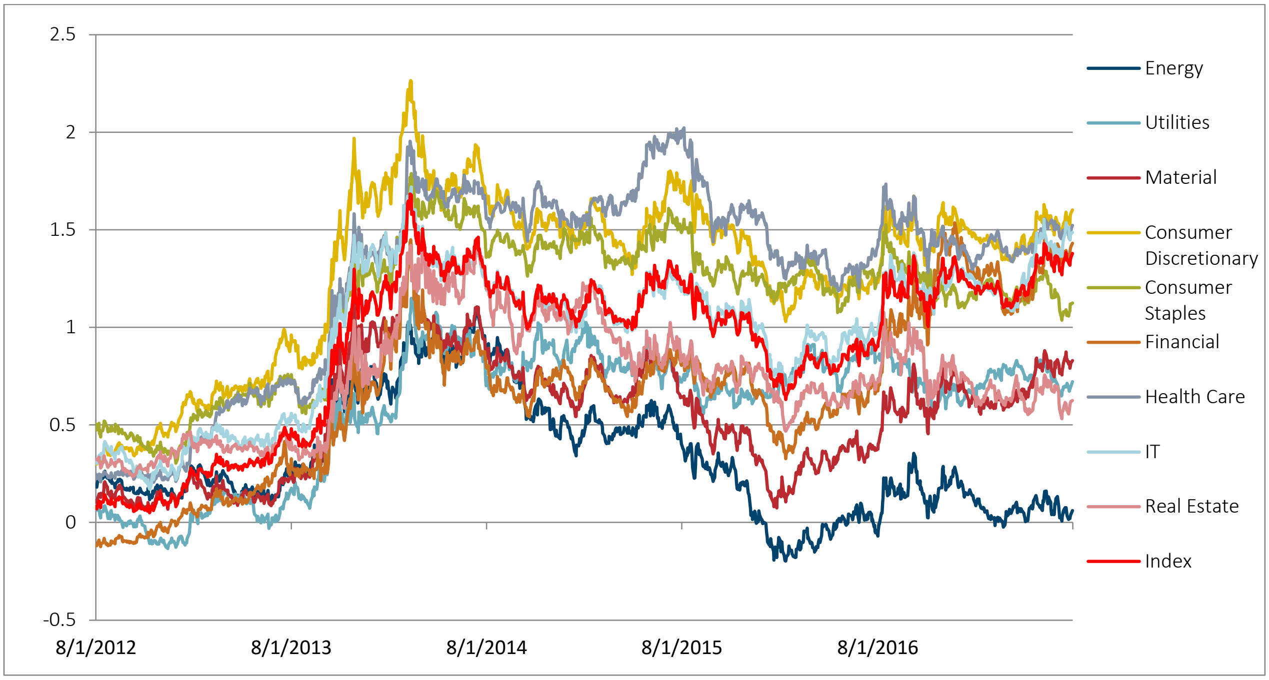


Figure D.2

Five-Year Rolling Treynor Ratio for U.S. Sector and Benchmark Indices

