Carbon Beta: A Market-Based Measure of Climate Risk*

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Abstract

Climate change poses a major challenge to society and the economy. While many companies are expected to lose from climate change, others could gain. Despite sustainable investments standing at record highs, investors struggle to address climate risks. We construct a proxy for a climate risk factor, the pollutive-minus-clean (PMC) portfolio, which captures unexpected changes in consumers' and investors' concerns regarding the climate. By regressing stock returns on the PMC factor we obtain estimates of asset-level climate risk exposure: 'carbon beta'. Extensive validation of our estimates confirms that variation in climate risk exposures aligns with related studies and reasonable priors. Our measure has desirable properties regarding availability, coverage, and informativeness compared to alternative climate risk measures. We study the interaction of carbon beta with several proxies for realisations in climate risk. Returns on stocks with high carbon betas are low during months in which the press reports more on climate change, during months in which temperatures are abnormally hight, and during periods of drought.

Keywords: Climate change, carbon risk, climate finance, asset pricing.
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1 Introduction

In the 2015 Paris Agreement, 196 states commit to holding global average temperature increases to below 2°C above pre-industrial levels (United Nations, 2015). The agreement explicitly calls for the role of the financial industry in helping to accomplish this goal. Investors are increasingly becoming aware of their moral obligation and the potentially enormous societal and economic consequences of unabated climate change. At the beginning of 2021, asset owners and investors representing over $100 trillion have signed up to the UN Principles for Responsible Investment (UNPRI). Nonetheless, many institutional investors report challenges in addressing climate risks, citing a lack of best practices, problems around data availability, and inherent difficulties with assessing climate change (see Krueger et al. 2020 and Giglio et al. 2020).

To help deal with some of these difficulties, we propose a complementary measure of climate risk determined by the extent to which an asset's return correlates with a carbon risk factor. Following the asset-pricing literature, we refer to this measure as *carbon beta*. Our measure holds several advantages over conventional measures of climate risk, of which corporate greenhouse gas emissions and emission intensities are the most prominent examples[1]. First, the cross-sectional coverage of our approach far exceeds those of conventional measures. We can estimate sensitivities towards a carbon factor for any asset for which returns are observed. Thus, our procedure allows estimations of carbon betas for asset classes that have no conventional carbon-related measures available, for which it is inherently difficult to construct such measures (e.g. commodities), or which are by their nature opaque (e.g. mutual funds and hedge funds for which the holdings data are not publicly available). The estimation procedure is transparant and consistent across assets and asset classes, and we do not rely on the voluntary disclosure of emissions-related information. Second, due to the market-based nature of our measure, carbon betas can potentially reflect market participants' future expectations. Besides a company's greenhouse gas emissions, factors such as the availability of clean technologies, quality of management, innovation ability, competition, and financial health likely affect a company's climate risk. If market participants impound future expectations about such aspects in asset prices, then carbon beta likely captures these too. Third, carbon betas allow a clear distinction between those companies that are expected to benefit from a low-carbon transition and those companies that are expected to lose from such a shift. Corporate emissions, on the other hand, are good at identifying climate "losers", that is, firms that are currently among the heaviest emitters (Sautner et al., 2021). Disclosed emissions implicitly assume that all emissions are equally harmful. Yet investors may not treat all emissions similarly. For example, when emissions occur in the production of goods that reduce emissions elsewhere (e.g. solar panels), or in sectors for which abatement is expected to be easier, carbon betas are likely to differ. To illustrate this point, note that the average annual direct emissions of Tesla, Inc., a manufacturer of electric vehicles, First Solar, a producer of solar panels, and W&T Offshore Inc., an independent oil & gas producer, are similar in magnitude, ranking close to the 80^{th} percentile of our sample. However, the average carbon beta of Tesla and First Solar is among the bottom *5%* and *10%*, while that of W&T's is in the *top* 5%. Seemingly, investors can hold widely varying expectations of climate risk exposure even for firms with similar emissions output..

The economic mechanism behind our carbon risk factor follows that of Pástor et al. (2020)'s ESG factor. If concerns regarding the climate unexpectedly rise, consumer demand will shift from *brown* products and services to *green* ones.[2] Producers of these products and services will benefit accordingly, which pushes up the valuation of green firms. At the same time, investors who care about the climate will substitute their brown asset holdings for greener alternatives, either because they derive more utility from holding green assets, because they are publicly pressured to do so, or because they anticipate the introduction of stricter environmental policies. We seek to capture such unexpected

[1] Emission intensities are defined as corporate greenhouse gas emissions scaled by revenues.

[2] We use "brown", "pollutive", and "unsustainable" interchangeably to describe firms, products, and services that are contributing to climate change, while we use "green", "clean", and "sustainable" to describe firms, products, and services that contribute much less to, or even help in mitigating, climate change.

shifts in concerns regarding the climate by a carbon risk factor. To roughly classify companies into green or brown, we use companies' relative greenhouse gas emissions. The motivation behind this choice is not that emissions are a perfect indicator of a company's *greenness* or *brownness*, but rather that as a group, heavy emitters are likely to be more negatively affected by increasing climate concerns than light emitters are. Our proxy for carbon risk thus consists of a long position in the stocks of the heaviest-emitting 30% of firms offset by a short position in stocks of the least-emitting 30% of firms[3]. We refer to this portfolio as the pollutive-minus-clean, or *PMC* portfolio.

We then perform time-series regressions of equity returns on the carbon risk factor – while controlling for additional factors known to drive returns – to determine stock return sensitivities to carbon risk. We regard the loading on the carbon risk factor, *carbon beta*, as our firm-level indicator of climate risk exposure. Assets with negative carbon beta have a tendency to appreciate in times when investors are concerned about the climate, proxied for by a reduction in the PMC portfolio's value. Such assets can be regarded as 'climate hedge' assets, because they deliver high returns when climate change concerns increase. If investors dislike states of the world in which climate concerns increase, they should be willing to accept lower expected returns for climate hedge assets, in return for their ability to insure climate risk. To the contrary, in times of increasing concern about the environment, assets with high carbon betas have a tendency to depreciate in conjunction with the PMC portfolio, because these assets are expected to be negatively affected by a low-carbon transition. As such assets are riskier and shunned by investors, they should trade at discounts, and offer higher expected returns as a result.

To make sure that our estimates of climate risk are sensible, not overly governed by industry effects, or driven by spurious correlations, we subject firm-level estimates to a battery of validation tests. The goal of these tests is to confirm that variation in carbon betas aligns with expectations based on prior research and consensus views. We first compare the climate risk exposures of industries. In line with commonly held views, we find the highest carbon betas in the Energy, Materials, and Utilities sectors. These sectors are collectively responsible for over 70% of scope 1 & 2 emissions in our sample, so their high loadings on the carbon risk factor are expected. To the contrary, we observe that firms in the IT, Financial, and Health Care sectors tend to exhibit negative carbon betas. This suggests that in times of unexpected increases in climate concerns, as measured by an underperformance of the pollutive versus the clean portfolio, the stocks of firms active in these sectors tend to generate high returns. Since IT, financial, and health care firms are oftentimes regarded as green, it seems plausible to suggest that investors substitute brown assets for stocks in these sectors in times when climate change concerns are more prevalent. Besides, financial firms might be favourably exposed to a low-carbon transition as for such a shift to occur, enormous investments are required, which the financial industry will largely facilitate. Turning to the firm-level drivers of corporate carbon risk, we theorise that smaller, more capital intensive, lower-valued, and less innovative firms are more exposed to climate risk. These predictions largely turn out to be true. We establish that firms with high carbon betas have lower market capitalisations, hold higher property, plant & equipment and investments relative to their assets, invest less in research & development, and trade at lower book-to-market ratios. Comparisons of carbon betas with alternative measures of climate risk reveal robust associations between carbon betas and emissions, emission intensities, Sautner et al. (2021) Climate Change Exposures, MSCI Climate-Value-at-Risk scores, and MSCI environmental scores.

To shed more light on the temporal dynamics of climate risks, we follow the approach by Engle et al. (2020), who construct a climate news index defined by the textual similarity between daily news articles and reports about climate change. We hypothesise that periods in which climate change

[3]Because corporate emissions and firm size are highly correlated, and because we prefer our PMC factor to be size-neutral, we define two separate PMC portfolios. One for smaller firms that trade below the median NYSE's market capitalisation and one for larger firms that trade above the median NYSE firm market capitalisation. We then construct the PMC portfolio by taking the average of the "small" and the "large" portfolios. The construction process of the PMC portfolio resembles that of the Fama and French (1993) value factor. For more information, see Section 3.1.

is frequently reported in the news tend to coincide with episodes of heightened uncertainty around future climate policies. This approach is analogous to that used in the economic policy uncertainty literature (see, e.g. Baker et al. 2016), and hence we refer to our index as the Climate Policy Uncertainty (CPU) Index. We find that in months when climate policy uncertainty increases, firms exhibiting higher carbon beta have lower returns, and vice versa. This effect is statistically and economically highly significant. A one standard deviation increase in the CPU index is associated with a 2.5%-point reduction in return for every one standard deviation increase in carbon beta. Based on observations that extreme temperature shocks reduce corporate earnings (Addoum et al. 2018; Pankratz et al. 2019) and disproportionally diminish the market values of pollutive firms (Choi et al. 2020), we perform a related analysis using extreme weather events in the United States. We find that during months with abnormally high temperatures, firms with high carbon betas tend to generate significantly lesser returns[4]. Also in periods of drought, a similar pattern is observed. While the economic magnitude of this effects is less, it remains sizeable and statistically highly significant.

