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

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November 2021

Abstract

Despite sustainable investments standing at record highs, it remains a challenge to quantify climate risk. We propose a proxy for a climate risk factor, the pollutive-minus-clean (PMC) portfolio, which captures differences in returns to firms that have high versus low corporate emissions. By regressing individual stock returns on the PMC factor, we obtain estimates of asset-level climate risk exposure: 'carbon beta'. Validation of carbon betas confirms that variation in climate risk exposures aligns with our prior expectations. Our measure has desirable properties regarding availability, coverage, and informativeness compared to conventional climate risk measures. We study the interaction of carbon betas with several proxies for realisations in climate risk. Returns to stocks with high carbon betas are lower during months in which climate change is more frequently discussed in the news, during months in which temperatures are abnormally high, and during exceptionally dry months. Unlike firm emissions and intensities, variation in carbon betas correlates with green patent issuance and forward-looking measures of climate risk.

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

JEL: G11, G12, Q54

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*The views represented in this paper are the authors' own and do not necessarily represent Robeco. We are grateful for helpful comments by seminar participants at Robeco and Vrije Universiteit Amsterdam.

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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. 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 convention in 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 alternative 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 other 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 does not directly rely on the voluntary disclosure of emissions-related information. Second, due to the market-based nature of our measure, carbon betas could 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 markets incorporate future expectations about these aspects in asset prices, then carbon beta picks those up too. Third, carbon betas allow a clear distinction between assets that are expected to benefit from a low-carbon transition and assets that are expected to lose from such a shift. Corporate emissions, on the other hand, are best at identifying "climate losers" (Sautner et al., 2021), that is, firms that are currently among the heaviest emitters and likely negatively impacted by a faster transition. Moreover, all emissions are assumed equally harmful, while investors might assign greater weight to some emissions over others. For example, for firms whose emissions occur in the production of goods that reduce emissions elsewhere (e.g. solar panels),

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

or that operate in sectors for which abatement is expected to be easier, investors might perceive lower risk exposures. To illustrate this point, note that the 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 all similar, ranking close to the 80th percentile of our sample. However, the average carbon betas of Tesla and First Solar are 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 the Pástor et al. (2020, 2021) model of an 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 their valuation. Simultaneously, 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. Our proxy for the carbon risk factor is intended to capture such relative changes in the valuation of *brown* compared to *green* firms. We construct the carbon risk factor by forming a long-short portfolio – as is common in the asset pricing literature (see, e.g. Fama and French 1993) – based on companies' relative emissions. The long leg of the portfolio contains relatively pollutive companies whereas the short leg contains relatively clean companies. To roughly classify companies into pollutive and clean groups, 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

[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.

[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.

are concerned about the climate. 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. Our results indeed indicate this to be the case.

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 of carbon betas to a battery of validation tests. The goal of these tests is to confirm that variation in carbon betas aligns with our expectations. We first compare 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, 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 after climate change concerns become more prevalent. Besides, financial firms might be favourably exposed to a low-carbon transition as for such a shift to occur, large investments are required, which the financial industry will help facilitate. We further investigate which firm characteristics correlate with carbon beta. We theorise that smaller, more capital intensive, lower-valued, less profitable, and less innovative firms are more exposed to climate risks. These predictions turn out to be largely true. We establish that firms with high carbon betas tend to have, *ceteris paribus*, lower market capitalisations, higher property, plant & equipment and investment as a fraction of assets, lower research & development expenses compared to assets, lower profitability, and higher greenhouse gas emissions. 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, and MSCI Climate-Value-at-Risk scores.

To shed more light on market responses to materialising climate risks, we construct an index similar to Engle et al. (2020)'s Climate Change News Index. This index is determined by the textual similarity between daily news articles published in the Wall Street Journal and a corpus of texts on climate

change, collected from official reports and Wikipedia. We hypothesise that periods in which climate change is frequently reported in the news tend to coincide with episodes of heightened uncertainty around future climate policies. As this approach is analogous to those in the literature on broader economic policy uncertainty (see, e.g. Baker et al. 2016), we refer to our index as the Climate Policy Uncertainty (CPU) index. We find that in months when CPU increases, firms exhibiting higher carbon beta have lower returns, and *vice versa*. Interestingly, asset prices adjust much more in response to increases in the CPU index than in response to reductions in the CPU index. When two stocks differ in carbon beta by one standard deviation and are otherwise equivalent, the return on the asset with the higher carbon beta is about 49bps lower for each standard deviation with which the CPU index increases. 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 similar analyses 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 lower returns.[4] The same pattern is observed in periods of extreme drought, although the economic significance of the effect is slightly smaller.