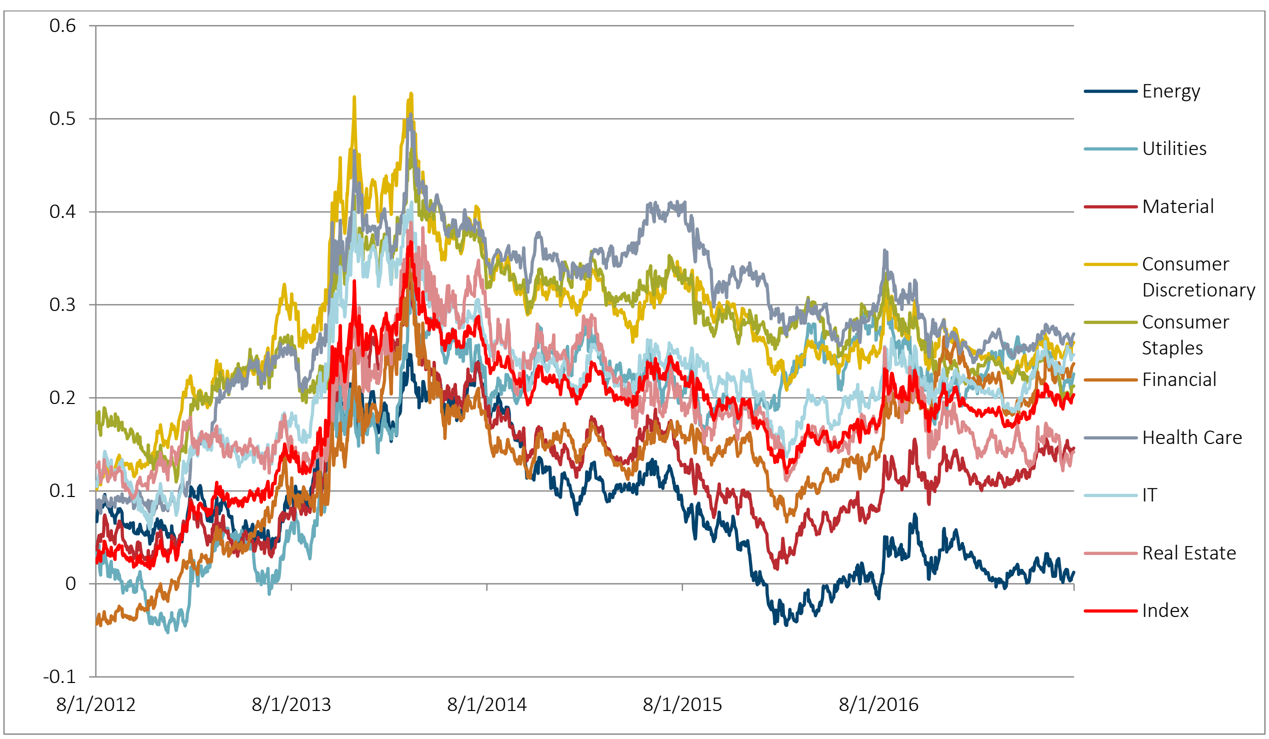


Figure D.3

Five-Year Rolling Sharpe Ratio for Canadian