Görgen et al. (2020) were the first to consider the concept of a carbon risk factor. Their factor is constructed from several ESG variables provided by MSCI, Sustainalytics, the Carbon Disclosure Project (CDP), and Thomson Reuters. The authors find that Fama and French (1993) and Carhart (1997) asset-pricing models perform significantly better after the inclusion of the carbon risk factor. They find no evidence of a carbon risk premium in the cross-section of returns and blame the missing premium on carbon risk being associated more with unrewarded cash flow risk than with discount rate risk. Görgen et al. (2020)'s paper is different from ours in a number of ways. First, the analysis in Görgen et al. (2020) focuses primarily on the carbon risk factor as a driver of stock returns, rather than on firm-level sensitivities towards this factor as a measure of carbon risk. Second, the construction of Görgen et al. (2020)'s carbon factor relies on a number of ESG variables designed to capture differences in a firm's climate change adaptability, its value chain, and the public's perception. Given the many variables available to choose from and considering that ESG data are notoriously inaccurate (see, for example, Chatterji et al. (2016), Kotsantonis and Serafeim (2019), and Berg et al. (2019)), we refrain from making additional assumptions on how firms are exposed to climate risks, other than that such exposure is roughly proxied for by carbon emissions.

This paper fits into a relatively recent literature that examines forward-looking, firm-level measures of climate risk. Sautner et al. (2021) and Li et al. (2020) construct measures of corporate climate risk from textual analysis of earnings calls transcripts. Both studies utilise a similar methodology that quantifies climate risk via the share of the earnings call conversations devoted to climate-related topics. Sautner et al. (2021) go to great lengths validating their Climate Change Exposure. The measure indicates higher exposure for companies listed in countries with stronger climate regulation. Compared to more traditional measures of carbon risk, a greater fraction of the variation in Climate Change Exposures occurs at the firm level rather than at the sector, year, or country level. Based on climate risk disclosures in annual reports, Kölbel et al. (2020) conclude that transition risks have statistically and economically significant effects on the spreads in CDS markets, while physical climate risks do not. Huynh and Xia (2020) consider the covariance between corporate bond returns and the Engle et al. (2020) climate change news index. Bonds with high climate news betas are more expensive, consistent with their potential to hedge against climate risks.

Our work adds to recent findings on the stock return implications of corporate carbon emissions. Two of the most comprehensive works on this topic are Bolton and Kacperczyk (2020) and Bolton and Kacperczyk (2021) who focus on the pricing of corporate carbon emissions in respectively U.S. and global equity markets. In the former study, the authors conclude that both direct (scope 1 & 2) and indirect (scope 3) emissions are associated with higher returns, yet only the indirect carbon emissions display explanatory power beyond the industry effect. The latter research utilises levels and percentage changes in firms' emissions as a proxy for long-term and short-term transition risks. A transition

[4]We define abnormally high temperates as average monthly temperatures that are above the 90^{th} percentile of past 30-year average temperatures for that respective month

risk premium is mostly present in the cross-section of North-American, European, and Asian stocks. In Australian, African, and South American stock markets transition risk does not seem to be priced. Additionally, the global carbon premium increased markedly following the 2015 Paris Agreement. A related study is by Monasterolo and De Angelis (2020), who investigate asset pricing effects of the 2015 Paris Agreement. They find that the systematic risk of low-carbon assets has decreased after the Paris Agreement, while carbon intense assets have become riskier. Using information from option prices, Ilhan et al. (2021) report larger downside tail risks for stocks with higher carbon intensities. Moreover, the costs of protection against these tail risks are higher at times of heightened attention to climate change. Li et al. (2019) examine the existence of a pollution premium in the cross-section of U.S. stock returns. Their focus lies on mandatory toxic emissions disclosures, rather than only on CO_2 emissions. A long-short portfolio sorted on toxic emissions generates a sizeable return spread of 5.52% per year. The authors explain this *'pollution premium'* through higher regulatory risks faced by pollutive firms and provide empirical support for this hypothesis.

Finally, our study relates to the growing field of *climate finance* which studies the interactions between climate change and financial markets. Addoum et al. (2018) examine the effects of extreme temperature shocks on corporate earnings and find that such shocks significantly impact earnings in over 40% of industries. Bansal et al. (2019) estimate stock return sensitivities to long-run temperature shocks and find that temperature-exposed stocks carry a risk premium. Hong et al. (2019) explore the prices of US food producing firms and conclude that they do not efficiently reflect long-run drought risks. Choi et al. (2020) study how people update their beliefs about climate change during period of high temperatures. The authors confirm that attention to climate change spikes during such periods, and that stocks of firms with low carbon emissions outperform their carbon-intensive peers. The effects coincide with selling from retail investors, yet better-informed institutional traders do not exhibit similar behaviour. For an excellent review of the literature in this field, see Giglio et al. (2020).

The remainder of this paper is organised as follows. Section 2 introduces our main sources of data and our dataset construction procedure. In Section 3, we describe the construction of the pollutive-minus-clean portfolio and the estimation of carbon betas. Results follow in Section 4, including the validation of our estimates and main analyses. Section 5 concludes.

2 Data

2.1 Stock market and corporate data

For the main analysis of this paper, we combine U.S. stock market data from the Center for Research in Security Prices (CRSP) with financial statements data from S&P Capital IQ Compustat. Our sample construction procedure largely follows Fama and French (1993). We utilise the WRDS Linking Table to match observations from CRSP's Monthly Stock File with Compustat's Fundamentals Annual database.[5] To mitigate survivorship bias resulting from Compustat's data collection procedure (Banz and Breen, 1986; Fama and French, 1993), we only include firms after they have appeared in Compustat for two consecutive years. We apply the Shumway (1997) adjustment to correct for the delisting bias in CRSP returns. Following Fama and French (1993), we delete observations with negative market capitalisation and negative book value. We only consider common equities traded on the NYSE, AMEX, or Nasdaq.[6]

We proceed by calculating several variables. Similar to Fama and French (1993), we calculate book value of equity in June of each year by summing the book value of stockholders' equity with deferred taxes and investment tax credits and subtracting the book value of preferred stock.[7] In case of missing deferred taxes and/or preferred stocks, we assume values equal to zero. If the book value of stockholders' equity is unknown, we use the difference between total assets and total liabilities as an approximation. At the end of each January, we compute the market value of each security by multiplying the absolute value of the share price with the total number of shares outstanding. We calculate market capitalisation by summing the market values of all securities belonging to the same company.[8] If several securities are linked to the same company, we delete all but the largest security measured in terms of market value. To compute book-to-market ratios, we divide book value of equity with the market capitalisation at the end of January of the associated year. We calculate 12-month-minus-1-month (12M-1M) momentum by summing a stock's return over the past 12 months, but excluding the most recent month. We download the daily returns of the stocks in our sample to estimate CAPM-implied market betas and idiosyncratic return volatilities. We base these estimations on rolling window regressions containing a year of daily returns. We obtain data on U.S. factor returns from Kenneth French's data library.[9]

Panel A of Table 1 reports descriptive statistics for our stock market data set. After merging CRSP with Compustat and applying our filters, the sample contains little over 570,000 monthly return observations for 11,752 unique firms. The average excess return (including dividends) equals 0.8% per month. Moreover, the average (median) firm in our sample has a market capitalisation of about \$7 billion (\$914 million). Average book-to-market, return on equity, leverage, and investment-to-assets equals 0.64, 0.24, 0.21, 0.03, respectively. The average firm has a market beta of 0.98 and idiosyncratic volatility of 32%. The sector composition of our sample is as follows. Roughly 20% of observations are linked to stocks in the Financial sector, 16% to IT, 12% to all of Health Care, Consumer Staples, and Industry, 6% to both Energy and Materials, and 4% to all of Real Estate, Utilities, Consumer Discretionary, and Communication Services.

2.2 Emissions data

We collect information on greenhouse gas emissions from S&P Trucost, a leading provider of corporate emissions data. Trucost data are either reported or estimated by Trucost's proprietary models.

[5] We only make use of the linking information if the link type is any of *LU*, *LC*, *LS*, *LX*, *LD*, *LN*, or *LO* and if the link primary is *P* or *C*. At the time of matching, the link must be valid according to the link date and link end-date.

[6] Share Codes 10 and 11 and Exchange Codes 1, 2, and 3.

[7] Variables are indicated by SEQ, TXDITC, and PSTK in Compustat.

[8] i.e. multiple PERMNOs falling under the same PERMCO.

[9] `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

Table 1: Descriptive Statistics CRSP - Compustat Merged The table reports descriptive statistics on the variables used in our analyses. *Panel A* reports company and market variables. *Panel B* reports Trucost emissions variables.

				Percentiles						
	N	Mean	SD	1%	5%	25%	Median	75%	95%	99%
Panel A: Firm-level and market variables										
Excess Return (%)	571,782	0.826	17.542	-39.755	-21.987	-6.371	0.290	6.784	23.752	52.410
Market Cap. (millions)	571,805	5,578	27,916	6	17	112	525	2,404	21,481	97,886
Book/Market*	551,781	0.748	0.723	0.048	0.088	0.288	0.543	0.916	2.315	3.581
Return on Equity*	571,667	-0.077	0.492	-2.347	-1.083	-0.062	0.066	0.130	0.324	0.536
Debt/Assets*	457,799	0.246	0.163	0.040	0.061	0.128	0.205	0.316	0.596	0.775
Investments/Assets*	565,301	0.085	0.117	0.000	0.000	0.000	0.024	0.132	0.353	0.475
Property, Plant, & Equipment/Assets*	461,023	0.447	0.391	0.002	0.020	0.131	0.319	0.691	0.934	1.226
Research & Development/Assets	231,576	0.108	0.124	0.001	0.004	0.019	0.062	0.146	0.391	0.545
Carbon Beta	479,306	0.014	1.264	-3.219	-1.810	-0.615	-0.032	0.591	1.978	3.621
CAPM Beta	532,792	1.019	0.362	0.246	0.417	0.794	1.021	1.241	1.613	1.937
Idiosyncratic Volatility (%)	532,792	45.427	28.682	13.017	15.443	24.850	37.198	56.920	107.717	143.300
Panel B: Emission variables										
Scope 1 Emissions (millions tons CO_2)	199,713	0.875	3.062	0.000	0.000	0.003	0.024	0.148	4.979	17.600
Scope 2 Emissions (millions tons CO_2)	199,713	0.212	0.512	0.000	0.000	0.006	0.030	0.130	1.183	2.805
Scope 3 Emissions (millions tons CO_2)	199,713	1.055	2.268	0.001	0.002	0.036	0.203	0.848	5.869	11.903
Scope 1 Emission Intensity (tons CO_2/\$ mln.)	199,713	153.634	519.304	0.430	0.557	3.591	14.144	32.940	734.434	3055.050
Scope 2 Emission Intensity (tons CO_2/\$ mln.)	199,713	28.303	35.763	1.029	1.127	7.547	16.160	35.954	105.956	182.756
Scope 3 Emission Intensity (tons CO_2/\$ mln.)	199,713	149.343	145.128	23.579	23.871	41.014	93.946	208.672	459.411	639.384

