Climate Aligned Investment Portfolios

Abstract

The purpose of this study is to construct climate portfolios with low exposure to climate related risks and to determine the similarity across key climate characteristics sourced from private commercial providers. In addition, the study provides evidence on the performance of climate portfolios against a broad-based market index. A secondary objective of the study focuses on testing the hedging ability of climate portfolios and mimicking portfolios against climate change news indices. Results show there are close similarities among carbon intensity and transition CVAR characteristics, while there is a negative association among these characteristics when compared to the technology opportunities CVAR. Furthermore, the portfolios constructed based on the mimicking approach, yield greater hedging performance when compared to portfolios constructed based on the underlying optimization model considered in the study. However, there is no significance to be found on the correlation estimates, suggesting no definite conclusion can be drawn with respect to hedging ability of climate characteristics. Finally, the study finds that most climate characteristics out-perform the broad-based market index, particularly from 2015 and onwards.

Keywords: climate risk, sustainable investing, climate news, hedging,
JEL codes: G12, G24, Q54.

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February 3, 2022

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1 Introduction

Over the last decades, institutional investors and financial institutions have been increasingly concerned with the systemic nature of climate risks and their impact on investment portfolios. These institutions are motivated by financial returns, but at the same time they also want to do good. A recent study by Krueger et al. (2020) revealed that institutional investors consider climate risks because of both financial and non-financial reasons. On the one hand, investors believe climate risks affect portfolio risk-return characteristics. On the other hand, investors also consider climate risks important to protect their reputations, as well as having moral and legal obligations with society and the environment. The study found that the two most common approaches towards managing climate risks by investors were risk management and stakeholder engagement. Divestment was the least used method.

Ideally, these investors would like to derisk their investment portfolios by limiting their exposure to sectors considered to be more vulnerable to climate related risks. In addition, they would like for these derisked portfolios to maintain a similar expected return profile as their initial portfolio. Some financial institutions, such as pension funds, would not only like to limit their exposure to climate risks, but to effectively hedge such risks to protect their long term pension schemes positions against the threats of climate change. A recent study by Anderson et al. (2016) proposes the construction of a "decarbonized index" investment strategy to hedge climate risk. The authors constructed a portfolio optimization model where they minimize the tracking error (TE) by first, excluding the worst stock performers in terms of carbon intensity, and secondly, by re-weighting the remaining stock constituents following a TE minimization problem. This study offered a simple and effective tool for investors to construct decarbonized indices for carbon intensity and other climate characteristics. Authors stressed the importance of generating synergies and incentives between the public sector and the financial industry to urge more investors to adopt these decarbonized index-investing strategies. As more and more investors "chip in", then a larger fraction of funding will be shifted towards green investment portfolios, which in turn will exert rising pressure to reduce carbon emissions across industries (especially brown industries). Other studies, approached climate risk hedging by constructing mimicking portfolios based on environmental scores sourced from commercial providers and tested their hedging performance against tailored hedging targets (Engle et al. (2020)). Faccini et al. (2021) constructed similar hedging targets as Engle, but with a greater frequency and targeted towards physical and transition risks.

The main challenge remains for investors on how to quantify such climate risks and how to redesign investment portfolios to achieve the desired objectives previously mentioned. As a response to demands from investors, a number of third party providers entered the market by providing several proxy's of climate risks in an attempt to close the data gap and provide investors with additional tools to manage and mitigate climate related risks. A common measure of climate risks is carbon intensity, which measures the total amount of carbon emissions (metric tonnes) emitted by a company, scaled by its revenue. In other words, the carbon intensity tracks the individual carbon footprint of each company (Bender et al., 2019). Other measures found in Bender's study include Brown Revenue (share of revenues from production activities related to fossil fuels), Green revenue (share of revenues originating from low-carbon technology products) and Fossil Fuel Reserves (total reserves greenhouse gas emissions in metric tonnes). Additional climate risk proxies include environmental score ratings, proxy's for low carbon innovation (green patents) as evidenced by Cohen et al. (2021) and MSCI climate value at risk (CVAR) metrics which focuses on policy and physical risks as well as green patents.

The next natural question is, how do investors use these climate metrics to construct investment portfolios with low climate change impact? A recent paper developed by Bolton et al. (2021) presents a methodology were authors construct a climate portfolio subject to a carbon budget. Authors claimed their portfolio was aligned with the Paris Agreement' target of limiting the average temperature rise to 1.5 Celsius. The authors constructed an optimization model where the objective was to minimize the tracking error of the resulting portfolio with respect to a reference index. In addition, they constrained the optimization to a sector deviation threshold, in order to preserve the sector weight composition similar to the benchmark index. Other authors propose a similar optimization model to accommodate for the typical institutional investor whom wants to reduce carbon footprint while preserving the risk-return characteristics as close as possible to the benchmark index. In this case, the objective was to minimize the exposure to a climate characteristic (for example, climate intensity) subject to a portfolio tracking error threshold. The optimizer could also be constrained to a minimum exposure to green revenues, or perhaps to a minimum exposure to climate adaptation ratings (Bender et al. (2019)). Another alternative proposed by Bender includes minimizing the portfolio variance at the same time the climate characteristic is minimized. Similar portfolio objectives are currently employed by institutional investors, tailored to their specific sustainability needs and using either third party or in-house developed climate risk metrics. A study conducted by LaPlante and Watson (2017) on environmentally conscious indices' performance against traditional market portfolios revealed that in most cases climate-aligned indices perform on par or better than the benchmark market indices during the 2009-2016 sample period. These findings suggest that betting on green investing can generate competitive returns while supporting lower carbon exposures.

Given the diversity in measures and levels of sophistication of each climate risk proxy, institutional investors may be easily overwhelmed with different data providers and what each metric captures. As such, the main question for investors remains, do these climate metrics capture the main drivers of climate risk and if so, do they drastically differ from one another? More specifically, how would investment portfolios with identical climate risk mitigation objectives perform when integrating climate risk measures from different commercial providers? In addition, to what degree are the resulting optimized portfolios similar (or different) and what drives these differences? The latter two questions are the main motivation for this study. A secondary objective of the paper is to contrast and compare the hedging performance of optimized climate portfolios versus mimicking portfolios constructed based on a number of climate characteristics. For this objective, the study closely follows the methodology presented by Engle et al. (2020) and relies on key hedging targets presented by authors (climate change news innovations) to test the hedging performance of the aforementioned climate portfolios.

Preliminary results find that climate-aligned portfolios can outperform the broad-based market index considered in this study over the 2012-2019 period. The out-performance premium widens with the introduction of the Paris Agreement in 2015, and steadily grows for the following 4 years. Similarity results derived from the study suggest that there is a strong association between MSCI's active weight performance of the transition risk pillar compared to the carbon intensity portfolio. This result aligns with expectations as both metrics capture dynamics of carbon emissions and carbon reduction targets. Furthermore, the aforementioned portfolios have a negative association with the technology opportunities portfolio, suggesting that the constituents lagging behind in climate policies have the most innovative capacity for low-carbon products. In addition, the physical risk portfolio has a moderate association with the transition and carbon intensity portfolios, suggesting climate policies can have a partial effect on physical events. In other words, portfolios that are tilted towards sectors less affected by climate policies are (to a certain extent) comparable to portfolios tilted towards sectors less affected by physical climate events.

Constructing climate portfolios to neutralize the effect of climate change news, effectively hedging against climate risk, has proven to be a challenging task. The climate portfolios presented in this study show no evidence of hedging ability to the different climate change news employed in this study. As a robustness check measure, this test has also been conducted to the Low minus High (LMH) mimicking portfolios for selected climate characteristics. Similar to Engle et al. (2020) findings, this study shows that characteristic weighted portfolios show a better hedging performance compared to optimized climate portfolios. Nevertheless, results found in this study show no significance of estimates.

2 Research Objective

This study has three main objectives. First, to construct tracking portfolios characterized by low climate risk exposure compared to the benchmark index, in this case, the MSCI World Index. To achieve this target, an optimization model is constructed where the goal is to minimize the value weighted exposure to the climate characteristic which will allow to obtain optimal climate portfolios characterized by low exposure to climate related risks.

The second objective of the study is to determine the similarity across climate portfolios with low climate risk exposures to estimate the extent to which these portfolios yield similar portfolio asset compositions (i.e in portfolio weights and sector asset composition).

The final objective of this paper is to test the degree to which climate portfolios are effective in hedging climate change news indexes. For this objective, the approach described by Engle et al. (2020) in their paper "Hedging Climate Change News" is closely followed.

3 Methods

For the first objective, each portfolio is formed by running the optimizer across six climate change characteristics: I) Overall CVAR II) Policy CVAR, III) Technology Opportunity VAR, IV) Aggressive Physical CVAR, V) Carbon Intensity, and VI) MSCI Environmental Score. As such, the following minimization problem is proposed:

$$\min_{w} \sum_{i=1}^{N} c_{ij} w_{ij}$$

subject to

$$\sum_{i=1}^{N} w_{ij} = 1 \tag{1}$$

$$\left| w_{ij}^{P} - w_{ij}^{I} \right| \leq \delta \tag{2}$$

$$w_{ij} \geq 0 \tag{3}$$

where c_{ij} is the value of the j^{th} climate characteristic for the i^{th} stock constituent of the benchmark index. The first constraint ensures the optimized weights sum up to 1. The second constraint ensures the weights, denoted as w_{ij}^{P}, of the tracking portfolio do not deviate more than 0.05 percent from the benchmark index weights (denoted as w_{ij}^{I}) for each individual stock constituent. The final constraint allows for no short selling. This constraint is further relaxed when constructing climate hedge portfolios.