Sector and Benchmark Indices

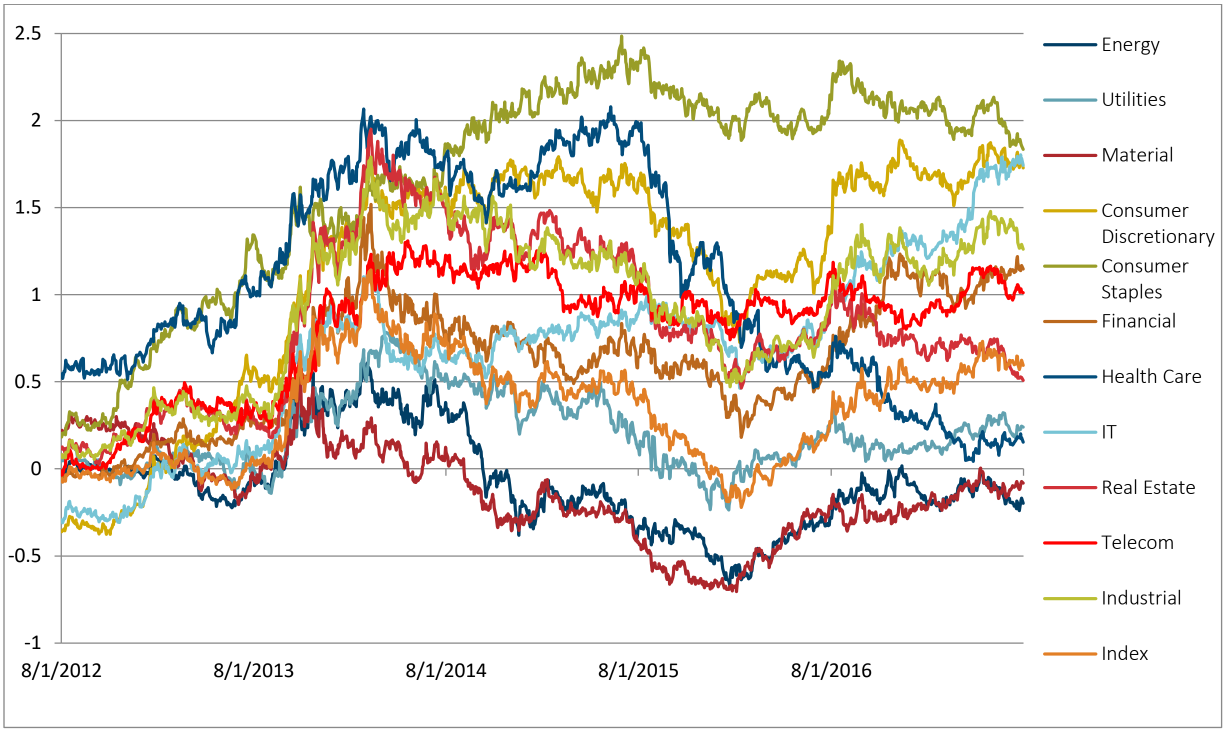
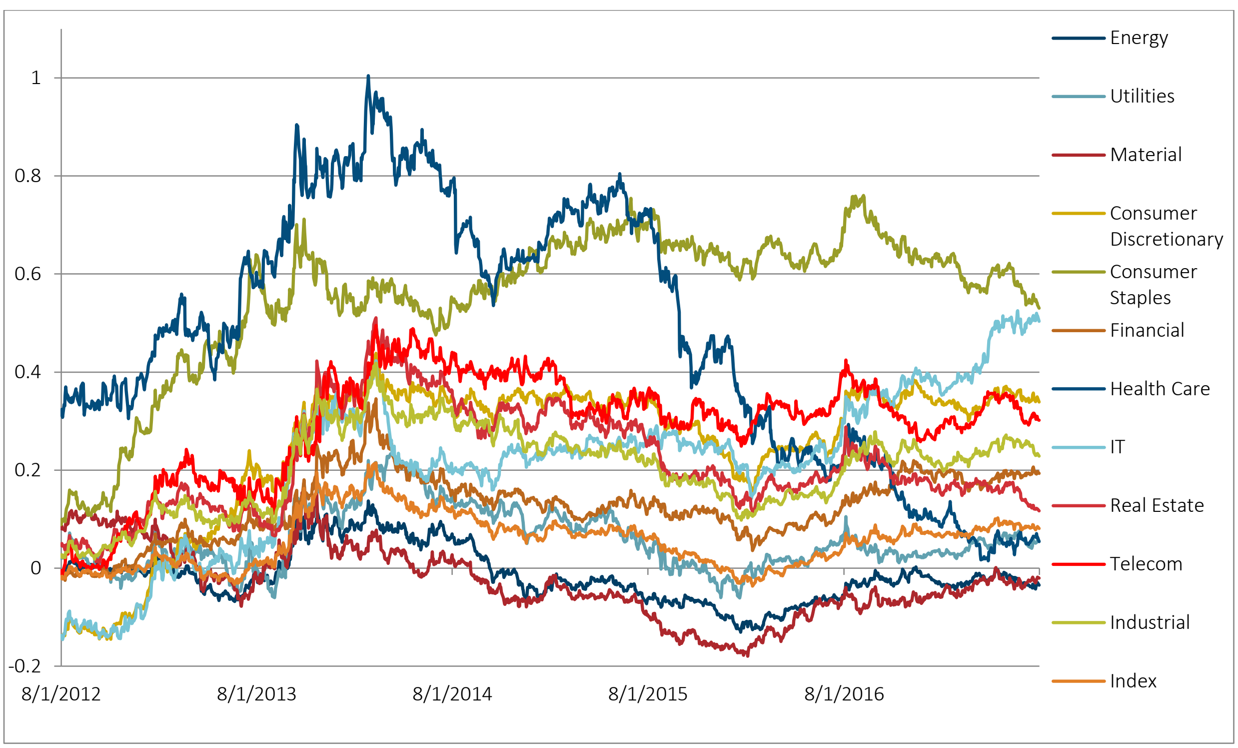