* Winsorized at the 1% level

Reported emissions originate from various sources, including the Carbon Disclosure Project (CDP), MSCI, Sustainalytics, Bloomberg, ISS, and corporate sustainability reports. The extent to which non-reported emissions are estimated varies. Some values are partial estimates, for example derived from a company's usage of fossil fuel. Other estimates might be derived from partial disclosure in corporate sustainability reports or from private conversations with company representatives. A majority of estimations result from Trucost's proprietary model, which utilises an extensive input-output model that associates business activities with environmental impacts. Trucost reports emissions according to the standards set forth by the Greenhouse Gas Protocol.[10] The Greenhouse Gas Protocol decomposes emissions into three "scopes". Scope 1 emissions include the direct emissions occurring in a company's production process. Scope 2 emissions are the indirect emissions associated with the purchase of electricity, heat or steam. All other emissions taking place in a company's value chain are accounted for as Scope 3. As our database only contains complete data for Scope 1 and Scope 2 emissions, we do not include any Scope 3 emissions into our analyses.[11] We sum the first and second scope to a combined Scope 1 & 2 measure, and calculate emission intensities for the combined and separate Scope 1 and 2 emissions by dividing each of the total emissions with the firm's revenues as reported by Trucost. In this paper, we refer to the combined Scope 1 & 2 emissions when using the terms *emissions* or *total emissions*, and we refer to the combined Scope 1 & 2 emissions scaled by revenues when we use the terms *emission intensity* or *intensity*.

After merging the Trucost data with our CRSP-Compustat, our sample contains roughly 27,000 firm-year observations, for around 3,500 unique firms. About 17,000 observations are estimated by Trucost's model, 4,000 are exact values reported by the company, and the remainder are based on varying levels of estimation. Panel B of Table 1 reports summary statistics on the Trucost emissions variables. The average firm in the Trucost sample differs from that in CRSP-Compustat (not reported in Table 1). Firms in Trucost tend to be larger than those in CRSP-Compustat, with mean (median) market capitalisations of \$11.6 billion (\$3.2 billion). Firms are generally more profitable (ROE of around 10%), lower-valued (Book-to-Market of 0.41), similarly leveraged (Debt-to-Assets of 0.21), and similarly capital intensive (Investments-to-Assets of 0.03). In terms of sector representation, the samples are relatively similar. Financials, IT, and Industrials all represent about 15% of the sample. Health Care and Consumer Staples both account for 12%. Both Energy and Materials have 7% of observations. Real Estate, Consumer Staples, Utilities, and Communication Services, represent between 5% and 3% of the sample.

2.3 Climate Policy Uncertainty Index

Engle et al. (2020) create an index for climate news risk from daily texts of newspaper articles published by the Wall Street Journal. We adjust their procedure to construct a similar metric. First, we collect a corpus of climate change texts. Our corpus includes the five Assessment Reports written by the UN Intergovernmental Panel on Climate Change (IPCC). Because these reports are technical (see Sautner et al. 2021; Li et al. 2020), we additionally download articles in the 'climate change' category on Wikipedia.[12] Our assumption is that the Wikipedia texts are more representative of the writing used in newspapers. We refer to the collection of texts from the IPCC reports and the Wikipedia articles as the *climate change corpus*, denoted by $\mathbb{C}_{CC}$. Additionally, we collect texts of daily articles published in the Wall Street Journal starting from 1997. The collection of each daily archive's texts is referred to as $\mathbb{C}_{WSJ,t}$. We determine the Climate Policy Uncertainty (CPU) Index as follows. We start by applying several text preprocessing steps commonly used in Natural Language Processing.[13] We then perform a Term Frequency - Inverse Document Frequency (TF-

[10] `https://ghgprotocol.org`.

[11] Our Trucost data only includes the downstream Scope 3 emissions, i.e. the indirect emissions that occur further down a company's value chain. These are emissions by a firm's customers, but not by its suppliers.

[12] `https://en.wikipedia.org/wiki/Category:Climate_change`

[13] These involve, in the following order: removing punctuation, tokenizing (splitting sentences into words), removing

IDF) transformation to convert our collections of text articles in numerical vector form.[14] We apply the same TF-IDF transformation to the climate change corpus $\mathbb{C}_{CC}$ and each day's collection of news article texts $\mathbb{C}_{WSJ,t}$, yielding TF-IDF denoted by $\boldsymbol{v}_{CC}$ and $\boldsymbol{v}_{WSJ,t}$. Finally, for each day we compare $\boldsymbol{v}_{WSJ,t}$ with $\boldsymbol{v}_{CC}$ by cosine similarity.[15] The intuition behind this approach is that when news articles use climate change terms in similar proportions as the texts related to climate change, the index indicates a high level of climate change news risk (Engle et al., 2020). We lower the frequency of our measure from daily to monthly by taking monthly averages of daily index levels. For ease of interpretability, we set the mean of our index equal to 100. In our analyses, we use innovations in climate change news risk determined by the residuals obtained from modelling the monthly index levels as an AR(1)-process.

Figure 1 plots the Climate Policy Uncertainty index through time. Along the horizontal axis, various events related to climate change are reported. As can be seen, the CPU index generally rises when such events occur. The index peaks in December 2009, when the 15$^{\text{th}}$ Conference of the Parties (COP15) was held in Copenhagen. COP15 was one of the earliest international conferences to bring climate change to the highest political level. As a result of the conference, the Copenhagen Accord was signed. The Accord expressed clear political intent to limit carbon emissions and respond to climate change. The CPU index reached its second-highest level in November and December 2015, during COP21 in Paris. At this conference, the Paris Agreement was negotiated – a legally binding, international treaty with the goal of limiting global warming to 2°C. Around the end of 2019, the index remained at elevated levels. This period marked a series of mass protests to demand action on climate change. These strikes coincided with the Climate Action Summit in New York.

2.4 Other data

We collect data from a variety of additional sources. In this section we briefly describe the various datasets used, the data collection procedure, and the purpose of collecting the data.

1. Sautner et al. (2021) Firm-Level Climate Change Exposure. We also compare our estimates of carbon beta with the Sautner et al. (2021) Climate Change Exposure. Sautner et al. (2021)'s measure is an indicator of climate change exposure constructed from corporate earnings calls. The measure indicates the extent to which climate change related words are used by the company's management and the analyst following the company during the earnings call. Besides general Climate Change Exposure, Sautner et al. (2021) determine separate vocabularies for risks, opportunities, and regulation related to climate change. We use the three components, as well as general climate change exposure in our analysis. The data are publicly available.[16] We rescale all Sautner et al. (2021) scores to take values between 0 and 100.

2. Temperature and drought statistics. We collect monthly temperature anomalies for the United States from the U.S. Climate Reference Network. A certain month's temperature anomaly is defined as the temperature deviation from that month's 30-year-average reference temperature. We download the Palmer Z-Index, a byproduct of the Palmer Drought Severity Index (PDSI; Palmer 1965) as a measure of drought severity. The PDSI uses precipitation, temperature, and geographic data to model the available quantities of water in the location of interest. As the PDSI is known to be inaccurate over short frequencies, we use the Palmer Z-Index which is specifically designed to be

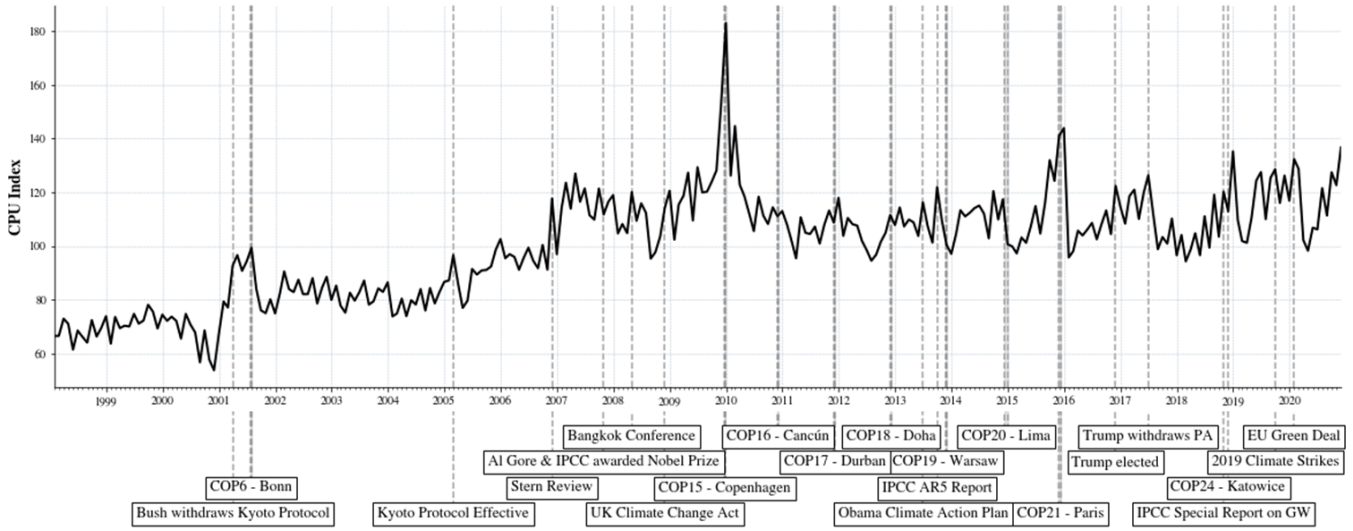
stop words, lemmatizing (reducing words to their word roots, e.g. the words 'climate' and 'climatology' both become 'climat'), and converting terms into bigrams (two-word collections of consecutive words).