Similarity metrics are also computed on the basis of resulting portfolio active weights for each optimization problem. The similarity metric chosen for this study is the the cosine similarity. It is defined as follows:

$$CS(P_A, P_B) = \sum_{n=1}^{N} w_{PA,n}.w_{PB,n} / (\sqrt{\sum_{n=1}^{N} w_{PA,n}^2} \sqrt{\sum_{n=1}^{N} w_{PB,n}^2}) \tag{4}$$

where N is the total number of stock constituents, $w_{PA,n}$ is portfolio A's weight in security N and $w_{PB,n}$ is portfolio B's weight in security N. The cosine similarity metric measures the similarity among portfolios based on derived portfolio weights. Mathematically, it is computed as the product of the pair of portfolio' weight vectors normalized by the vector's length. In other words, cosine similarity represents the dot product of weight vectors scaled by magnitude. Identical portfolios are represented by a cosine of 100 while portfolios with no relationship have a cosine of 0.

For the final objective, climate hedge portfolios are constructed considering a similar optimization formulation previously defined. The key differences are that constraint (3) is relaxed to allow the optimizer for short selling. In addition, the threshold imposed on the constituent level weight constraint, denoted as δ, is further relaxed from 0.05% to 0.3%. Following Asgharian (2004), this study also constructs rank based mimicking portfolios whereby stock constituents are sorted on their factor loadings (climate charateristics). These stocks are further grouped in low and high loading portfolios. Finally, the factor mimicking portfolio is constructed by taking a long position in low factor loadings (representing low exposure to climate) and a short position in high factor loadings (representing a greater exposure to climate related risks). The mathematical formulation of low and high factor portfolios are defined below:

$$w_{ij}^L = 1 - \frac{c_{ij} - min_i(c_{ij})}{max_i(c_{ij}) - min_i(c_{ij})} \tag{5}$$

$$w_{ij}^H = 1 - \frac{max_i(c_{ij}) - c_{ij}}{max_i(c_{ij}) - min_i(c_{ij})} \tag{6}$$

where w_{ij}^L and w_{ij}^H represent the low(high) factor weights for the i^{th} stock constituent and j^{th} climate characteristic. These factor weights are then normalized to sum up to one. The weight distribution of the low(high) factor portfolio is ranked based where the largest weights are concentrated in maximum values climate characteristics. These weights are gradually decreased as the value of climate characteristics approaches to the median. The resulting low-high factor portfolios are constructed by computing the premium of stock returns of the long leg (low climate factor) over the short leg (high climate factor).

4 Data

This study employed a variety of proprietary data points provided by Robeco Institutional Asset Management. Historical returns for MSCI World Index constituents are considered spanning from 2012 to 2019. Table 1 shows descriptive statistics on monthly returns for MSCI World constituents for the 2012-2019 sample period. The index has on average 1500 stock constituents across 23 developed market countries. Approximately 86 percent of constituents are listed on five main developed market countries (namely the United States, Japan, UK, Canada and France), the remaining are concentrated on other developed markets. Figure 1 shows historical monthly return performance for the index over the sample period. The poor index performance during 2015 was largely cause by the Shanghai stock exchange crash in June of 2015 which triggered U.S markets to halter their buy orders and input a great number of sell orders pushing down the price significantly during the following months. The index showed improvement as the world market gradually improved and re-grain growth during the 2016-2017 period.

During the second half of 2018 (particularly during Q4-2018), the index saw the worst performance since the eurozone debt crisis of 2011, falling by 7.8 percent. This was mainly due to the US-China trade wars, coupled with slow global GDP growth. In addition, the dip of the UK stock market due to brexit concerns also weighted in on MSCI's performance during the same period.

Table 1: Descriptive Statistics MSCI World Monthly Returns

Year	Mean	SD	Min	25%	Median	75%	Max
2015	0.0009	0.075	−0.425	−0.045	−0.002	0.044	0.561
2016	0.007	0.080	−0.474	−0.037	0.006	0.053	0.780
2017	0.017	0.057	−0.506	−0.016	0.015	0.049	0.417
2018	−0.010	0.074	−0.513	−0.054	−0.007	0.035	0.556
2019	0.017	−0.076	−0.431	−0.024	0.019	0.061	0.829
Overall	0.006	0.074	−0.513	−0.035	0.007	0.049	0.829

Table shows descriptive statistics on MSCI index constituents' returns over the 2015-2019 sample period

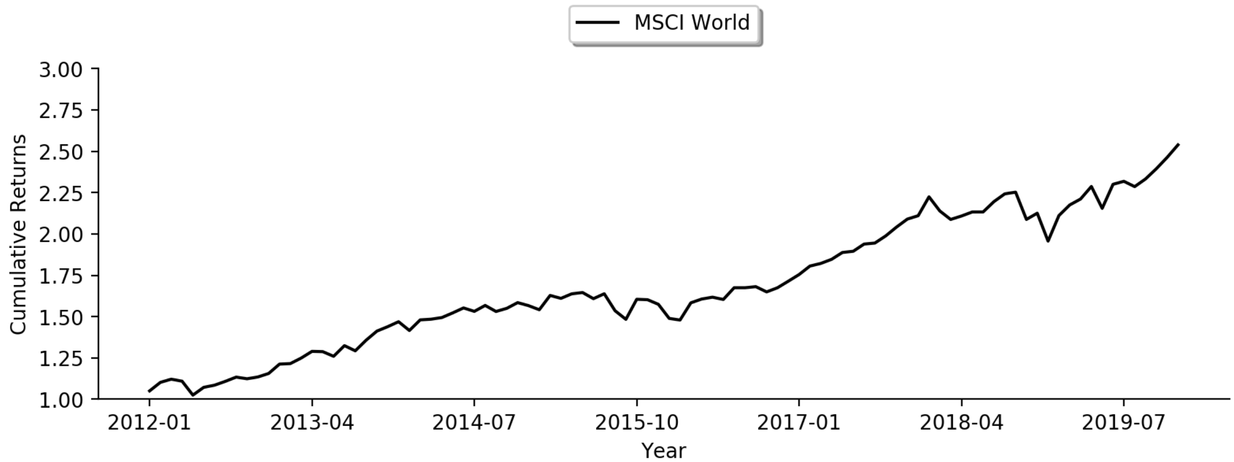

Figure 1: This figure shows the cumulative returns of MSCI World Index over the 2012-2019 period

In addition to stock returns, three climate characteristics are considered, namely, MSCI's Climate Value at Risk (CVAR), Carbon Intensity and MSCI's Environmental Score. For CVAR, only year 2021 is considered as there is no history on this metric. CVAR is a forward looking metric that reflects the climate change risk exposure in relation to the enterprise market value. This metric is computed at the portfolio or security level (equity and fixed income). The CVAR is composed of three main pillars, namely, Policy Value at Risk (VAR), Physical VAR and Technological Opportunities. The policy VAR represents a downside risk exposure to transition costs as a result of climate change policies. This pillar is bounded between -100 and 0, the latter representing a low vulnerability to climate policy (and consequently associated with low transition costs), and the former representing high vulnerability or exposure to climate change policies (high transition costs). The construction of this pillar follows a proprietary methodology developed by MSCI. The general modelling steps are defined below:

1) Voluntary greenhouse gas emissions (GHG) reduction targets proposed by each country via Nationally Determined Contributions (NDC)

2) MSCI further classifies GHG emission reduction targets by sector level and company

3) Forecasting carbon prices derived from integrated assessment models (IAM's)

4) Computing transition costs for the next 15 years

5) Computing present value of GHG reduction costs

6) Computing Policy VAR (present value of GHG costs / Enterprise Market Value)

The Policy VAR follows a top-down approach whereby the first step in the construction of this metric is to gather the GHG reduction targets provided by each country as part of the Paris Agreement NDC's. Once the national reduction targets are collected, these are distributed proportionally for each sector of the economy based on the sector's current emissions. In other words, the sectors that emit the most GHG, will be the ones attributed with greater reduction targets. Finally, using proprietary asset location data, MSCI distributes sector-level reduction targets to individual company level targets.

Given the objective of the policy CVAR is to quantify transition costs, the next step is to forecast carbon prices derived from integrated assessment models (IAM's). IAM's are sophisticated models that link key factor inputs such as economic growth, population, GHG emissions, electricity mix, carbon sequestration estimates and other climate variables in a coherent integrated framework to ultimately forecast carbon prices. The next step in the process is to compute the transition costs by taking product between the company level reduction targets and the forecasted carbon prices for a future window of 15 years, and discounting such costs to the present. Finally, discounted costs are expressed in relation to the enterprise market value which represents the policy VAR. This metric is computed for various climate scenarios, the MSCI CVAR documentation can be referred for additional modelling details.

The physical VAR represents the exposure to physical impact of extreme weather events as a result of climate change. The pillar ranges from -100 to +100, the latter representing a high level of resiliency to physical risks (revenue gains and/or low costs related to weather events) and the former representing a high vulnerability to physical risks (in turn, associated with higher costs). It is important to note that this pillar can represent opportunities (revenue gain) or costs that derive as a result of extreme weather events (chronic and acute events). The general modelling steps are described below:

1) Forecast of annual revenue loss (gain) due to exposure to chronic events for a 15-year period

2) Forecast of annual expected loss from asset damage due to exposure to acute events

3) Computing present value of future revenue loss and asset damage loss

4) Compute Physical VAR (present value of losses gains / enterprise market value)

MSCI makes use of physical climate change models as well as statistical extrapolation of historical data to forecast company-level vulnerabilities and expected revenue gain or costs as a result of weather events. This study is not intended to dive deep into the underlying models but instead to provide the reader an high level overview on the logic behind the construction of each CVAR pillar. For further details on how these metrics are constructed, please refer to MCSI's methodology fact sheets.

Finally, the technology opportunity pillar represents an upside exposure to low carbon revenues as a result of climate change policies and low carbon product offering (green patents).

This pillar is bounded between 0 and 100. A score of 0 reflects a poor level of green revenues and poor preparedness on technological innovation related to low-carbon products. In turn, a score of 100 reflects high levels of green revenues and greater innovative capacity of low-carbon technologies (as a result of patent quality). MSCI makes use of a proprietary methodology on patent quality whereby each patent is assigned a quality score. Based on such patents, and the current share of low carbon revenue of each company, MSCI forecasts estimates of future low carbon revenues and computes carbon profits for next 15 years. Finally, future profits are discounted to the present and expressed in relation to the Enterprise market value to arrive at the Technology VAR metric.