Figure D.4

Five-Year Rolling Treynor Ratio for Canadian Sector and Benchmark Indices



Appendix E: Scenarios in the Mercer Framework for Estimating the Impacts of Climate Change Risk

Table E.1

Climate Change Scenarios for Quantification of Climate Change Risk

Scenario	Description
Transformation	• Ambitious mitigation strategies • Limiting global warming to 2°C above preindustrial era • Emissions peak by 2020, then reduction by 56% relative to 2010 levels by 2050 • Fossil fuels representing less than half of the energy mix in 2050 • Estimated annual emissions in 2050 of 22 gigatons of equivalent carbon dioxide (Gt CO_2e)
Coordination	• Effectively aligned and cohesive mitigation strategies • Global warming is 3°C above preindustrial era • Emissions peak by 2030, then reduction by 27% relative to 2010 levels by 2050 • Fossil fuels representing 75% of the energy mix in 2050 • Estimated annual emissions in 2050 of 37 Gt CO_2e
Fragmentation (low damage)	• Limited or uncoordinated mitigation strategies • Global warming to 4°C above preindustrial era • Emissions peak after 2040, increasing by 33% over 2010 levels by 2050 • Fossil fuels representing 85% of the energy mix in 2050 • Estimated annual emissions in 2050 of 67 Gt CO_2e
Fragmentation (high damage)	As per Fragmentation (low damage), except with an assumption of higher economic damages

Appendix F: Tables and Graphs for Portfolio Optimization Example in Section 4.2.2

Table F.1

Mean Return Vector of the Stocks in the Asset Universe (Preadjustement)

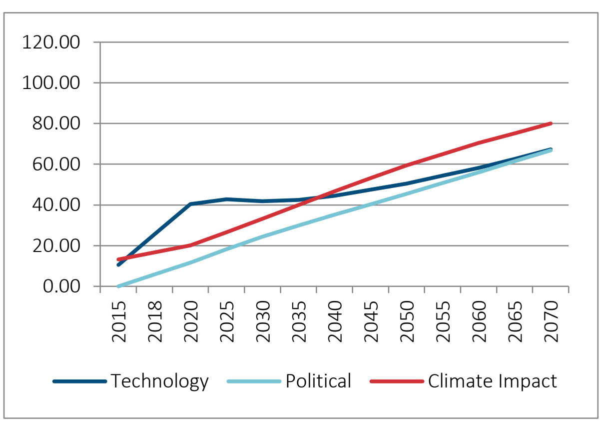
Stock Symbol	Mean Return (Annual)
EBAY	21.29%
DIS	20.17%
GE	9.98%
TWX	23.21%
SBUX	19.54%
PEP	13.58%
KO	8.55%
WMT	8.57%
GIS	9.20%
PG	9.91%
XOM	2.45%
SU.TO	9.90%
DUK	10.79%
CVX	5.39%
COP	2.98%
GS	19.19%
MS	24.16%
BMO.TO	13.62%
JPM	22.09%
C	19.48%
MFC.TO	20.39%
CL	11.45%
JNJ	16.23%
UPS	11.76%
BA	25.51%
CNR.TO	20.18%
ORCL	15.21%
INTC	11.95%
GOOGL	21.12%
MSFT	23.42%
DOW	17.17%
SPG	9.28%
T	10.03%
RCI-B.TO	14.38%
AEP	15.70%

The covariance matrix for the stocks' returns are omitted due to space limitations.