[14] The TF-IDF algorithm converts words, in our case bigrams, into scores determined by the word's frequency within a document, penalised by its frequency across documents. Hence, a word occurring often in one document but not frequently in other documents receives a high score, as it is regarded as being informative for that certain document.

[15] Formally, the cosine similarity between two vectors is defined as the cosine of the angle between them, or equivalently by the inner product of the vectors normalised to have unitary length. The cosine similarity reaches its maximum of 1 when the angle between $\boldsymbol{v}_{CC}$ and $\boldsymbol{v}_{WSJ,t}$ equals 0°.

[16] Available at: `https://osf.io/fd6jq/`

Figure 1: Wall Street Journal Climate Policy Uncertainty Index
The figure plots the Wall Street Journal based Climate Policy Uncertainty Index over time alongside various events related to climate policy. The Climate Policy Uncertainty Index is defined as the cosine similarity between daily articles published in the Wall Street Journal and a corpus of documents on climate change. We follow the procedure set forth by Engle et al. (2020) to construct the Climate Policy Uncertainty index.



more responsive over short-term periods. Negative values of -4 indicate severe drought, 0 indicates regular conditions, and values of +4 indicate unusually wet spells.

3. MSCI Climate-Value-at-Risk. We obtain Climate-Value-at-Risk (CVaR) data from MSCI for about 2,200 firms in our sample. CVaR is specifically designed to capture forward-looking valuation assessments regarding climate risk and opportunities.[17] The measure includes a wide array of firm-specific information, including - but not limited to - corporate emissions data, green patent issuance, exposure to extreme weather, coastal flooding, and wildfire risks, green revenues, and policy and technology scenarios. Values for CVaR are bounded by -100 and 100, where -100 (100) indicates a company expected to majorly suffer (benefit) from climate change. We reverse the sign of CVaR to align with traditional Value-at-Risk, and divide the measure by 100 to make its scale comparable to other variables used.

4. MSCI Country Indices. For tests on international carbon betas, we download information on the returns of 48 national equity indices from Refinitiv (formerly Thomson Reuters) Eikon. All index prices are denominated in U.S. dollars. We collect data from January 2011 to December 2020.

5. Green Patents. We follow Cohen et al. (2020) in downloading patents issued in the United States from 2010 to 2019 through the USPTO's Bulk Data Storage System.[18] The USPTO provides the text files for all patents issued in the United States from 1976 onwards. To link our dataset to green patent issuance, we map assignee names of patent grants to company names in Compustat by applying a similar TF-IDF transformation as in section 2.3. This NLP technique allows us to implement approximate-string matching and at the same time provides a confidence level for the matching outcome. We only match records if the confidence is above 80%. At this confidence level, a manual inspection of matching outcomes yields very little incorrect matches, albeit at the risk of overlooking some valid links. We mitigate this issue by additionally downloading patent to company mapping from the Compustat Link table of WRDS' newly released US Patents (Beta) product.[19] As of writing, the patent and patent-company linkage data are only available for the 2011 - 2019 period. For this period, our patent database and that of WRDS cover almost the same patents.[20] A slight difference in coverage is likely the result of retrospective changes in USPTO's data, or of errors in our automated retrieval of several patent's text files. When our own matching algorithm disagrees with that of WRDS, we follow the link proposed by WRDS. For patents outside the 2011 - 2019 window, we entirely rely on our own linking table. As the WRDS patent database does not include any patent classification fields, we have to use our own patent data to classify green patents. We do so following the guidelines of the OECD as described in Haščič and Migotto (2015). The guidelines describe search strategies for the identification of patent classes related to a wide variety of green technologies, for example environmental management, water pollution abatement, waste management, adaptation, biodiversity protection, renewable energy, greenhouse gas capture and storage, and fuel efficiency. We supplement the guidelines of the OECD with the International Patent Classification (IPC) Green Inventory.[21] In our analyses, we mainly proxy for green innovation by *Green Share*; the number of green patents as a percentage of the total number of patents issued to a company (Cohen et al., 2020). We are able to download over 750,000 unique patents, matched to over 5,000 firms. A little under 10% of total patent issues are classified as green. The top green patent issuers are IBM, Sony, Qualcomm, Intel, Apple, and General Electric.

[17] `https://www.msci.com/documents/1296102/16985724/MSCI-ClimateVaR-Introduction-Feb2020.pdf/f0ff1d77-3278-e409-7a2a-bf1da9d53f30`

[18] `https://bulkdata.uspto.gov`

[19] Available at: `https://wrds-www.wharton.upenn.edu/pages/analytics/wrds-us-patents/`.

[20] We obtain over 99% of the patents in the WRDS database for the 2011 - 2019 period for which WRDS had patent data available.

[21] See `https://www.wipo.int/classifications/ipc/green-inventory/home`

3 Methodology

3.1 The Pollutive-Minus-Clean portfolio

We regard the Pollutive-Minus-Clean (PMC) portfolio as an observable proxy for a carbon risk factor partly responsible for driving stock returns. The PMC portfolio captures unexpected changes in concerns that investors and customers have regarding the climate. The intuition behind the carbon risk factor is close to that of Pástor et al. (2020)'s ESG factor. In the model of Pástor et al. (2020), ESG risks materialise via two channels, the *customer* and the *investor* channel. A similar mechanism applies to carbon risk. When climate concerns unexpectedly rise, for example because the predicted path of temperature warming worsens, *customer* demand shifts from "brown" to "green" products and services. Lower demand negatively shocks the profitability of pollutive companies, and hence reduces these companies' market values, while the opposite holds true for clean companies. The second channel involves investor's preferences. Investors likely derive more utility from sustainable investments in times of climate stress, either because they intrinsically care about the climate or because they face public pressure to divest from brown assets. Indeed, Choi et al. (2020) report that stocks with high carbon intensity underperform stocks with lower carbon intensities during abnormally warm months, and that this finding is mainly driven by retail investors selling carbon-intensive stocks. Furthermore, investors may anticipate governments imposing stringent climate change policies, as the likelihood of policy interventions increases in times of heightened environmental concerns (see e.g. Pástor and Veronesi (2013) for political risk in general).[22] Selling pressure and higher discount rates induced by heightened climate concerns cause pollutive firms to depreciate, and clean firms to appreciate, in value. As the PMC portfolio holds a net long (short) position in brown (green) stocks, both channels lead to a reduction in the PMC portfolio's value. The opposite occurs when concerns regarding climate change unexpectedly lessen, and the return on the PMC portfolio thus improves.

We construct the PMC portfolio in similar fashion as the Fama and French (1993) SMB and HML portfolios. PMC is a self-financing portfolio which takes a long position in the most polluting 30% of firms and a short position in the least polluting 30% of firms. We perform this sorting on scope 1 and 2 emissions, as reported or estimated by Trucost. We do not consider scope three emissions for several reasons. First, our data does not include the complete scope 3 emissions, but only the downstream component which measures emissions further "down" a company's value chain[23]. As different firms operate at different levels in the value chain, downstream emissions are less comparable between companies. Second, scope 3 emissions data are by definition estimated rather than not reported. There are considerable complexities in accurately modelling emissions associated with all activities in a company's value chain. As a result, Busch et al. (2018), Berg et al. (2019), and Kalesnik et al. (2020) report much lower correlations for scope 3 emissions than for scope 1 and 2 emissions. Third, because scope 3 emissions are double-counted for firms active in the same value chains (see Kalesnik et al. 2020), they are much larger in magnitude than scope 1 and 2 emissions. Hence, combined scope 1, 2 & 3 emissions tend to be dominated by their scope 3 components and are relatively similar to scope 3 emissions in isolation. While constructing the PMC portfolio, we adjust for the size bias that results from sorting on corporate emissions. We do so by explicitly forming separate portfolios for firms valued below and above the median NYSE firm, following Fama and French (1993). For each year we form four portfolios; Small / Polluting (SP), Big / Polluting (BP), Small / Clean (SC), and Big / Clean (BC). The return on the PMC portfolio is then given by

$$r_{PMC,t} = \frac{r_{SP,t} + r_{BP,t}}{2} - \frac{r_{SC,t} + r_{BC,t}}{2}, \tag{1}$$

[22] Governments may, for example, price or limit emissions, or subsidise or mandate cleaner products or services.

[23] E.g. for a gas station, downstream emissions include emissions from the cars consuming the station's gasoline, while upstream emissions include the emissions involved with the extraction of crude oil or refining of oil into gasoline.