Overall, the CVAR metric provides insights into the potential future winners and losers as a result of climate change policies, extreme weather impact and technological innovation. CVAR aids institutional investors answer the following key questions: Who will bear the greater burden on an aggressive climate policy target and what magnitude does that burden represent? Which companies are at the forefront of technological innovation in low-carbon products and how does this translate into potential future green revenues? Which companies are going to be the most affected by business interruption and physical asset damage as a result of extreme weather events? In turn, which companies will be more resilient to such events?

Table 2 shows the average scores of CVAR and its sub-components by Industry Sector. A lower score represents a greater exposure to climate risk while a higher represents greater resistance or resilience to it. The table shows that stock constituents part of the Health Care, Financials and Information Technology have the lowest exposure to climate value at risk. In part, this is due to their low exposure to policy risk given these sectors are characterized by low carbon emissions which translates into less future costs to transition away from carbon generating activities. In addition, physical risks for these companies are also fairly low which implies that company facilities are strategically located in places where there is not a directly threat of physical asset damage occasioned by extreme weather events. As a result of not being as exposed to climate related risks as other sectors (such as Energy and Utilities), these sectors also score low on the technology pillar which is a proxy for the innovation in low carbon patents and products. This could largely be due to a lack of incentive to do so given their activities are already considered "green" (for the most part), and further innovation in low carbon products is not part of their core business strategy.

Not surprisingly, stock constituents with the greatest exposure to climate risks are those operating in the Energy, Materials and Utilities sectors whom score the lowest in climate value at risk metrics. Nevertheless, these these sectors are among the highest in terms of technological innovation in low carbon products. This could be in part explained by the fact that some companies are preparing themselves for the future transition to a lower carbon economy, which implies heavy investments in Research and Development which leads to a greater number of low-carbon patents being issued by such companies.

Table 2: MSCI Climate Value at Risk Average Scores for Selected Period

GICS Sector	MSCI CVAR	Policy CVAR	Physical CVAR	Technology CVAR
Energy	−55	−61	−6	11
Materials	−34	−43	−5	14
Utilities	−30	−49	−7	25
Consumer Staples	−21	−17	−7	2
Consumer Discretionary	−10	−15	−7	12
Industrials	−8	−16	−5	13
Real Estate	−8	−3	−6	1
Communication Services	−7	−3	−4	0
Health Care	−6	−3	−3	0
Financials	−5	−2	−3	0
Information Technology	1	−3	−3	7

This table shows the average scores of CVAR and its corresponding pillars for the 2021 period. Aggregate CVAR, policy CVAR pillar and physical CVAR pillar ranges from -100 to 100, the latter representing a more favorable score (sectors that have resiliency to both climate policies and physical impact of weather events). The technology pillar ranges from 0 to 100, the latter representing a greater share of green innovation

For carbon intensity, year 2019 is considered as it contains the most data points for the MSCI World index constituents. Carbon intensity represents the amount of carbon emissions (measured in metric tons) per unit of revenue of each constituent present in the index. More specifically, this metric is computed by taking the carbon emissions (scope 1 and 2) in relation to company's sales (in millions) for each constituent. The normalization by sales allows comparison between companies of different sizes.

The last climate characteristic considered in this study is MSCI ESG ratings which measure entity level resilience to long term financial ESG risks (MSCI Methodology Source). Given this study is particularly focused on reducing climate related material risks, the environmental pillar (E-score for short) was employed for further analysis. MSCI's E-Score is a weighted average score that ranges from 0 to 10 (10 being stocks least exposed to environmental risks) across five main environmental themes: Climate Change, Natural Capital, Pollution and Waste, and environmental opportunities. The E-weight, represents the "contribution of the industry, relative to all other industries, to the negative or positive impact on the environment or society as well as the timeline within it is expected that such risk or opportunity materializes" (MSCI). The weights range from 0 to 100, the latter being the most contribution of environmental issues, relative to social and governance issues.

Following Pastor et al. (2022), the unadjusted greenness score is constructed for MSCI World stock constituent i at time t as follows:

$$Gr_{i,t} = -(10 - EScore_{i,t}) X Eweight_{i,t}/100 \quad (7)$$

where Escore and Eweight are MSCI's ratings for the most recent 2021 period. The standalone E-score is the company i's individual rating on environmental risks ranging from 0 to 10, the latter representing excellent environmental score. The Eweight measures the environmental impact of constituent i ranging from 0 to 100, the latter contributing the largest to environmental issues. As mentioned by Pastor et al. (2022) in their study on "Dissecting Green Returns", if Eweight were not to be included, then each individual constituent in the sample would be similarly green, which is not ideal. By including the Eweight, the E-score is adjusted based on each stock's impact on the environment. In other words, the Eweight adjusts for the relative impact of each stock constituent to the environmental themes considered in the Escore, therefore resulting in a weight-adjusted Escore that better represents each constituent's contribution to environmental issues. The average greenness score by sector is reported on Table 3. The closer the score to 0, the more green the sector is.

Table 3: Greenness Average Scores for Selected Period

GICS Sector	Greenness Score
Communication Services	−0.07
Health Care	−0.25
Financials	−0.44
Information Technology	−0.70
Consumer Discretionary	−0.94
Industrials	−0.98
Real Estate	−1.11
Utilities	−1.43
Consumer Staples	−1.59
Energy	−2.15
Materials	−2.31

This table shows the average greenness scores of MSCI's environmental pillar for the 2021 period. A value closer to 0 represents more green and environmentally responsible sectors while more negative values represent browner sectors

5 Results and Discussion

Table 4 shows the summary results of the optimized absolute weights on six climate characteristics in total. Three of them are sub-components of the overall CVAR (namely policy CVAR, physical CVAR and technology CVAR). Climate intensity and policy CVAR optimized weights exhibit comparatively similar results which aligns with expectations given that both metrics contain carbon emissions information embedded in such metrics. As such, they both increase their share of weights in less carbon intense sectors (such as Financials, Information Technology and Real Estate) and reduce their share in more carbon emitting industries (Energy, Utilities and Materials). The physical CVAR' optimized weights deviate the least from the benchmark with the greatest decrease found on the Energy and Utilities sectors (decrease by 6.5 and 7.4 percentage points with respect to benchmark). This is reasonable as these sectors score among the highest in exposures to physical related risks. Notable results are shown on the optimized weights of the Technology pillar where a substantial decrease of financial sector's share is found (38 percentage points dip with respect to benchmark). This is as expected given this sector shows no green innovative capacity whatsoever (score of 0). Intuitively, given the Financial sector has low exposure to transition risks, this sector is less incentivized to invest in green technologies, thus, their low-carbon innovative capacity is not substantial, hence, their decreased share in the technology pillar portfolio. Conversely, the Utilities and Materials sector actually increase their share by 87 and 45 percentage points respectively compared to the benchmark. These sectors characterized as pollutive, are actually at the forefront of green patent quality and innovation, hence, their increase in share of weights.

The Greenness score portfolio shows interesting results whereby the optimizer reduced the share of weights (compared to the benchmark) away from the least environmentally friendly sectors (Utilities, Materials and Energy) but in a with a lower decrease when compared to the carbon intensity and CVAR portfolios. This can be partially explained by the fact that the E-scores captures both positive and negative environmental impact dynamics for each stock constituents and the degree to which this impact is affected by each constituent (E-weight). As such, the environmental opportunities (positive impact) themes embedded on the E-score may serve as a buffer to the remaining negative impact themes (carbon emission, water stress, pollution, waste, and others), thus making the allocation of constituent weights less pronounced.

Table 4: Selected Climate Portfolio Optimized Weights Allocations Relative to MSCI World Benchmark (measured in % points)

GICS Sector	Greenness Score	Carbon Intensity	Overall CVAR	Policy CVAR	Technology CVAR	Physical CVAR
Panel A: Optimized Weights % point change against benchmark						
Communication Services	6.67	12.72	1.8	18.97	−18.12	2.2
Consumer Discretionary	1.75	5.71	7.9	−2.78	−0.28	2.5
Consumer Staples	−4.06	−4.35	−12.5	−12.14	−26.57	−5.5
Energy	−10.71	−30.94	−26.0	−36.31	13.03	−6.5
Financials	3.30	16.11	1.8	14.59	−38.90	1.0
Health Care	2.54	7.07	−1.4	4.88	−15.46	−1.7
Industrials	2.26	0.13	15.4	0.40	43.06	3.2
Information Technology	0.11	7.10	5.3	5.86	0.85	0.3
Materials	−14.83	−56.04	−23.6	−47.01	44.08	2.2
Real Estate	2.57	25.09	7.5	40.68	16.01	3.6
Utilities	−4.77	−64.03	−15.8	−50.89	87.63	−7.4
Panel B Climate Objective Performance						
% Improvement to Benchmark	5.62	77	50	49	133	23

Panel A of table shows percentage change of optimized weights of climate portfolios compared to the MSCI World Benchmark. A 0.05 % restriction is imposed to the optimization at the individual constituent level to preserve sector level weights of benchmark index. Panel B shows the percentage point change by which the climate factor has been reduced (for climate intensity) and increased (for CVAR) as a result of the optimization with respect to the benchmark value. It represents a proxy for the climate objective performance for each portfolio

The percentage improvement represents the percentage reduction in climate risk exposure of each portfolio with respect to the benchmark. The carbon intensity portfolio shows a 77 percent reduction in carbon intensity with respect to the MSCI World Index's carbon intensity profile. Similarly, the overall CVAR portfolio shows a 50 percent reduction of climate risk exposure with respect to the benchmark. The technology CVAR portfolio represents a 133 percent improvement in exposure to green innovation compared to the benchmark. Finally, greenness score shows a 5.6 percent improvement in exposure to more green constituents compared to the benchmark index. The relatively large improvement in climate objectives for these portfolios suggest that reducing the exposure to key climate risks is relatively inexpensive for the institutional investor given the asset composition in sector level weights is well preserved compared to the benchmark index when imposing a 0.05% weight restriction at the constituent level (see Figures 15, 16 and 17 in Appendix). These improvements yield relatively similar results to Anderson et al. (2016), where authors find an 82% reduction in carbon emissions intensity (compared to 77% in this study) as a result of their optimized low carbon index portfolio. These results suggest that institutional investors committed to decarbonize and derisk their investment portfolio, can do so at a small cost (ceteris paribus). As a result, more financial institutions would be motivated to re-engineer their portfolios towards low-climate exposed indices. If sufficient investors adopt this approach overtime, this will ultimately yield positive externalities given that capital funding will be redistributed towards sectors and companies that exhibit more sustainable business models.