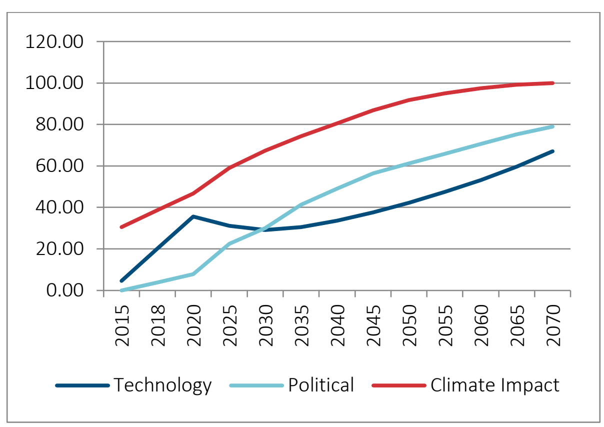
Figure F.1

Factor Paths Under Difference Climate Change Scenarios

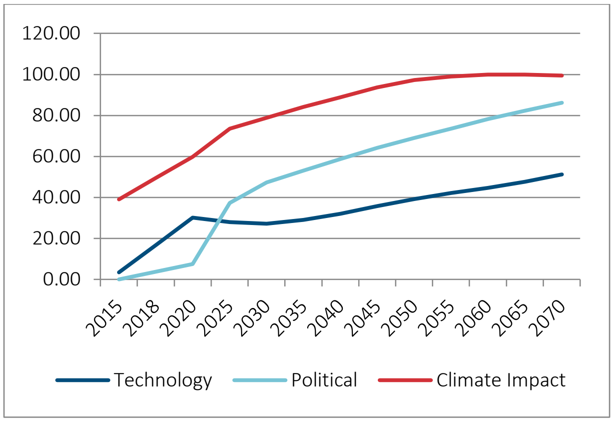
(1) Fragmentation (weak pledge)



(2) Coordination (500 ppm)



(3) Transformation (450 ppm, with permit)



(4) Transformation (450 ppm, no permit)

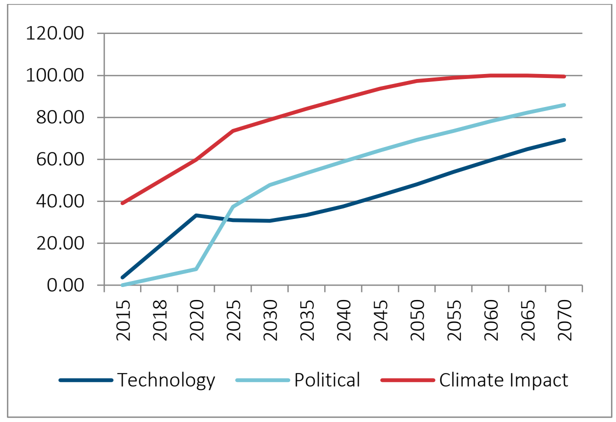


Table F.2
Benchmark Optimal Portfolio (Premitigation of Carbon and Climate Change Risk)

Stock Symbol	Weight
EBAY	0.84%
DIS	4.02%
GE	1.86%
TWX	5.11%
SBUX	3.17%
PEP	4.70%
KO	0.00%
WMT	5.73%
GIS	0.00%
PG	3.57%
XOM	0.00%
SU.TO	0.00%
DUK	13.00%
CVX	0.00%
COP	0.00%
GS	0.00%
MS	0.00%
BMO.TO	18.00%
JPM	0.00%
C	0.00%
MFC.TO	0.00%
CL	0.00%
JNJ	5.00%
UPS	2.21%
BA	0.00%
CNR.TO	5.79%
ORCL	3.29%
INTC	2.08%
GOOGL	6.32%
MSFT	0.30%
DOW	0.00%
SPG	0.00%
T	0.00%
RCI-B.TO	5.00%
AEP	10.00%