Table 2: Factor Return Descriptive Statistics
This table reports the mean monthly returns, the monthly return volatilities, and pairwise return correlations of the market (RMRF), value (HML), size (SMB), momentum (UMD), and carbon (PMC) factors. Returns on the RMRF, HML, SMB, and UMD factors are obtained from Kenneth French's website. The sample period is January 2004 to December 2020. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

			Correlations				
	Mean Return (%)	Std. Dev. (%)	RMRF	HML	SMB	UMD	PMC
RMRF	0.62	4.35	1.00	-	-	-	-
HML	-0.12	2.71	0.24^{***}	1.00	-	-	-
SMB	0.14	2.40	0.34^{***}	0.19^{***}	1.00	-	-
UMD	0.17	4.62	-0.43^{***}	-0.33^{***}	-0.10	1.00	-
PMC	-0.28	1.97	-0.13^{**}	0.18^{***}	-0.09	0.13^{*}	1.00

where $r_{PMC,t}$ is the return on the Pollutive-Minus-Clean factor in month t and $r_{SP,t}$, $r_{BP,t}$, $r_{SC,t}$, and $r_{BC,t}$ are the returns, respectively, on the Small / Polluting, Big / Polluting, Small / Clean, and Big / Clean portfolios in month t. Figure 2 displays the cumulative log return on the PMC portfolio. The mean return on the PMC portfolio has been negative over the 2007 - 2020 period, coinciding largely with decarbonisation efforts from institutional investors and a strong rise in the interest for sustainable investments. Table 2 compares the PMC factor to the Fama and French (1993) factors and the Carhart (1997) momentum factor. Returns on the PMC portfolio are slightly negatively correlated with the market factor, indicating that the pollutive leg on average contains firms with slightly lower systematic risk. The PMC portfolio correlates positively with value. This is expected, as the most pollutive firms tend to be value firms, while cleaner firms tend to be growth firms. The Fama and French (1993) procedure we follow to ensure size neutrality seems to work, as can be seen from the insignificant association between the carbon and size factors.

Figure 2: Performance of the PMC Portfolio
The figure plots the cumulative log return on the pollutive-minus-clean portfolio. The PMC portfolio is constructed by taking a long position in the 30% of firms with the highest carbon emissions, offset by a short position in the 30% of firms with the lowest emissions. Similar to Fama and French (1993), we enforce size-neutrality by defining the PMC portfolio separately for samples of small and large firms. Details of the construction procedure are describe in Section 3.1.



3.2 Estimating Carbon Beta

To estimate firm sensitivities to the PMC factor, we run time-series regression of the corresponding firm's equity returns to an Fama and French (1993) 3-factor model augmented by the momentum factor and the PMC factor. The regression is specified as

$$Re_{it} = \alpha_i + \beta_i^{RMRF} RMRF_t + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t + \beta_i^{UMD} UMD_t + \beta_i^{PMC} PMC_t + \epsilon_{it}, \quad (2)$$

where Re_{it} is the excess return on stock i in month t, α_i is the stock's risk-adjusted outperformance, β's denote sensitivities to the risk factors, $RMRF_t$, SMB_t, HML_t, UMD_t, and PMC_t are respectively the returns on the market, size, value, momentum, and carbon risk factors, and ϵ_{it} is the residual term. We use a 60-month estimation window for our regressions. If 60 months of return data are not available, we run the regressions with at minimum a 36-month window.

4 Results

4.1 Validation of carbon beta estimates

We start our analysis by validating our firm-level estimates of carbon risk in several ways. Our goal is to confirm that variation in carbon betas aligns with prior expectations from related studies on other climate risk measures and with commonly held views on climate risk exposures. We first compare estimates of carbon beta across sectors and headquartered states. We then run cross-sectional regressions to uncover how firm characteristics drive corporate climate risk. We also exploit international variation in carbon beta and relate this to differences in country's energy structures and cross-country performance on climate change mitigation. Next, we perform a firm-level comparison of carbon beta with alternative measures of climate risk, among which Sautner et al. (2021)'s measure constructed from analyst earnings calls.

4.1.1 Sector variation in Carbon Betas

Figure 3a displays differences in carbon beta estimates across GICS industry sectors. The figure reports the estimated coefficients from regressing individual stock's carbon betas on their respective industry dummies, given by the specification:

$$CB_{it} = \sum_{k=1}^{11} \mathbb{I}[k_i = k] + \epsilon_{it}, \tag{3}$$

where CB_{it} is firm i's carbon beta at the end of time t, k denotes any of 11 GICS industry sectors, and $\mathbb{I}[k_i = k]$ indicates whether or not stock i's industry classification belongs to industry k. The coefficients obtained from this regression can be interpreted as sector-average carbon betas. Figure 2A shows that the Energies, Utilities, and Materials sectors exhibit the highest carbon betas. In contrast, for the Financials, IT, and Health Care sectors, we observe negative median carbon betas. These findings are in line with commonly held beliefs about the relative carbon risk exposure of sectors. While the figure shows differences in the median carbon risk exposure across sectors, the variation of carbon betas within specific sector is also informative. For example, the Energies sector houses several firms with very high carbon betas, however also includes some firms that hold negative exposure towards climate-change related risks (not reported). Note that in later regression specifications, we always include industry fixed effects, so that we only exploit variation in carbon betas *within* industries, rather than the variation *across* industries reported in Figure 2A. We believe this is a conservative approach, as we control for any potential unobserved industry effect and are able to circumvent the effects of potential industry biases in the definition of the carbon risk factor.

Table 10 in the Appendix additionally reports on the top and bottom *sub*industries in terms of median carbon beta. The subindustries *Coal & Consumable Fuels*, *Oil & Gas Drilling*, and *Oil & Gas Exploration & Production* rank at the top, while the subindustries *Diversified Banks*, *Investment Banking & Brokerage*, and *Systems Software* rank at the bottom.

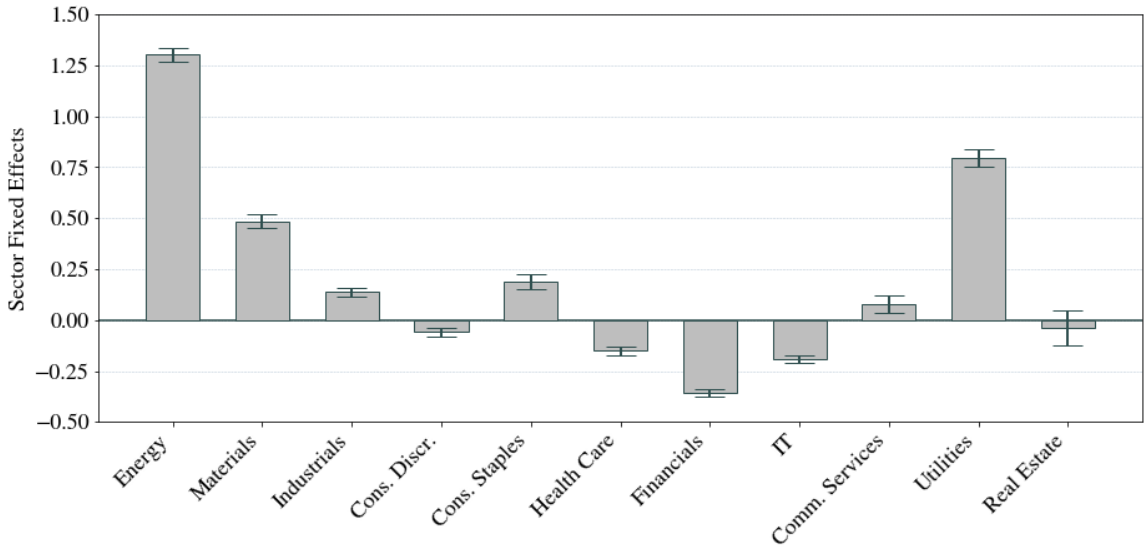
4.1.2 Country Variation in Carbon Beta

We now seek to exploit international variation in a sample of carbon betas estimated from the returns of different MSCI Country indices. We base our carbon beta estimation on a sample of 48 different MSCI country indices.[24] We estimate carbon betas with the same estimation window and control factors as described in Section 3, yet now utilise Ken French's Developed Market factors rather than the U.S. factor equivalents.

[24]Subsection 2.4 describes our data collection procedure for these indices.

Figure 3: Industry Sector and Geographic Variation in Carbon Beta
The figure displays the coefficients estimated by regressing Carbon Beta on GICS Industry Sector fixed effects (Panel A) and Country fixed effects (Panel B). Panel A utilises the sample of carbon betas of the CRSP-Compustat Merged universe, while Panel B utilises an international sample of carbon betas estimated from 48 MSCI Country Indices described in Section 2.4. The coefficients in Panel A are estimated with the specification in Equation 3, while Panel B follows a similar specification. The 95% confidence intervals displayed in Panel A are based on standard errors adjusted for clustering at the firm-level.

(a) Industry Sector Fixed Effects



(b) Country Fixed Effects

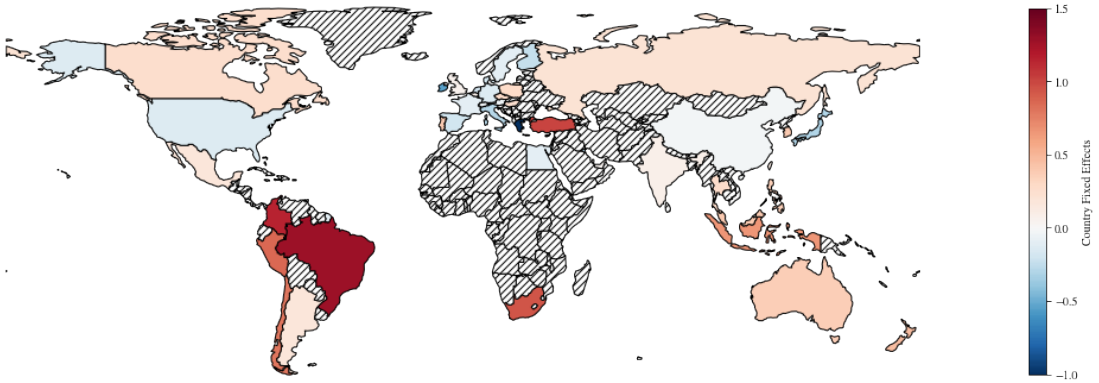


Figure 3b shows the coefficients from regressing international carbon betas on their respective country dummies, similar as in equation 3. As can be seen, carbon betas in South America, South Africa, and Australia are relatively high. On the one hand, this might be related to the vast amounts of natural resources present in these regions and the carbon intensity of the industries involved with extracting them. On the other hand, these regions are well-known to have weak climate policies in place. Countries in Europe, generally, have low to negative carbon betas. This might be a reflection of the European Union being on the forefront of regulating climate change. The difference between the U.S. and Canada is also striking. While both nations have a large oil & gas industry, the U.S. at the same time houses many technology companies. Besides, Canada's petroleum industry is especially polluting as a large part of its petroleum resources are found in oil sands.