In 2015, the UN Climate Change Conference was held in Paris, which gave birth to the Paris Agreement signed by 196 member countries whom aligned with aggressive sustainability objectives by 2050. As a result, the financial industry has increasingly adopted several strategies to integrate sustainability metrics into their investment portfolios by either increasing its participation in firms with low climate impact, divesting their portfolios from firms with greater share of brown revenues, or other similar strategies. Figure 2 shows the cumulative return performance of three of such portfolio strategies, namely minimizing exposure to: (1) climate risks (CVAR portfolio), (2) carbon intensity and (3) environmentally harming stocks (Greenness Score). As such, the graph shows the historic cumulative return performance of MSCI World Index compared to their tracking climate portfolios estimated in this study. As observed by the graph, all climate portfolios closely mimic the index, some of them outperforming the index on every year (CVAR portfolio). Up until 2015, the out-performance of climate portfolios is relatively small, where the greatest out-performance is approximately 0.25 % points. With the introduction of the Paris Agreement and elevated international concerns on climate change, this premium widens for the 2015-2019 period.

Similar findings are presented by Pastor et al. (2022) where authors conclude that out-performance of green assets are mainly driven by climate-concern shocks. Another paper by Van Der Beck (2021) shows that out-performance of ESG funds and green ETF's are mainly driven by price pressure that arises as a result of the movement of AUM (assets under management) towards more sustainable stocks. Consequently, the realized out-performance of sustainable funds are not necesarily equivalent to future expected out-performance over less sustainable stocks. Table 5 shows annual return performance of the index with its climate tracking portfolios. Evidently, the CVAR portfolio performs the best among the climate portfolios, even during the Asian Crisis of 2018. Carbon intensity and Greenness Score show very close return characteristics year over year compared to the benchmark.

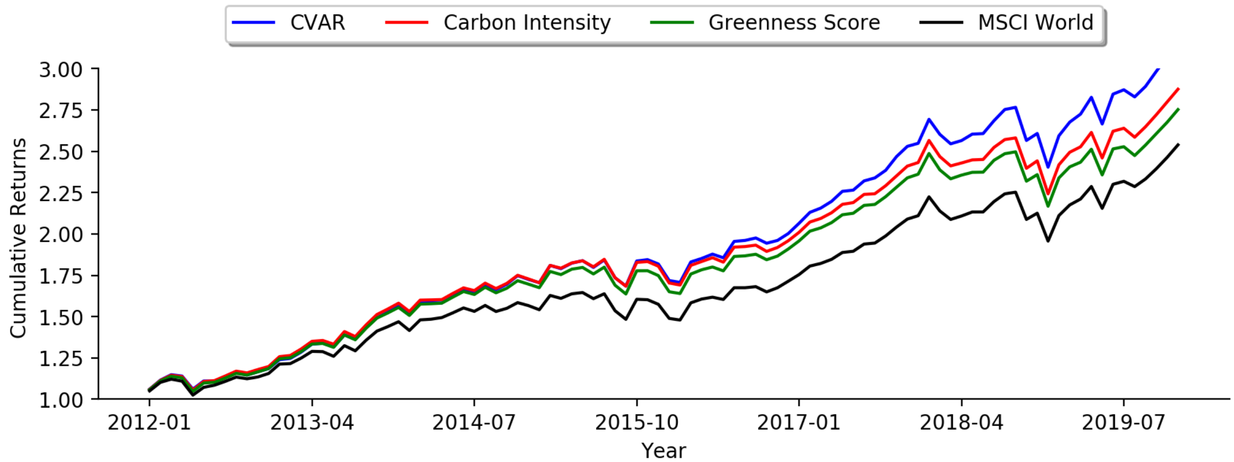

Figure 2: This figure shows the cumulative return performance of MSCI World Index and selected climate portfolios over the 2012-2019 period

Table 5: Annual Return Performance of Selected Portfolios over the 2015-2019 period

		Portfolio Optimized For:		
Year	MSCI World Index	Overall CVAR	Carbon Intensity	Greenness Score
2015	0.013	0.061	0.052	0.038
2016	0.09	0.102	0.087	0.094
2017	0.21	0.244	0.218	0.215
2018	−0.066	−0.049	−0.071	−0.076
2019	0.27	0.284	0.258	0.248
Overall*	0.096	0.122	0.102	0.097

This table exhibits the annual return performance (in %) of selected climate portfolios against the MSCI World Benchmark Index over the 2015-2019 period. *This value represents the annualized total return for each portfolio for the 5 year sample period (2015-2019)

Similarity Results In Sustainable Equities Portfolios

Table 6 and 7 exhibit the cosine similarity and Pearson correlation results on the active weight for the six climate portfolios presented in this paper. A similarity of 100 represents perfect association of portfolios while a value of 0 represents no association. The highest degree of similarity is found between the policy CVAR and the climate intensity factor with a similarity score of 71. This result is as anticipated given that both metrics contain embedded information of carbon emissions (climate intensity) and emission reduction targets (policy CVAR) based on a 1.5% climate scenario. Conversely, the policy CVAR and the technology pillar exhibit a similarity score of -10. This fundamental difference is due to the fact that the policy CVAR portfolio optimized tilting towards the “winners” on climate change policies (in other words, it optimized based on industry sectors least exposed to climate change policies) and divesting away from “losers”, while the technology portfolio optimized on “winners” on green innovation, which in turn are the ”losers” of the policy CVAR portfolio. Close similarity scores are exhibited between the climate intensity portfolio and the technology CVAR portfolio.

The physical CVAR portfolio shows a moderate similarity to both the policy CVAR and the climate intensity CVAR with scores of 42 and 38 respectively. This gives the indication that information captured by the physical CVAR is indeed different than the latter two metrics.This moderate positive association may be due to some sectors having a greater score to physical and policy climate risks (such as Energy), while other sectors have overlap in exposures but to a lesser degree.

Naturally, divesting away from climate policies “losers” constituents (objective function of policy VAR portfolio) would yield comparable outcomes than divesting away from physical risks “losers” stocks (physical VAR portfolio) given that an aggressive action to limit climate change to 1.5 degrees Celsius is expected to contribute to the reduction of chronic and acute weather events. Conversely, divesting away from less physical risk resilient stocks, does not yield the same result as divesting away from less green innovative stocks (as reflected in similarity score of 6 between physical CVAR and technology portfolios).

Furthermore, the Greenness Score shows a moderate similarity score of 51 and 56 with respect to CVAR and climate intensity portfolios. This is as expected given MSCI scores also capture dynamics of carbon emissions and product carbon footprint. Contrarily, the similarity among the E-Score and the Technology CVAR is very low which gives an indication that the environmental opportunities do not represent a strong weight in the final greenness score.

Table 6: Cosine Similarity in active weights of Selected Climate Portfolios

Climate Portfolios	Overall CVAR	Policy CVAR	Technology CVAR	Physical CVAR	Carbon Intensity	Greenness Score
Overall CVAR	100					
Policy CVAR	49	100				
Technology CVAR	27	−10	100			
Physical CVAR	50	42	6	100		
Carbon Intensity	55	71	−20	38	100	
Greenness Score	51	52	4	42	56	100

This table shows the cosine similarity matrix of optimized active weights for the selected climate characteristics. A cosine similarity of 100 represents perfect similarity while a similarity of 0, no relationship.

Table 7: Pearson Correlation Coefficient (active weights) of Selected Climate Portfolios

Climate Portfolios	Overall CVAR	Policy CVAR	Technology CVAR	Physical CVAR	Carbon Intensity	Greenness Score
Overall CVAR	1					
Policy CVAR	0.46***	1				
Technology CVAR	0.28***	−0.10***	100			
Physical CVAR	0.48***	0.41***	0.06**	1		
Carbon Intensity	0.53***	0.69***	−0.2***	0.38***	1	
Greenness Score	0.51***	0.52***	0.04	0.42***	0.56***	1

This table shows the Pearson correlation coefficient of optimized active weights for the selected climate characteristics.*,** and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. A correlation coefficient of 1 represents perfect association while a coefficient of 0, no association.

Hedging Climate News Innovations

This section of the study focuses on constructing climate portfolios to test their ability of hedging climate change news indexes. The climate portfolios previously constructed where optimized to closely mimic the benchmark index while minimizing the exposure to key climate risks. Although these portfolios are less exposed to climate change risks, this does not necessarily imply they are fully derisked. This section focuses on constructing climate change portfolios following a similar mathematical construction as found in section 3, but allowing the optimizer to consider short selling, and further relaxing the constituent level weight constraint from 0.05% to 0.3%.

Climate change news series innovations were extracted from Engle et al. (2020) and Huij et al. (2021). Engle's climate change indexes where constructed via natural language processing algorithms to extract high-dimensional data from various climate change news sources. The first index is constructed using The Wall Street Journal (WSJ) as the main data source. This index mainly captures all type of news (positive and negative) related to climate risks. The second climate news index, namely "the Crimson Hexagon Negative Sentiment Climate Change News Index", was designed to solely capture innovations on negative climate change news. This index incorporates broader news coverage (not only coming from a single newspaper source) and it also applies sentiment analysis to climate related articles to measure the intensity of negative climate change news in the market (Engle et al. (2020)). Finally, the Climate Policy Uncertainty Index (CPU), constructed by Huij et al. (2021), was considered in this study given the previous two measures were only available up to 2018, while the CPU contained more recent data points. This index captures the textual similarity between daily collections of news articles in the Wall Street Journal and reports on climate change. If such news are similar, they reflect more frequent discussions around climate change.