Table F.3

Optimal Portfolio With Mitigated Climate Change Risk Exposures

Stock Symbol	Weight (I_R Based)	Weight (I_P Based)
EBAY	0.000%	0.000%
DIS	4.322%	4.217%
GE	0.739%	0.903%
TWX	6.358%	6.311%
SBUX	3.581%	3.569%
PEP	8.766%	8.409%
KO	0.360%	0.688%
WMT	5.117%	5.027%
GIS	0.000%	0.000%
PG	2.757%	2.876%
XOM	0.000%	0.000%
SU.TO	0.000%	0.000%
DUK	4.616%	3.656%
CVX	0.000%	0.000%
COP	0.000%	0.000%
GS	0.000%	0.000%
MS	0.000%	0.000%
BMO.TO	22.000%	22.000%
JPM	0.000%	0.000%
C	0.000%	0.000%
MFC.TO	0.000%	0.000%
CL	0.000%	0.000%
JNJ	11.291%	11.457%
UPS	0.000%	0.000%
BA	0.000%	0.000%
CNR.TO	1.364%	1.531%
ORCL	2.610%	2.646%
INTC	1.020%	1.138%
GOOGL	6.699%	6.659%
MSFT	1.672%	1.556%
DOW	0.000%	0.000%
SPG	0.000%	0.000%
T	1.221%	1.734%
RCI-B.TO	12.679%	12.811%
AEP	0.000%	0.000%
EUA	2.830%	2.811%

Appendix G: Example of EU ETS

Consider company A at the beginning of Phase 1 of the EU ETS (a closed trading phase) running from January 2005 to December 2018. The noncompliance penalty is €40 per ton of excess emission. At the beginning of the phase, company A learns that its emission allocations for the three years are 4,000, 3,500, and 3,200 tons, respectively.

Company A receives 4,000 EUAs in February 2005. It emits 3,800 tons of CO_2 equivalents by the end of 2005. It submits 3,800 EUAs to cover this emission by the compliance filing deadline, banking 200 EUAs for use in 2006, giving a total of 3,700 EUAs for 2006. Due to a heightened production level to meet elevated demand, company A's 2006 emission totals 4,200 tons, exceeding its available EUA balance. However, the compliance filing deadline for 2006 is in April 2007, and the 2007 EUAs are delivered to company A in February 2007. Hence, company A effectively has 6,900 EUAs by the filing deadline, from which 4,200 are submitted for emission coverage, leaving only 2,700 EUAs to use in 2007. In other words, 500 EUAs are "borrowed" from the 2007 allocation. For the final year, we look at two scenarios:

Scenario 1: The company's 2007 emission totals 3,000. It must purchase 300 EUAs in the market before April 2008 to cover its emissions or pay a penalty of €40 per ton of excess emission.

Scenario 2: The company's 2007 emission totals 2,400. It has 300 excess EUAs, which it can sell in the market before April 2008. Any unsold EUAs expire without value.

It can be inferred from this example that the terminal value of the EUA in this closed trading phase is determined by the market's aggregate emission amount and available allowances for the terminal year. With sufficient liquidity, competitions in the market bring the market price of a EUA to one of its boundary values: either the penalty level of €40 or 0. Such a terminal condition does not exist for an open trading phase.

Appendix H: Example of Stranded Asset Risk Quantification

All notations used in this example are as defined in section 3.3.

Consider an oil reserve on company A's balance sheet. The reserve level is 2 million tons, with a current market value of \$3 million. It is expected that over the next year the emission control scheme will reduce the emission cap of company A so the oil reserve may become stranded, when a maximum exploitable reserve (in tons) is assumed to follow a uniform distribution:

$$C \sim Unif(1700000, 2200000)$$

We also know that company A has no debt, and the reserve comprises 10% of the company's total asset value. So we can calculate the expected loss from stranded asset risk over the coming year for company A and the corresponding impact on stock return.