4.1.3 Carbon Beta and Firm Characteristics

In this section, we investigate the extent to which heterogeneity in firm characteristics drives corporate climate risk exposure. Based on economic theory and findings from prior research, there are reasons to believe firm characteristics are drivers of corporate climate risk. Larger firms, for example, are better equipped to deal with transition risks as they are more diversified across operating activities.[25] Larger firms can also exert greater lobbying power, leaving them less exposed to potentially adverse effects of climate regulation. Firms that have more physical assets, to the contrary, are exposed climate regulation and fossil fuels via the carbon emissions and energy requirements of their assets. Moreover, physical assets are vulnerable to increased frequency and severity of natural disasters caused by climate change, such as damages from hurricanes, wildfires, or flooding (Li et al., 2020). Lastly, it is more difficult for capital-constrained firms to make investments in low-carbon technologies. Their inability to adapt leaves these firms with greater transition risks. The opposite holds for firms that actively invest in research & technology. Such firms will either already have low-carbon technologies available, or are better able to capitalise on technologies as soon as they come available.

To test our convictions, we estimate via cross-sectional (pooled) regression

$$CB_{it} = \lambda X_{it} + c_i + \mu_t + \epsilon_{it}, \tag{4}$$

where CB_{it} is a firm i's carbon beta at the end of time t, X_{it} is a vector of firm characteristics from Compustat (including the natural logarithm of market capitalisation, Book / Market, Return on Equity, Debt / Assets, CapEx / Assets, Property, Plant & Equipment / Assets, and Research & Development / Assets), c_i is a sector fixed effect, and μ_t is a time fixed effect. We cluster standard errors by firms, because regressions residuals for the same firm are correlated. The inclusion of fixed effects mitigates omitted variable bias as it controls for possible unobserved factors that vary across industry sectors and across time.

Table 3 reports our regression estimates. Our specification includes GICS2 industry sector fixed effects, so identification only comes from different firms active in the same sector. As a result, our coefficients need to be interpreted within industries. We find that firms (operating in the same industries) with larger market capitalisations do indeed exhibit lower carbon betas. Moreover, firms with higher carbon betas are valued lower (they trade at higher book-to-market ratios), hold more physical assets (property, plant & equipment) on their balance sheets, and are more capital intensive (as measure by the ratio of capital expenditures to assets). Sautner et al. (2021) and Shive and Forster (2020) find similar results for other measures of firm-level climate risks. We report a statistically strong negative coefficient on Research&Development expenses to assets, suggesting that innovation leads to lower climate risk exposure. Lastly, contrary to our expectations, differences in firm profitability (as measured by return-on-equity) and firm leverage (debt-to-assets), *within industries*, seem largely unrelated to climate risk exposure.

[25] Bolton and Kacperczyk (2020), for example, find a negative relationship between company size and emission intensity.

Table 3: Carbon Beta and Firm Characteristics
This table reports the regression coefficients obtained from regressing monthly, firm-level estimates of Carbon Beta on several firm-specific characteristics and three alternative measures of carbon risk. The regression equation is given by Equation 4. Firm-specific characteristics are derived from Compustat data. Emissions and emissions intensity are obtained via Trucost. Specification (2) additionally includes the natural log of combined scope 1 & 2 emissions as an explanatory variable. Standard errors are clustered at the firm-year level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable: Carbon Beta	
	(1)	(2)
ln(Market Cap.)	-0.010*	-0.038***
	(0.006)	(0.014)
Book/Market	0.057***	0.083***
	(0.021)	(0.031)
Return on Equity	-0.092***	-0.052
	(0.029)	(0.041)
Debt/Assets	-0.073	-0.125
	(0.084)	(0.089)
Investment/Assets	0.194*	0.341**
	(0.113)	(0.152)
Property, Plant, & Equipment/Assets	0.189***	0.132**
	(0.038)	(0.052)
Research & Development/Assets	-0.619***	-0.742***
	(0.182)	(0.254)
ln(Scope 1 & 2 Emission)†	-	0.106***
	-	(0.032)
Industry FE	Yes	Yes
Year - Month FE	Yes	Yes
N.o. Obs.	339,206	142,875
R^2-Adj.	0.157	0.261

† Variables are standardised

4.1.4 Covariation with Alternative Measures of Climate Risk

We compare carbon betas with alternative firm-level measures of climate risk by pairwise correlation. We consider the natural log of firm emissions, emission intensity, the Sautner et al. (2021) measure of corporate Climate Change Exposure (CCE), and MSCI's Climate-Value-at-Risk. Sautner et al. (2021)'s CCE indicates the extent to which conversations in corporate earnings conference calls are devoted to discussing topics related to climate change regulation, opportunities, and physical risks. MSCI Climate-Value-at-Risk is designed as a forward looking measure of climate risk that incorporates, among others, information on green revenues, green innovation, physical climate risk exposure, and policy scenarios (see Section 2.4 for more information). Table 4 reveals robust associations between carbon beta and each of the four alternative measures. The correlation coefficients are highly significant and their signs are in line with expectations. Interesting to note is that while the log of emissions and emission intensities show "only" a 51% correlation, the pairwise correlation coefficients of carbon beta and the log of emissions and of carbon beta and emission intensities are close, at 28% respectively 24%. This suggests that while there is different information in emissions and intensities, there is still a high overlap between the information in emissions and emissions intensities deemed relevant to carbon beta. Moreover, the robust correlations between carbon beta and the more forward-oriented climate-value-at-risk and Sautner et al. (2021) are reassuring, as they suggest that carbon beta partly picks up the information that these measures have been designed to capture,

such as green innovative ability and analyst's perceptions of corporate climate risk.

Table 4: Carbon Beta and Alternative Measures of Climate Risk
This table reports pairwise correlation coefficients between carbon beta and alternative firm-level measures of climate risk. The sample period is January 2007 to December 2020. Sautner et al. 2021 CCE is the Sautner et al. 2021 Climate Change Exposure measure. MSCI CVaR is the MSCI Climate-Value-at-Risk measure. Emissions and emission intensity data are from Trucost. Other data collection procedures are described in Section 2.4. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Carbon Beta	ln(S1&2 Emissions)	S1&2 Intensity	Sautner et al. 2021 CCE	MSCI CVaR
Carbon Beta	1.00	-	-	-	-
ln(S1&2 Emissions)	0.28^{***}	1.00	-	-	-
S1&2 Intensity	0.24^{***}	0.51^{***}	1.00	-	-
Sautner et al. 2021 CCE	0.14^{***}	0.22^{***}	0.45^{***}	1.00	-
MSCI CVaR	0.22^{***}	0.41^{***}	0.41^{***}	-0.04^{**}	1.00

We now conduct a more detailed comparison between estimates of carbon beta and the Sautner et al. (2021)'s CCEs, where we exploit the fact that Sautner et al. (2021)'s measure can be decomposed into exposures to regulatory, climate opportunities, and physical risk exposures. This allows us to test which of these three aspects of climate change risks are best reflected by carbon beta. The three subcomponents are also available for download at `https://osf.io/fd6jq/`. We estimate a similar regression model as Equation 4, yet we only include one or all three of the CCE subcomponents. In our regressions, we standardise the carbon beta and exposure variables for reasons of comparability and interpretability. Again, we cluster standard errors at the firm level. Table 5 reveals a strong relationship between carbon beta and most of the Sautner et al. 2021 CCE subcomponents. The physical climate risk indicator might be an exception. Although the association is statistically significant, the economic magnitude is small. The low coefficient of determination of Specification 4 also reveals that the physical climate change exposure is of little help in explaining variation in carbon beta. This finding does not come at a surprise to us. Physical climate risks are idiosyncratic in nature and largely unrelated to corporate carbon emissions (much more so with geographic exposures). Hence, our approach is unlikely to pick up differences in physical climate risk exposure, and our analysis confirms that carbon betas are much more related to regulatory and opportunity risks that are more systematic in nature.

Table 5: Carbon Beta and the Sautner et al. (2021) Climate Change Exposures
CCE is Sautner et al. (2021) Climate Change Exposure defined as the extent to which a company's earnings analyst calls are devoted to discussing the regulatory risks, opportunities, and physical risks related to climate change. This table reports the coefficients obtained from estimating a similar regression as in Equation 4. All variables are standardised. Standard errors are clustered at the firm level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable: Carbon Beta				
	(1)	(2)	(3)	(4)	(5)
CCE	0.158***	-	-	-	-
	(0.012)	-	-	-	-
$CCE_{Regulatory}$	-	0.102***	-	-	0.076***
	-	(0.009)	-	-	(0.011)
$CCE_{Opportunities}$	-	-	0.125***	-	0.098***
	-	-	(0.011)	-	(0.010)
$CCE_{Physical}$	-	-	-	0.020**	-0.005
	-	-	-	(0.009)	(0.007)
N.o. Obs.	131,073	92,060	131,073	131,073	92,060
R^2-Adj.	0.042	0.021	0.026	0.001	0.044

4.2 Carbon Beta and Realisations of Climate Risk

In this section we investigate return dynamics of firms during periods of time in which climate change risk partly materialises. We evaluate two proxies for materialising climate risks. First, we consider shocks to an index that captures how frequent climate change is reported in the news. Second, we consider extreme weather events in the U.S., as research shows that during extreme weather events, investors grow concerned about climate change (see, e.g. Choi et al. (2020)). Our interest lies specifically in the effect on stock returns of the interaction term between carbon beta and the proxy for materialising climate change. That is, we seek to answer the question: How are the effects of materialising climate change different for high versus low-carbon-beta firms?