In Engle's study , the authors construct characteristic weighted portfolios based on environmental scores from various sources (MSCI and Sustainalytics) as well as incorporating green energy ETF's to ultimately test the ability of such portfolios to neutralize or hedge climate change news innovations. This study adds to the literature by constructing optimized climate hedge portfolios of three climate characteristics, namely CVAR, Carbon Intensity, and the Greenness Score. In addition, the low minus high (LMH) mimicking portfolios are constructed for the same climate characteristics.

Table 9 shows the cross correlations of the selected optimized climate portfolios and mimicking portfolios against the three climate indexes for the 2012-2018 period. Figures 3 through 6 show the hedging performance of selected LMH climate factors with respect to the different climate index innovations. Hedging performance of these factors are (in most cases) greater than hedging ability of the optimized climate portfolios, as shown in Table 9. These results aligns with Engle's study where authors find that characteristic-weighted portfolios (such as the Fama French Factors and mimicking portfolios based on Sustainalytics E-scores) have a better hedging performance of climate related risks (cross-correlation of 15-18 % for Sustainalytics mimicking portfolio) compared to their ETF's counterparts.

Table 8: Cross Correlations of Climate Portfolios against Climate Change Innovations

	CCI^{WSJ}	CCI^{CPU}	CCI^{CHNEG}
$r_t^{MSCI\_World}$	-0.06	0.03	-0.05
$r_t^{CP\_CVAR}$	-0.02	0.03	-0.01
$r_t^{CP\_CI}$	-0.07	0.08	0.04
$r_t^{CP\_GS}$	0.009	0.09	0.06
$r_t^{LMH\_CVAR}$	0.06	-0.008	0.12
$r_t^{LMH\_CI}$	-0.02	0.09	-0.008
$r_t^{LMH\_GS}$	-0.02	0.10	0.01

This table shows the cross correlation for the returns of the MSCI World Index, Climate Portfolios (denoted as CP), and the LMH factors against the WSJ, CPU and the Crimson Hexagon climate change indexes (denoted as CCI) for the 2012 to 2018 period. *,** and *** denote statistical significance at the 10%, 5%, and 1% level, respectively

Results depicted in Table 9 show that the benchmark index has no clear ability to hedge climate change news. This aligns with expectations as there is no "free lunch" given climate change innovations cannot simply be hedged by investing in the market. In other words, an investor simply betting on the market is not clearly committed to neutralizing or reducing climate change risks. Furthermore, neither climate portfolios nor mimicking portfolios seem to hedge WSJ climate change news during the sample period. Instead, these portfolios perform better for CPU and the Crimson Negative indexes. In particular, climate intensity and greenness portfolios show a positive 8% and 9% hedging performance against the CPU.

Similarly, the LMH factors for the aforementioned climate characteristics show a slightly better performance with a 9% and 10% hedging performance respectively. The largest hedging performance is seen on the LMH CVAR portfolio with a 12% hedging ability against the Crimson Index. It is important to note that these results should be interpreted with caution given cross-correlation have no significance.

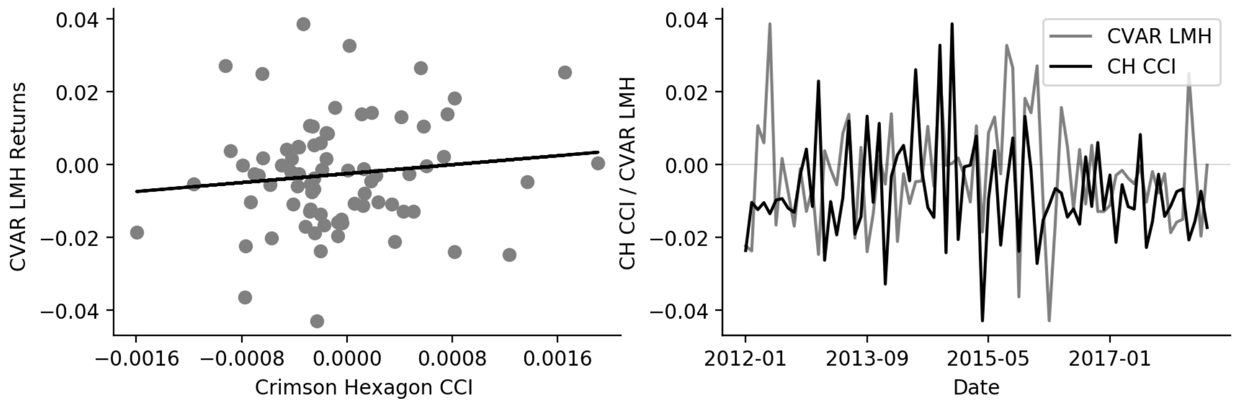

Figure 3: This figure shows the cross correlation performance of the LMH CVAR factor with respect to the CH Negative News Climate Index over the 2012-2018 period

Cross-Correlation: 0.12

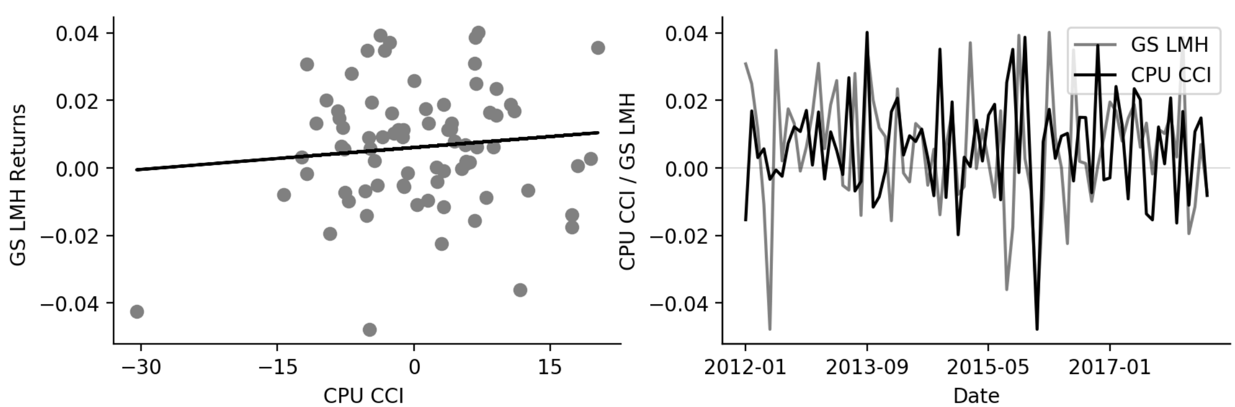

Figure 4: This figure shows the the cross correlation performance of the LMH Greenness factor with respect to the CPU index over the 2012-2018 period

Cross-Correlation: 0.10

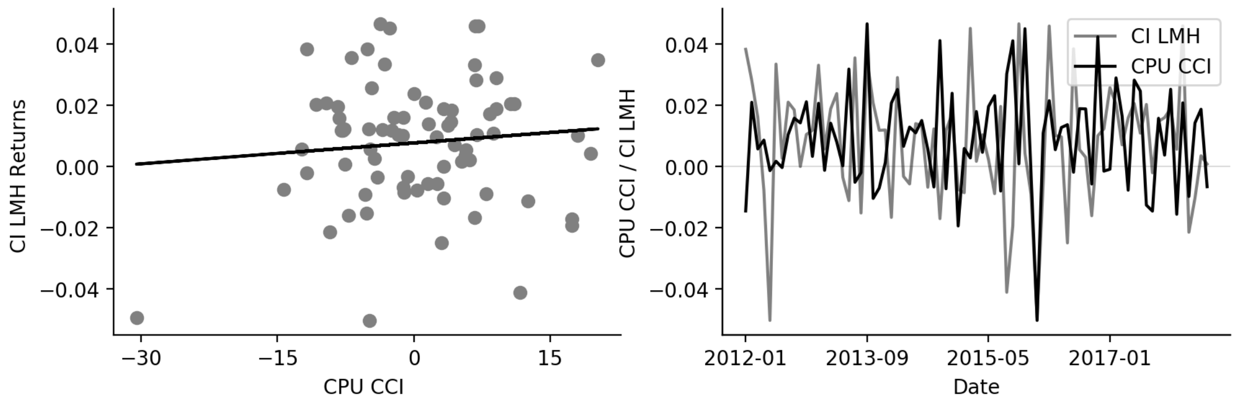

Figure 5: This figure shows the the cross correlation performance of the LMH Carbon Intensity factor with respect to the CPU index over the 2012-2018 period

Cross-Correlation:0.09

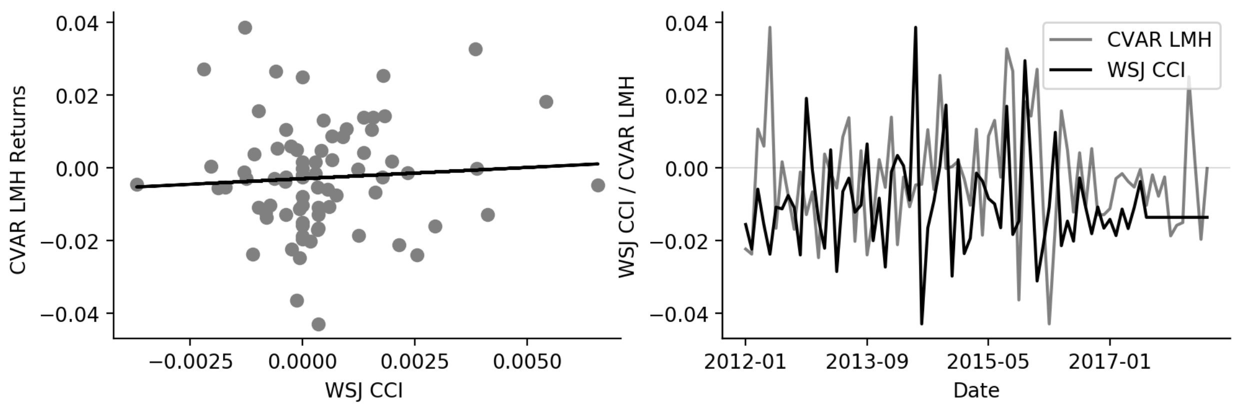

Figure 6: This figure shows the the cross correlation performance of the LMH CVAR factor with respect to the WSJ index over the 2012-2018 period