<u>Solution</u>

Given

$$PS = Pr(C < 2000000) = 0.4$$

$$LGS = \frac{E(2000000 - C|C < 2000000)}{(PS)(2000000)} = 0.1125$$

$$SAR = 3000000(LGS)(PS) = 135000$$

we can translate the risk to return impact as follows:

$$\Delta r = \left(\frac{-135000}{3000000}\right)(0.1) = -0.45\%$$

Glossary

Black funds: mutual funds that mainly invest in stocks from the carbon-intensive industries.

Carbon emission allowance: a tradable permit that gives the holder the right to emit one unit of carbon dioxide equivalent into the atmosphere. It is the core instrument used under a cap-and-trade scheme governed by the respective policymakers for the purpose of emission control.

Carbon footprint: the amount of carbon dioxide equivalents emitted due to the consumption of fossil fuels or other activities by a particular entity. For a stock, this term refers to the carbon footprint of the underlying company.

Carbon intensity: a measure of carbon footprint normalized by the magnitude of the associated business activity. There is no consensus on the definition of this measure, but a convenient, intuitive formula is dividing the net annual emissions by the annual sales. For a stock, this term refers to the carbon intensity of the underlying company.

Carbon-intensive industry: a general term referring to an industry sector whose regular operations and activities are associated with a heavy emission of carbon pollutants. Such industries often include but are not limited to oil and gas extraction and production, mining, chemicals, transportation and materials.

Carbon offsetting: the feature in which an instrument directly reduces a carbon footprint and a carbon risk exposure of an investment portfolio when added to it.

Carbon risk: a general term referring to the risk in an investment instrument or portfolio by having significant stakes in companies with a high carbon footprint.

Closed trading phase: an ETS trading phase in which unused allowances at the end of the phase expire without having any value. Phase 1 of the EU ETS from 2005 to 2008 is a closed trading phase, which provided a pilot experience to the regulators.

Covariance matrix: a symmetric square matrix containing the expected annual returns of the assets in the asset universe considered for portfolio optimization. Indexing using the row by column convention, the (*i,j*) entry of the matrix represents the covariance between asset *i* and asset *j*. The diagonal of the matrix stores the variances of the assets (such as the covariance of an asset's return with itself). By nature, covariance matrices are positive semidefinite.

Decarbonization: the intent or effort to reduce the carbon risk exposure of an investment portfolio.

EUA: acronym for European Union allowance, the carbon emission allowance issued under the EU ETS. Each EUA gives the holder the right to emit one metric ton of carbon dioxide equivalent over a compliance year.

EU ETS: acronym for the European Union Emission Trading Scheme, which is the first and largest emissions trading scheme in the world. It was launched in 2005 to fight global warming after the Kyoto Protocol was enacted and operates under the typical cap-and-trade principle. The scheme has been divided into a number of "trading phases": Phase 1 ran from 2005 to 2007; Phase 2, from 2008 to 2012; and Phase 3, which is currently in force, runs from 2013 to 2020. Regulatory parameters, including the maximum emission amounts permitted for each company or installation in each year of the phase, are set at the beginning of the phase based on previous experience. EUA is then auctioned off or allocated for free and can subsequently be traded. Each installation must monitor its emission and ensure that it submits enough allowances to the authorities to cover its emission at the end of the year (referred to as a *compliance filing*). If emission exceeds what is covered by its allowances, a penalty must be paid per unit of excess emission. Such a system forms a cost-effective way of reducing emissions without any significant government intervention. Within a trading phase, allowances can be *banked*, meaning unused allowances are automatically carried over to subsequent years. In addition, there exists an implicit "borrowing" mechanism to cover the current year's extra emission by using the following year's allowances. This is possible because each year's compliance filing deadline is after the following year's allowance allocation date. However, the treatment of unused allowances at the end of a trading phase differs based on the phase being open or closed. An example of the EU ETS is presented in Appendix H to facilitate understanding of how the scheme functions.

Green bonds: bonds issued by governments or corporations to fund projects that benefit the environment and mitigate climate change.