4.2.1 Carbon Beta and Climate Policy Uncertainty

We follow Engle et al. (2020)'s procedure for constructing an index of climate change news. The index levels are determined by the text similarity of news articles in the Wall Street Journal with a corpus of climate change terms. For a detailed overview of the construction procedure, see Section 2.3. We theorise that periods of high climate change news risk are indicative of increased expectations of tightening climate change regulation. Following similarly constructed indices for other forms of economic policy uncertainty (see Baker et al. (2016)), we refer to this index as the Climate Policy Uncertainty index.

As a test, we study the effects of innovations in the Climate Policy Uncertainty index and interactions with carbon beta on stock returns. Our specification is as follows

$$R_{it} = \alpha + \beta CB_{it} + \theta\, \Delta CPU_t + \gamma\, CB_{it} \times \Delta CPU_t + \lambda X_{it} + c_i + \mu_t + \epsilon_{it}, \tag{5}$$

where $R_{i,t}$ is the excess return on company i's stock in month t, CB_{it} denotes the stock i's Carbon Beta at month t, ΔCPU_t is the change in the Wall Street Journal based Climate Policy Uncertainty

Table 6: Carbon Beta × WSJ Climate Policy Uncertainty and Stock Returns
This table reports the coefficients obtained from estimating regression Equation 5. Standard errors are clustered at the firm level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable: *Monthly excess return (×100)*		
	(1)	(2)	(3)
Carbon Beta†	0.005	-	-
	(0.046)	-	-
Carbon Beta† × ΔCPU	-2.552***	-	-
	(0.453)	-	-
Scope 1 & 2 Intensity†	-	-0.126***	-
	-	(0.030)	-
Scope 1 & 2 Intensity† × ΔCPU	-	-0.321*	-
	-	(0.192)	-
ln(Scope 1 & 2 Emissions)†	-	-	-0.115*
	-	-	(0.067)
ln(Scope 1 & 2 Emissions)† × ΔCPU	-	-	-0.266
	-	-	(0.341)
Controls	Yes	Yes	Yes
Year - Month FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
N.o. Obs.	145,094	145,094	145,094
R^2-Adj.	0.277	0.275	0.274

† Variables are standardised

index at month t, $X_{i,t}$ is a vector of control variables including the firm characteristics in Equation 4 as well as the stock i's CAPM beta, idiosyncratic volatility, and 12-month momentum (excluding the most recent month), c_i is the industry effect, and μ_t is the time effect.

Table 6 reports our findings. Our results indicate a statistically and economically significant negative coefficient on the *Carbon Beta* × Δ*CPU* interaction term. This means that stocks with higher carbon betas experience lower returns during months in which the Climate Policy Uncertainty index increased. We do not find the same effect when interacting innovations in the CPU with emissions or emissions intensities. This evidence thus indicates that carbon beta is able to effectively sort stocks according to their climate-change-related risk exposure. The evidence is also consistent with an explanation of carbon beta being well-able to identify the green firms that act as hedging assets against sudden realisations of climate change risks.

4.2.2 Stock returns during extreme weather events

Bansal et al. (2016) and Choi et al. (2020) theorise and empirically find that pollutive firms tend to exhibit poorer returns during spells of extreme weather since the effects of climate change are more salient in such periods. We use temperature anomaly observations from the U.S. Climate Reference Network and values of the Palmer Z-Index above the 90$^{\text{th}}$ percentile of past 30-year observations to classify periods of high temperatures and extreme drought. We estimate the regression model

$$R_{it} = \sigma EW_t + \eta CB_{it} + \phi EW_t \times CB_{it} + \lambda X_{it} + c_i + \mu_t + \epsilon_{it}, \tag{6}$$

where R_{it} is firm i's excess stock return in month t, EW_t is an extreme weather dummy equalling 1 if month t's temperature anomaly or drought severity ranks above the 90^{th} percentile, CB_{it} is the carbon beta, X_{it} is a vector of control variables including the firm characteristics in Equation 4 as well as the stock i's CAPM beta, idiosyncratic volatility, and 12-month momentum (excluding the most recent month), c_i is a sector fixed effect, and μ_t is a time fixed effect.

We indeed find that firms with higher carbon beta experience lower returns during extreme weather events. The results are presented in Table 7. We perform the same analysis for three alternative measures of carbon risk, namely Scope 1 & 2 emissions intensity, the natural logarithm of Scope 1 & 2 emissions, and MSCI Climate-Value-at-Risk. Both emissions variables and CVaR exhibit the same return tendency on extreme temperature days. These results conform those of Choi et al. (2020) regarding the negative returns observed on an emissions-sorted long-short portfolio during periods of high abnormal temperature. We report the strongest statistical and economic significance for our measure of carbon beta. During months that show a temperature anomaly above the 90^{th} percentile, a unit increase in carbon beta tends to decrease excess returns by 0.73%. Turning to drought spells, carbon beta is the only proxy that shows a significant interaction effect with returns.[26] These findings can be explained in several ways. For one, it could be the case that during extreme weather events, investors are more aware of the consequences of climate change, leading them to disproportionally sell holdings they perceive as contributing towards a changing climate. In this case, carbon beta partially captures investors' perception of firm-specific contribution to climate change. Second, investors might regard extreme weather events as realisations of climate risk, and therefore buy stocks which they deem a 'hedge' against such risk. Here, negative carbon betas proxy for such hedging potential. Third, we cannot rule out the potential direct effect of extreme weather events on certain companies' earnings. For example, high temperatures and an associated lower demand for heating might temporarily depress the earnings of companies in the energy sector. In this case, our findings only indicate a correlation between the extent to which a firm's profitability is sensitive to weather-related conditions and carbon beta.

4.3 Capturing forward looking aspects of carbon risks

4.4 Green Innovation (in the Energy Sector)

Cohen et al. (2020) report a striking disconnect: firms operating in the Energy sectors are responsible for a large share of greenhouse gasses and are amongst the worst performers on environmental issues, yet they are the most active in patenting low-carbon technologies. As green innovation likely helps firms in reducing their exposure towards climate-related risks and might even help in benefiting from a transition to a cleaner economy, we expect carbon beta to partially pick up such differences. Especially in the Energy sector we expect this result to appear, as here the "ESG-innovation disconnect" is most apparent. To test this hypothesis we exploit the main measure of green innovation used by Cohen et al. (2020): *Green Share*, defined by the fraction of total patents issued by a company classified as green at time t. Specifically, we estimate the regression equation

$$S_{it} = \sigma GreenShare_t + \lambda X_{it} + c_i + \mu_t + \epsilon_{it}, \tag{7}$$

where S_{it} is either firm i's Carbon Beta, Scope 1&2 Emissions Intensity, or the natural logarithm of Total Scope 1&2 Emissions in month t; X_{it} is a vector of control variables proxying for firm size, valuation, profitability, leverage, investments, capital intensity, and innovation; c_i is an optional sector fixed effect; and μ_t is a time fixed effect.

Table 8 reports our regression results for a number of specifications. In columns 1, 2, and 3, we regress

[26] Generally, the interaction effect becomes stronger (more negative) when increasing the threshold for an 'extreme' weather event further above the 90^{th} percentile and when focusing our analysis on more recent time periods.

Table 7: Stock Returns, Carbon Beta, and Extreme Weather Events
This table reports the coefficients obtained from estimating regression Equation 6. Returns are multiplied by 100. Standard errors are clustered at the firm level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable: Monthly return (×100)		
Panel A: Returns during high temperature anomalies			
Carbon Beta†	0.019	-	-
	(0.045)	-	-
Carbon Beta† × Temp Anomaly	-0.410***	-	-
	(0.129)	-	-
Scope 1 & 2 Intensity†	-	-0.104***	-
	-	(0.031)	-
Scope 1 & 2 Intensity† × Temp Anomaly	-	-0.218***	-
	-	(0.076)	-
ln(Scope 1 & 2 Emissions)†	-	-	-0.045
	-	-	(0.064)
ln(Scope 1 & 2 Emissions)† × Temp anomaly	-	-	-0.331**
	-	-	(0.153)
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year - Month FE	Yes	Yes	Yes
N.o. Obs.	146,557	146,557	146,557
R^2-Adj.	0.247	0.249	0.247
Panel B: Returns during drought spells			
Carbon Beta†	0.009	-	-
	(0.054)	-	-
Carbon Beta† × Drought	-0.522***	-	-
	(0.112)	-	-
Scope 1 & 2 Intensity†	-	0.116***	-
	-	(0.031)	-
Scope 1 & 2 Intensity† × Drought	-	-0.174**	-
	-	(0.088)	-
ln(Scope 1 & 2 Emissions)†	-	-	-0.071
	-	-	(0.062)
ln(Scope 1 & 2 Emissions)† × Drought	-	-	-0.096
	-	-	(0.093)
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year - Month FE	Yes	Yes	Yes
N.o. Obs.	146,557	146,557	146,557
R^2-Adj.	0.246	0.245	0.242