Cross-Correlation: 0.06

For the sake of completeness, this study has also followed Engle's regression approach, where hedge portfolios have been constructed considering climate portfolio returns along with the famous 5 Fama French factors for the developed market (namely, Small minus big, High minus Low, Conservative Minus Aggressive, Robust minus Weak and market returns). The dependant variable considered were the hedge targets (i.e climate change news indices) while the regressors where the fama french factors and the climate hedge portfolios lagged by one month. Regression results be found in the Appendix (Tables 10 and 12). In line with Engle's findings, the out of sample hedging ability of MSCI CVAR and the greenness score portfolios are substantially higher (and positive) for the Crimson Negative Climate Change News Index compared to hedging performance against the WSJ Index. Similar results are shown for the carbon intensity climate portfolio. Figures 9,10 and 11 show the out of sample hedging performance of key climate characteristics against the Crimson Hexagon Climate Index. The Greenness Score climate portfolio exhibits the greatest out of sample hedging performance against the crimson negative news index coefficient (cross-correlation of 0.31) followed by the CVAR hedge portfolio (cross-correlation of 0.29). These results suggest that long positions should be held in these climate portfolios to reduce climate risk exposures. Nevertheless, the results should be taken with a grain of salt given regression estimates are not statistically significantly different from 0.

Can climate portfolios outperform during periods of high climate change news volatility?

This section of the study focuses on the performance of climate portfolios in periods where climate change news indices increased the most (10% worst months). To avoid redundancy, only the CPU and the Crimson Negative indices are considered for this analysis. Figures 7 and 8 show the return performance of selected climate portfolios against the MSCI World Benchmark Index. A student t-test is conducted to test if there is a fundamental difference in the mean returns of climate portfolios against the benchmark index. Results are presented in Table 9.

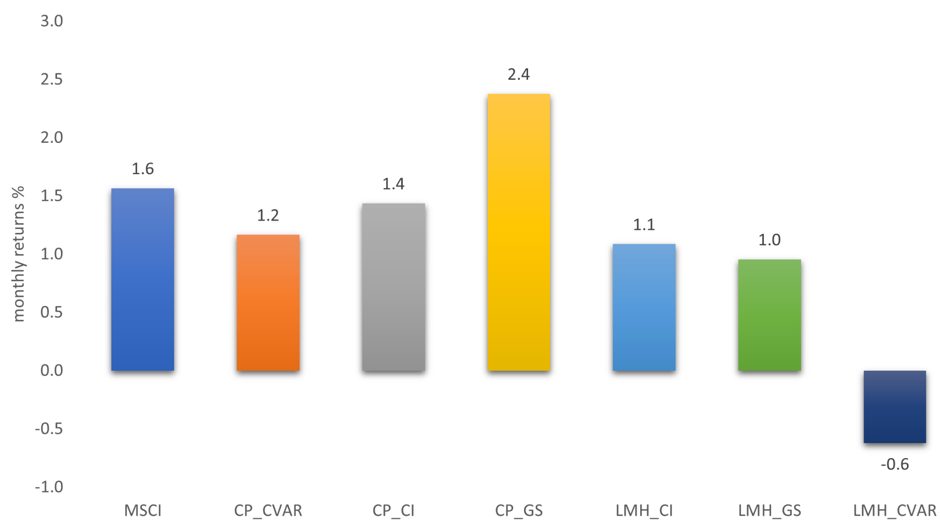

Figure 7: This figure shows the return performance of selected climate portfolios and the MSCI World Index for the 10% worst months, corresponding to the months where CPU index increased the most.

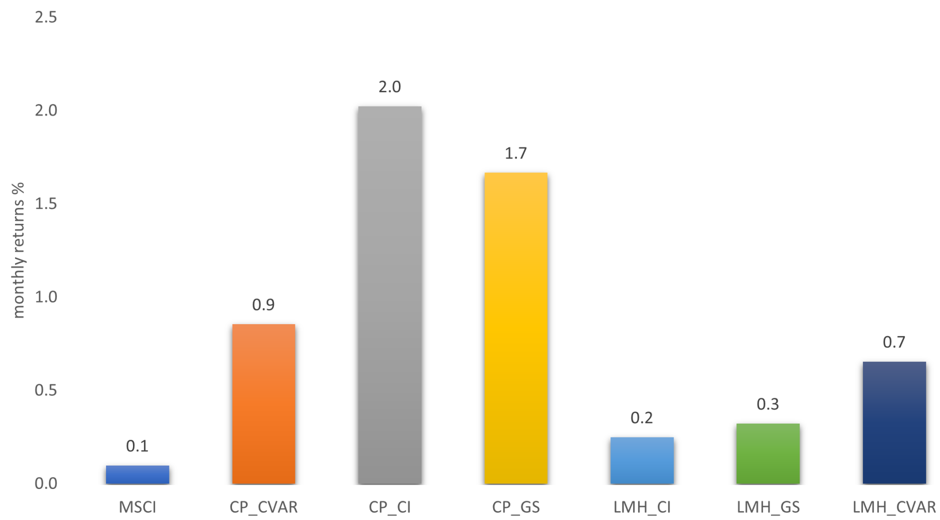

Figure 8: This figure shows the return performance of selected climate portfolios and the MSCI World Index for the 10% worst months, corresponding to the months where Crimson Hexagon index increased the most.

In theory, the climate portfolios should out-perform the MSCI benchmark index during the worst 10% months of climate change news, given that these portfolios are less exposed to great increases in climate change news.Nevertheless, results conducted on the CPU's worst months suggest that only the greenness score climate portfolio shows the an out-performance against other climate portfolios and the benchmark index. This result is in part a consequence of the broader CPU news coverage, which aligns with the greenness information content that covers both physical and transition risks, as well as green technology developments. In contrast, during the periods where the Crimson Hexagon index increased the most, the portfolio that showed the greatest return performance were the CVAR, carbon intensity and greenness score. This is reasonable, as the Crimson Index covers mostly negative climate change news, which can be better captured by carbon emissions dynamics. Nevertheless, according to the student-t test results, most of the difference in returns with the benchmark are non-significant.

Table 9: Independence T-Test of Selected Portfolios vs Benchmark

	CCI^{CPU}	CCI^{CHNEG}
$r_t^{CP\_CVAR}$	0.31	0.41
	(0.75)	(0.68)
$r_t^{CP\_CI}$	0.1	−0.69
	(0.091)	(0.49)
$r_t^{CP\_GS}$	0.66	−0.94
	(0.51)	(0.35)
$r_t^{LMH\_CVAR}$	2.05	0.89
	(0.059)*	(0.38)
$r_t^{LMH\_CI}$	0.45	0.16
	(0.65)	(0.86)
$r_t^{LMH\_GS}$	0.58	0.12
	(0.56)	(0.9)

This table shows the independence test of the mean returns of selected climate portfolios against the benchmark index. Rejecting the null hypothesis provides evidence for different returns. Sample sets cover the 10% worst months for the CPU and Crimson Hexagon Climate Index. T-values are presented and p-values are reported in parentheses. *,** and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

6 Conclusion

One of the main objectives of this study was to understand the fundamental differences of commercial climate risk metrics available at the disposal of institutional investors and if such metrics capture similar information or if they are fundamentally different. In addition, the study exhibits the cumulative return performance of such metrics over the last 5 years when holding the optimization constraints and objective function (minimizing climate related risks) constant. As such, this study presents a simple, yet robust methodology on mimicking a well-known stock index by minimizing its exposure to climate related risks, carbon intensity and environmentally harming stocks (Greenness Score) while maintaining its return characteristics as close as possible to the benchmark reference. The study found that there is a strong association between the carbon intensity portfolio and the policy (transition) CVAR portfolio given that both metrics have embedded similar information (carbon footprint and carbon reduction targets). Contrarily, the study finds negative association between the technology CVAR when compared to the policy and carbon intensity pillars given the “winners” of the former portfolio are the “losers” of the latter ones. Moreover, the E-Score shows a moderate association with the CVAR portfolio. This can be explained by the fact that the E-Score is constructed using 13 climate topics including carbon emissions, green opportunities and pollution control, while the CVAR is constructed using carbon reduction targets, exposure to chronic and acute events (physical risks) and technology opportunities. Although some themes overlap, the metrics do not show a strong association.

These climate risk proxies have their unique way of capturing climate characteristics and dynamics. Some of them capture similar trends while others have different objectives. It is ultimately up to the institutional investor to determine which climate investment strategy is best suited for his or her specific need. Would it be more appropriate to divest away from carbon polluters? Or is more effective to incentivize high emitting constituents by increasing the exposure to low carbon product offering? These are questions only institutional investors and asset managers can answer. The added value of this study lies in the enlightenment of key information gains when considering to adopt (or to abandon) alternative commercial proxies of climate risk.

Finally, this study has found that optimized climate portfolios have minimal ability to hedge climate change news. In addition, portfolios constructed following the mimicking approach show a better ability to hedge climate change news. Nevertheless, these results should be taken with a grain of salt, given that cross correlations estimates are insignificant. In summary, the study has found no clear evidence to assert that either climate portfolios optimized (CVAR, Grenness Score and Carbon Intensity) nor mimicking portfolios (LMH climate factors) have the ability to capture climate change innovations during the 2012-2018 period.

Limitations and Future Research

Historical availability of climate risk metrics from commercial sources is challenging to acquire. This was the case for the Climate Value at Risk (CVAR) and E-scores derived from MSCI which only had data availability for the 2021 period. In addition, carbon intensity data for MSCI world constituents were derived for the 2019 period, given this was the year with the most comprehensive carbon emissions data for MSCI world constituents. The underlying climate portfolios obtained from the optimization models was conducted for this time period, given the limiting historical data for the previously mentioned climate metrics. Subsequently, historical return performance of climate portfolios were back-tested based on optimal portfolio weights of 2019-2021 period. The lack of historical data is associated with potential selection bias, in which the sample period considered in this study was not randomly chosen. Instead, targeted years of study were selected due to previously mentioned data limitations. To partially offset this effect, the universe of constituents considered where approximately 1500, representing a broad-based stock index, namely, the MSCI World Index.