Green funds: mutual funds that mainly invest in the green stocks and green bonds markets.

Green index: a stock index consisting of green stocks from certain markets.

Green stocks: shares of companies whose primary business is beneficial to the environment. Such companies are concentrated in sectors such as alternative energy, pollution control and recycling.

Integrated assessment models (IAMs): a set of scientific models used in the environmental sciences and environmental modeling, integrating knowledge and methodologies across multiple disciplines. In climate change research, such numeric models are commonly used to predict future climate scenarios as well as quantify their potential impact on the economy.

Mean vector: a vector containing the expected annual returns of the assets in the asset universe considered for portfolio optimization.

Open trading phase: an ETS trading phase in which unused allowances at the end of the phase are carried over for use in the subsequent phase. In practice, these unused allowances are banked and later registered as the new allowances issued for the subsequent phase coming into force. Phases 2 and 3 of the EU ETS are both examples of open trading phases.

Risk-adjusted returns: a measure of investment performance where the asset's excess return (meaning average return minus the risk-free return) is normalized by the risk of the returns (such as volatility, beta and drawdowns). Two commonly used measures are the Sharpe ratio - the average excess return in the measurement window divided by the volatility of the return, and the Treynor ratio - the average excess return in the measurement window divided by the beta of the return.

Stranded assets: assets that become obsolete or nonperforming well before the end of their expected useful lives. In the context of climate change risk, this term refers to fuel supply and energy generation resources that, at some time prior to the end of their economic lives, are no longer able to earn an economic return as a result of changes associated with the transition to a low-carbon economy (mostly regulatory changes).

Strategic asset allocation: a step in dynamic investment management and portfolio optimization that involves setting the portfolio weights for various asset classes and market sectors. The allocation of weights should serve the purpose of investment and varies heavily among portfolios.

Tactical asset allocation: a step in dynamic investment management and portfolio optimization in which the initial strategic asset allocation is adjusted to reflect new views on the risk-return profiles of particular sectors.

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About The Society of Actuaries

The Society of Actuaries (SOA), formed in 1949, is one of the largest actuarial professional organizations in the world dedicated to serving 28,000 actuarial members and the public in the United States, Canada and worldwide. In line with the SOA Vision Statement, actuaries act as business leaders who develop and use mathematical models to measure and manage risk in support of financial security for individuals, organizations and the public.

The SOA supports actuaries and advances knowledge through research and education. As part of its work, the SOA seeks to inform public policy development and public understanding through research. The SOA aspires to be a trusted source of objective, data-driven research and analysis with an actuarial perspective for its members, industry, policymakers and the public. This distinct perspective comes from the SOA as an association of actuaries, who have a rigorous formal education and direct experience as practitioners as they perform applied research. The SOA also welcomes the opportunity to partner with other organizations in our work where appropriate.

The SOA has a history of working with public policymakers and regulators in developing historical experience studies and projection techniques as well as individual reports on health care, retirement and other topics. The SOA's research is intended to aid the work of policymakers and regulators and follow certain core principles:

Objectivity: The SOA's research informs and provides analysis that can be relied upon by other individuals or organizations involved in public policy discussions. The SOA does not take advocacy positions or lobby specific policy proposals.

Quality: The SOA aspires to the highest ethical and quality standards in all of its research and analysis. Our research process is overseen by experienced actuaries and nonactuaries from a range of industry sectors and organizations. A rigorous peer-review process ensures the quality and integrity of our work.

Relevance: The SOA provides timely research on public policy issues. Our research advances actuarial knowledge while providing critical insights on key policy issues, and thereby provides value to stakeholders and decision makers.

Quantification: The SOA leverages the diverse skill sets of actuaries to provide research and findings that are driven by the best available data and methods. Actuaries use detailed modeling to analyze financial risk and provide distinct insight and quantification. Further, actuarial standards require transparency and the disclosure of the assumptions and analytic approach underlying the work.

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