† Variables are standardised

Table 8: Carbon Beta and Green Innovation (in the Energy Sector)
This table reports the coefficients obtained from estimating regression Equation 7. Green Share (%) is the measure of green patent innovation from Cohen et al. (2020). We collect data on U.S. patents from the U.S. Patent Office's Bilk Data Storage System. Standard errors are clustered at the firm level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable				
	Carbon Beta	Carbon Beta	Carbon Beta	S1&2 Intensity	ln(S1&2 Emissions)
Green Share (%)	-0.135*	-2.252***	-0.752***	-2.387	1.153*
	(0.081)	(0.303)	(0.237)	(1.975)	(0.698)
ln(Market Cap.)	-0.001	-0.028	-0.108***	-0.388**	0.949***
	(0.005)	(0.021)	(0.027)	(0.187)	(0.050)
Book/Market	0.121***	0.191**	0.006	-0.969	0.901***
	(0.020)	(0.082)	(0.108)	(0.745)	(0.202)
Return on Equity	-0.115***	-0.325**	-0.160	2.449**	0.955*
	(0.027)	(0.139)	(0.115)	(0.970)	(0.493)
Debt/Assets	-0.021	-1.962***	-1.641***	7.401***	6.912***
	(0.057)	(0.481)	(0.593)	(2.695)	(1.195)
Investments/Assets	0.202**	-0.031	0.484	-30.535***	-2.549
	(0.096)	(0.852)	(0.928)	(5.342)	(1.845)
PP&E/Assets	0.200***	0.301***	0.437***	1.821***	0.539***
	(0.030)	(0.089)	(0.101)	(0.544)	(0.189)
R&D/Assets	-0.808***	-7.481**	-11.542**	66.241***	-5.123
	(0.131)	(3.347)	(5.458)	(22.483)	(8.313)
Year - Month FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	No	No	No	No
Industry	All	Energy	Energy	Energy	Energy
Sample	All	All	Trucost	Trucost	Trucost
N.o. Obs.	143,584	5,273	3,818	4,034	4,034
R^2-Adj.	0.158	0.446	0.492	0.109	0.700

carbon beta on green innovation and firm-level control variables using respectively the complete sample, only the observations of firms in the Energy sector, and only the observations of firms in the Energy sector for which Trucost data are available. For the complete sample, which includes industries other than the Energy sector, a weak, yet statistically significant negative relation is observed between green innovation and carbon beta. This suggest that in general, firms that are more active in green innovation tend to have lower climate risk exposure as indicated by carbon beta. The negative relationship between carbon beta and green innovation is much more pronounced within the Energy sector (columns 2 and 3). In our full sample of Energy firms (column 2), a unit increase in green share (theoretically, the maximum increase possible in green innovation) is associated with a 2.25 unit reduction in carbon beta, which amounts to almost 2.5 times the average cross-sectional standard deviation. In the larger and more liquid sample of Energy firms for which Trucost data is available (column 3) the relationship remains statistically and economically significant. Moving the analysis to emission intensity (column 4) and the natural logarithm of emissions as the dependent variable, we do not find a similar effect for green innovation. To the contrary, total emissions and green share are weakly positively related in the Energy sector. This finding has important implications for investors, as it suggests that divestment from the strongest-emitting firms in the energy sector implicitly leads to divestment from those firms that are most actively involved in green innovation.

4.5 Unobserved factors of Forward-Looking Climate Risk

MSCI's Climate-Value-at-Risk (CVaR) is a measure specifically developed to incorporate forward-looking and corporate valuation assessments of the impact of climate change and related policies. A wide variety of factors are included in its estimation. Importantly, firm emissions and green patent innovations are main determinants of CVaR. The measure however also incorporates various proxies for physical climate risks, transition scenario analyses, low-carbon revenues, and abatement policies. The objective of our analysis is to analyse wether or not carbon beta correlates with forward-looking aspects of carbon risk captured by CVaR yet unrelated to emissions nor green innovation. To do so, we will estimate the regression equation

$$CVaR_{it} = \alpha + \sigma GreenShare_{it} + \lambda ln(Emissions)_{it} + \kappa CB_{it} + c_i + \mu_t + \epsilon_{it}, \tag{8}$$

where $CVaR_{it}$ is MSCI's Climate-Value-at-Risk; $GreenShare_{it}$ is a firm's share of green patents relative to its total patents; $ln(Emissions)_{it}$ is the natural logarithm of scope 1&2 emissions; CB_{it} is a firm i's carbon beta at time t; and c_i is an optional industry fixed effect.

Regression estimates are presented in Table 9. The first specification (column 1) does not include sector fixed effects while the second specification (column 2) does. Emissions and green innovation are positively, respectively negatively, associated with CVaR. This result is mechanical, as emissions and green innovation are components used in the estimation of CVaR. In both specifications, the coefficient on carbon beta is positive and statistically significant. Our findings indicate a strong economic association between components of CVaR unrelated to emissions characteristics and green innovation and between carbon beta. This suggests that carbon beta incorporates other factors included in CVaR, for example, exposure to low-carbon technologies, favourable exposure towards carbon abatement policies, or green revenues. Even while controlling for industry effects, the coefficient on carbon beta remains statistically significant, indicating that this information which is captured by carbon beta does not just vary at the industry level and must thus partly be firm-specific.

Table 9: Carbon Beta and Unobserved Climate Risk Factors

This table reports the coefficients obtained from estimating regression Equation 8. MSCI CVaR is MSCI's Climate-Value-at-Risk. Standard errors are clustered at the firm level. Specification (1) does not control for industry fixed effects, while Specification (2) does. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable: MSCI CVaR	
	(1)	(2)
Intercept	-0.389***	0.144
	(0.045)	(0.094)
Carbon beta	0.045***	0.015**
	(0.009)	(0.007)
ln(Emissions)	0.044***	0.030***
	(0.004)	(0.005)
Green Share (%)	-0.311***	-0.326***
	(0.109)	(0.104)
Industry FE	No	Yes
N.o. Obs.	94,881	94,881
R^2-Adj.	0.235	0.341

5 Conclusion

We propose a complementary measure of climate risk determined by the extent to which an asset's return correlates with a carbon risk factor. This carbon risk factor seeks to capture unexpected changes in consumers' and investors' concern about the climate. As a candidate for the carbon risk factor, we propose the pollutive-minus-clean (PMC) portfolio. The PMC portfolio is a self-financing portfolio created by a long position in the 30% of stocks with the highest carbon emissions, offset by a short position in the 30% of stocks with the lowest emissions. After regressing individual stock returns on the PMC's portfolio's returns and the Carhart (1997) four-factor returns, we regard the loadings on the PMC portfolio as our firm-level measure of climate risk.

Our approach holds several advantages over conventional approaches that assess asset-level climate risks. First, we can estimate climate risk exposure for a wide array of companies. The coverage of our measure far exceeds that of commercially available alternatives, and it does not suffer from any selection effects. Our framework is not limited to a specific asset class. The concept is applicable to any asset for which a sufficient return history can be observed. Second, our measure is broad in scope, as it reflects the market's consensus view on a company's climate risk. Due to the market-based nature of our measure, potentially any aspect deemed relevant to climate risk exposure might be reflected. For example, the availability of clean technologies, a company's innovative ability, leadership quality, industry competition, and financial condition. We confirm this hypothesis by regressing carbon beta on financial firm characteristics, showing that carbon beta varies according to our expectations. For example, larger and more innovative firms have lower climate risk exposure, while capital intensive, carbon intensive, and lower-valued firms have higher climate risk exposure. Furthermore, comparisons of carbon beta estimates with alternative (commercial) measures of climate risk at the firm-level reveal robust positive associations.

A shortcoming of our approach lies in the use of emissions as the basis for the PMC portfolio. As corporations only started reporting emissions in the mid 2000's, our proxy for the carbon risk factor only covers a limited history. Other proxies for the carbon risk factor could be considered. One could use the price of emission allowances, for example, now that emissions trading schemes are becoming more and more prevalent. Weather-related securities, or certain commodities, might also be suitable candidates. Even non-tradable carbon risk factors could be evaluated, akin to the Climate Policy Uncertainty index which we utilised.

Investors can use our framework as a tool for creating climate-aware investment strategies. As it is transparent, accessible, and easily replicated, a majority of investors are able to utilise our approach. Carbon betas could thus be used by investors for whom it is too costly to make use of commercial alternatives, e.g. small retail investors or low-cost ETF providers.[27] Investors can use our approach as a screening tool, flagging perhaps the companies that are generally not regarded as pollutive but whose carbon beta indicates a significant exposure to climate risks. Perhaps more interestingly, carbon beta can also be employed as an indicator of 'climate hedge' potential. Our results indicate that during months in which uncertainty surrounding future climate policy spikes, assets with low carbon betas outperform assets with high carbon beta. We observe similar returns patterns for months with abnormally high temperatures, and for months that are exceptionally dry in precipitation. Lastly, (systematic) investors could target aggregate portfolio levels of carbon beta, depending on their views about future climate pathways. Investors who would not like to completely divest from a pollutive sector, for example because they want to engage with companies, could otherwise impose limits on their 'brown' portfolio's carbon beta. Our findings suggest that such a strategy for the oil sector yields exposure to companies that are highly active in researching green technologies, and thus in the future might become climate enablers.

[27] The authors intend on making publicly available carbon beta and related code, free-of-charge, in a transparent and highly customisable way.

6 Appendix

Table 10: Descriptive Statistics on Top and Bottom Subindustries by Carbon Beta
This table reports the mean and median carbon beta of the top and bottom 10 GICS-subindustries by median carbon beta. The table also reports the number of firms by subindustry and the number of return and carbon beta observations by subindustry. Data is from January 2007 to December 2020.

Sub-Industry	**Mean**	**Median**	**N. Firms**	**N. Obs.**
Panel A: top 10 sub-industries by median carbon beta				
Coal & Consumable Fuels	1.60	1.74	22	1,726
Oil & Gas Drilling	1.95	1.67	18	1,781
Oil & Gas Exploration & Production	1.57	1.49	201	15,378
Oil & Gas Equipment & Services	1.44	1.42	101	8,203
Independent Power Producers & Energy Traders	1.55	1.38	17	961
Heavy Electrical Equipment	1.28	1.25	13	818
Gold	1.37	1.09	14	1,194
Oil & Gas Storage & Transportation	1.16	1.08	30	2,071
Steel	1.24	1.08	40	3,968
Integrated Oil & Gas	1.10	0.99	4	751
Panel B: Bottom 10 sub-industries by median carbon beta				
Diversified Banks	-0.92	-0.85	10	1,080
Investment Banking & Brokerage	-0.54	-0.60	56	5,362
Systems Software	-0.51	-0.55	96	5,949
Financial Exchanges & Data	-0.47	-0.51	15	1,988
Homefurnishing Retail	-0.58	-0.50	12	1,108
Interactive Media & Services	-0.27	-0.41	36	2,562
Home Improvement Retail	-0.16	-0.39	7	688
Asset Management & Custody Banks	-0.34	-0.39	70	6,567
Communications Equipment	-0.36	-0.38	159	12,794
Regional Banks	-0.43	-0.36	654	61,840

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