Climate change is a long-term risk and the effectiveness of hedging strategies may not be well known until the climate event materializes at some point in the future. In addition to this, establishing a hedging target is not as straightforward as one might think. There are various types of climate risks and the dynamics among them is complex. This study incorporated monthly climate hedge targets constructed by Engle et al. (2020) and Huij et al. (2021) but there are several other hedge targets with greater frequency (daily) and targeted towards specific climate risks. For instance, Faccini et al. (2021) constructed climate risk proxies for market wide physical and transition risks across four climate news topics: news about international climate summits, narrative indices, global warming, and natural disasters. The former two capture news about transition risks, while the latter two capture news about physical risks. An interesting test would be to construct long-short portfolios using CVAR's pillars on transition and physical risks and test their individual hedging performance against Faccini's transition and physical climate news indices.

Furthermore, this study has found that hedging performance is very sensitive to timing, as varying results were found when considering different time periods. Moreover, choosing the right climate characteristics for hedging innovations is tricky, as these characteristics have different information content. Enhanced approaches to constructing hedge portfolios should be considered as future research. For example, Alekseev et al. (2021) built hedge portfolios exploiting the availability of cross-sectional information instead of relying on historical data. Authors propose a quantity-based approach which focuses on predicting mutual funds' portfolio re-balancing as a response to climate change news.

7 Appendix

Table 10: CH Negative Climate Change News Index Time Series Regression

	(1)	(2)	(3)
r_{t-1}^{CI}	-0.0014		
	(0.021)		
r_{t-1}^{CVAR}		0.0059	
		(0.017)	
r_{t-1}^{GS}			0.0076
			(0.021)
SMB_{t-1}	-0.0082	-0.0069	-0.0066
	(0.009)	(0.008)	(0.008)
HML_{t-1}	0.0128	0.0141	0.0141
	(0.009)	(0.009)	(0.009)
EXr_{t-1}	0.0015	-0.0055	-0.0072
	(0.020)	(0.016)	(0.021)
RMW_{t-1}	0.0048	0.0050	0.0050
	(0.012)	(0.012)	(0.012)
CMA_{t-1}	-0.0196	-0.0195	-0.0201
	(0.012)	(0.012)	(0.013)
Constant	-2.075e-06	-2.379e-05	-2.078e-05
	(0.000)	(0.000)	(0.000)
R-Squared	0.087	0.089	0.089
N	60	60	60

Sample period is between June 2012 and June 2017.

Standard errors are reported in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

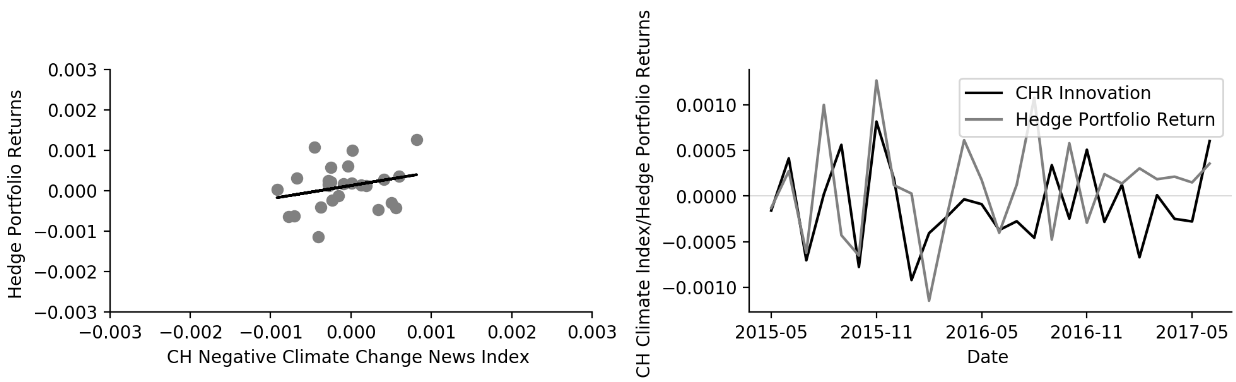

Figure 9: This figure shows the out of sample fit of the Carbon Intensity (CI) hedge portfolio with respect to the CH Negative News Climate Index over the June 2012-June 2017 period

Cross-Correlation: 0.26

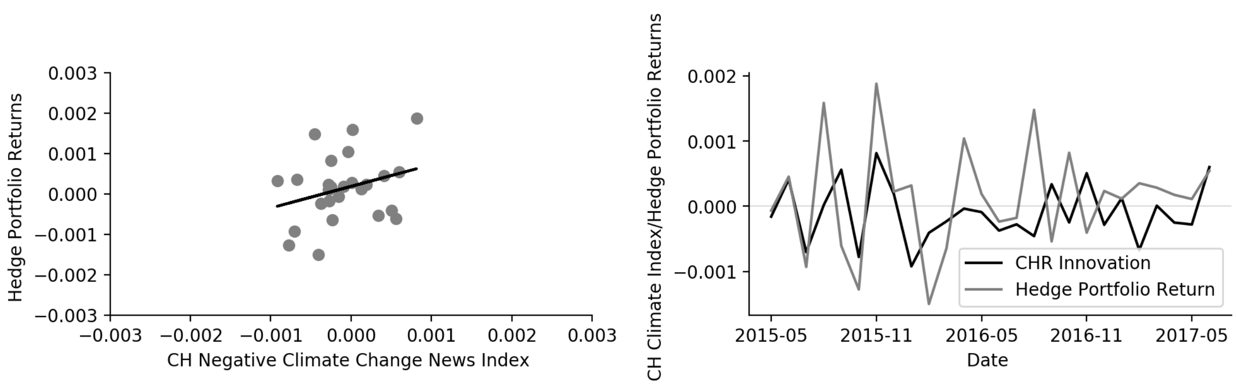

Figure 10: This figure shows the out of sample fit of the CVAR hedge portfolio with respect to the CH Negative News Climate Index over the June 2012-June 2017 period

Cross-Correlation: 0.29

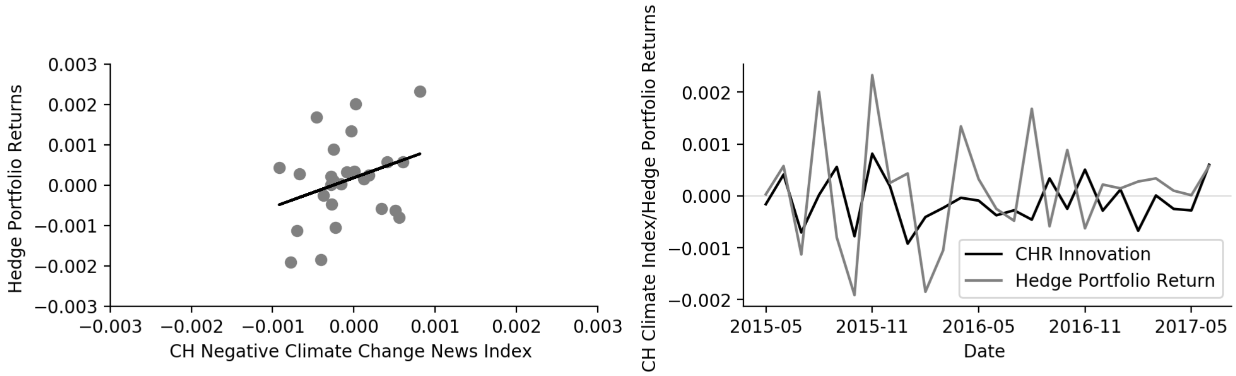

Figure 11: This figure shows the out of sample fit of the Greenness hedge portfolio with respect to the CH Negative News Climate Index over the June 2012-June 2017 period

Cross-Correlation: 0.31

Table 11: Cross Correlations of CH Negative Climate News Index

	CCI^{CHNEG}	H^{CI}	H^{CVAR}	H^{GS}
CCI^{CHNEG}	1			
H^{CI}	0.26	1		
H^{CVAR}	0.29	0.97	1	
H^{GS}	0.31	0.95	0.99	1

This table shows the out of sample cross correlation for selected climate portfolios and the CH Negative Climate News Index for the 2012-06 to 2017-06 period

Table 12: WSJ Climate Change News Index Time Series Regression

	(1)	(2)	(3)
r^{CI}_{t-1}	-0.0154		
	(0.051)		
r^{CVAR}_{t-1}		-0.0102	
		(0.041)	
r^{GS}_{t-1}			-0.0003
			(0.053)
SMB_{t-1}	-0.0586***	-0.0573***	-0.0556*
	(0.021)	(0.020)	(0.021)
HML_{t-1}	0.0416*	0.0426*	0.0444**
	(0.022)	(0.021)	(0.021)
EXr_{t-1}	0.0142	0.0090	-0.0004
	(0.040)	(0.016)	(0.052)
RMW_{t-1}	0.0287	0.0296	0.0297
	(0.030)	(0.029)	(0.029)
CMA_{t-1}	-0.0907***	-0.0917***	-0.0914***
	(0.031)	(0.031)	(0.031)
Constant	0.0006	0.0006**	0.0006**
	(0.000)	(0.000)	(0.000)
R-Squared	0.291	0.291	0.290
N	60	60	60

Sample period is between June 2012 and June 2017.

Standard errors are reported in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

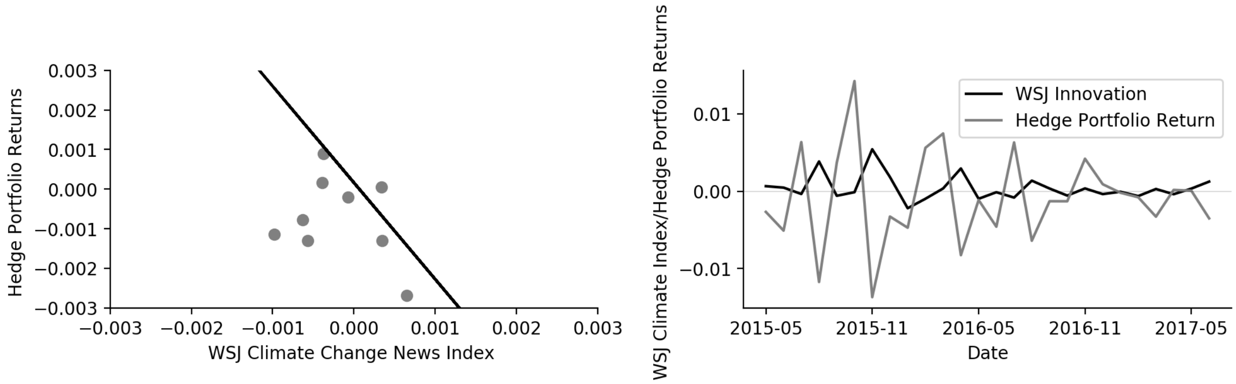

Figure 12: This figure shows the out of sample fit of the Carbon Intensity hedge portfolio with respect to the WSJ News Climate Index over the June 2012-June 2017 period

Cross-Correlation: -0.64

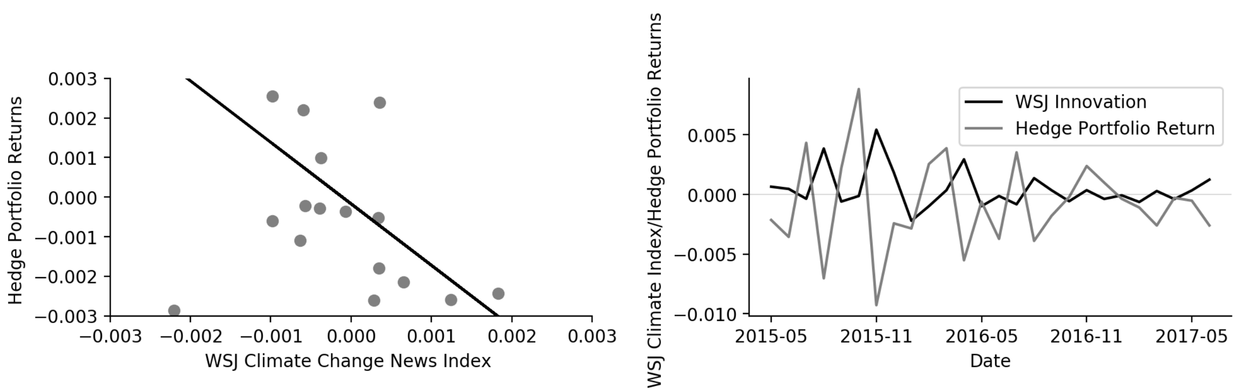

Figure 13: This figure shows the out of sample fit of the CVAR hedge portfolio with respect to the WSJ News Climate Index over the June 2012-June 2017 period

Cross-Correlation: -0.65

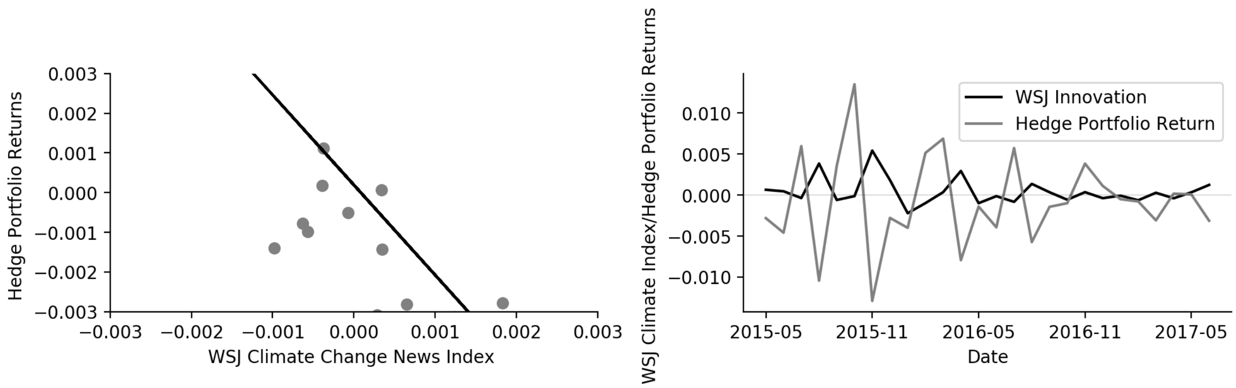

Figure 14: This figure shows the out of sample fit of the Greenness hedge portfolio with respect to the WSJ News Climate Index over the June 2012-June 2017 period

Cross-Correlation: -0.64

Table 13: Cross Correlations of WSJ Climate News Index

	CCI^{CHNEG}	H^{CI}	H^{CVAR}	H^{GS}
CCI^{CHNEG}	1			
H^{CI}	−0.64	1		
H^{CVAR}	−0.65	0.97	1	
H^{GS}	−0.64	0.95	0.99	1

This table shows the out of sample cross correlation for selected climate portfolios and the WSJ Climate News Index for the 2012-06 to 2017-06 period

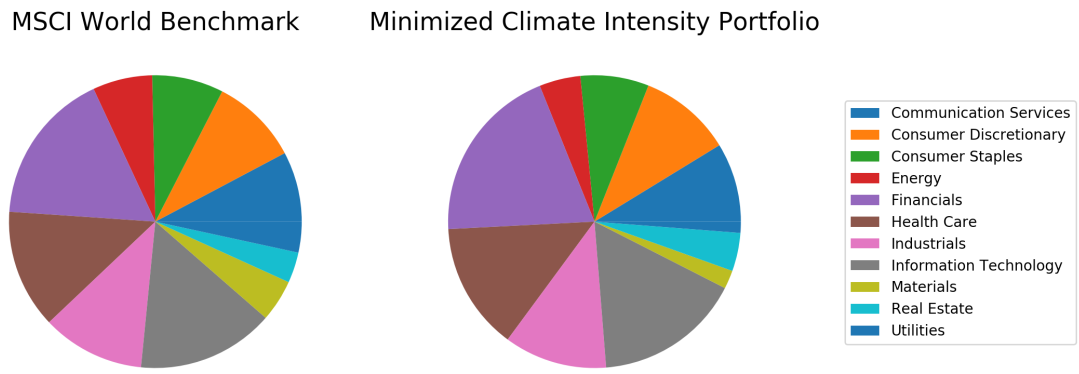

Figure 15: Figure shows the initial weight distribution of the MSCI World Index compared to the weights resulting from the Climate Intensity minimization problem. A 0.05 % restriction is imposed to the optimization at the individual constituent level to preserve sector level weights of benchmark index

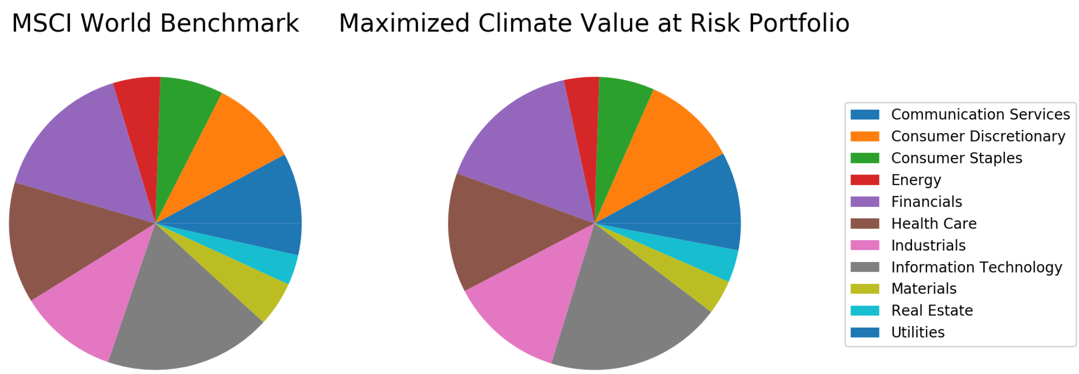

Figure 16: Figure shows the initial weight distribution of the MSCI World Index compared to the weights resulting from the CVAR maximization problem. A 0.05 % restriction is imposed to the optimization at the individual constituent level to preserve sector level weights of benchmark index

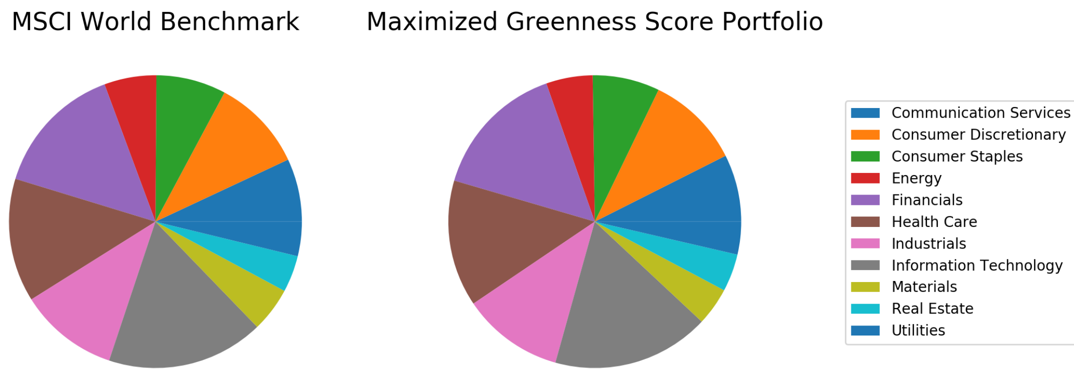

Figure 17: Figure shows the initial weight distribution of the MSCI World Index compared to the weights resulting from the greenness score maximization problem. A 0.05 % restriction is imposed to the optimization at the individual constituent level to preserve sector level weights of benchmark index

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