Recent work by Cohen et al. (2020) finds that green innovation is largely driven by firms in the Energy sector, yet paradoxically firms in the Energy sector are generally also the worst performers on environmental issues. Inspired by this striking disconnect, we analyse the association between between *green* patenting activity and our measure of climate risk. We do so by downloading all patents issued by the U.S. Patent Office from 2010 to 2020 and linking their associated patent classes to green patent inventories. Our results indicate a weakly negative, yet statistically significant, association between carbon beta and green innovation, even while controlling for general (non-green) innovation activity. When we turn our analysis to only firms those firms active in the Energy sector, the effect becomes much more pronounced. This finding seems to suggest that firm-level differences are taken into consideration by market participants and picked up by our estimation of climate risk exposure. Surprisingly, we do not find similar results when we focus our analysis on carbon intensities our carbon emissions as the indicator of climate risk exposure.

Our study relates to the growing field of *climate finance*, which studies the interactions of climate change with 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. Relatedly, Huyhn et al. (2021) establish that mutual fund managers divest from pollutive firms after they experience increased local air pollution. Bansal et al. (2019) estimate stock return sensitivities to long-run temperature shocks and find that temperature-exposed stocks carry a risk

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

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. Engle et al. (2020) construct portfolios with the purpose of hedging innovations in climate change news. We adopt their methodology of quantifying climate change news. 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 the field of climate finance, see Giglio et al. (2020).

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. After conducting a Campbell and Vuolteenaho (2004) decomposition, the missing premium is attributed to carbon risk being associated more with unrewarded cash flow risk than with discount rate risk.[5] Görgen et al. (2020)'s paper is different from ours in a number of ways. First, the paper of Görgen et al. (2020) primarily adopts an asset pricing perspective of the carbon risk factor as a driver of stock returns, while our paper focuses more on firm-level sensitivities towards such a 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)) and costly to obtain, 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.

Our 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

[5] Campbell and Vuolteenaho (2004) predict that cash-flow risk should be priced at a larger premium than discount rate risks, as the latter is more transitory in nature. Görgen et al. (2020) however observe the reverse to be the case in their sample period. Explanations for this finding could lie in the time-varying component of the price of cash-flow risk and in the fact that after the global financial crisis cash-flow shocks have been predominantly upward (Maio, 2013; Campbell et al., 2013).

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. Similarly, Alekseev et al. (2021) evaluate climate hedging portfolios formed by going long (short) the stocks that are disproportionally bought (sold) by mutual fund managers after they have experienced local extreme heat events.

Finally, 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 (2021a) and Bolton and Kacperczyk (2021b) 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 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. Hsu 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 an annual return spread of 5.52%. The authors explain this *'pollution premium'* through higher regulatory risks faced by pollutive firms and provide empirical support for this hypothesis.

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 observations from Compustat's Fundamentals Annual at the end of June of the previous year.[6] 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.[7] In all return regressions, we exclude penny shares that trade below $5 and microcap stocks that rank among the bottom 10% of market capitalisation, evaluated at the end of December of the previous year.

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.[8] 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.[9] 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 also compute ratios for book leverage (debt to assets), investment to assets (capital expenditures to assets), return on equity (firm profitability to equity), property, plant & equipment to assets, and

[6] 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.

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

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

[9] I.e. multiple PERMNOs falling under the same PERMCO.

research & development expenses to assets. All accounting variables are winsorized at the 2% level to mitigate the effect of outliers and potential data errors. We calculate 12-month-minus-1-month (12M-1M) momentum by compounding a stock's return over the past 12 months, but excluding the most recent month. We utilise daily returns obtained from CRSP's daily security file to estimate CAPM-implied market betas and idiosyncratic return volatilities. Estimations are based on rolling windows containing one year of daily return observations. Additionally, we obtain data on U.S. factor returns from Kenneth French's data library.[10]

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 over 6,900 unique firms. The average excess return (including dividends) equals 0.83% per month. Moreover, the average (median) firm in our sample has a market capitalisation of about $5.6 billion ($525 million). Average book-to-market, book leverage, and investment-to-assets equals 0.77, 0.25, 0.09, respectively. The average firm has a market beta of 1 and idiosyncratic volatility of 45%. The sector composition of our sample is as follows. Roughly 18% of observations are linked to stocks in the Financial sector, 17% to IT, 15% to all of Health Care and Industrials, 13% to Consumer Discretionary, around 5% to all of Energies, Materials, and Consumer Staples, 3% to all of Telecommunications and Utilities, and less than 1% to Real Estate.

2.2 Emissions data

We collect information on greenhouse gas emissions from S&P's Trucost, a leading provider of corporate emissions data. Trucost data are either reported or estimated by Trucost's proprietary models. 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.[11] 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

[10] `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`
[11] `https://ghgprotocol.org`.

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.o. Obs.	Mean	SD	1%	5%	25%	Median	75%	95%	99%
Panel A: Firm-level and market variables										
Excess Return (%)	571,733	0.826	17.545	-39.756	-21.988	-6.371	0.289	6.783	23.752	52.423
Market Cap. (millions)	571,756	5,579	27,917	6	17	112	525	2,404	21,483	97,891
Book/Market*	552,678	0.774	0.923	0.045	0.089	0.288	0.543	0.916	2.272	4.208
Return on Equity*	571,618	-0.080	0.522	-2.563	-1.083	-0.062	0.066	0.130	0.324	0.532
Debt/Assets*	457,749	0.245	0.163	0.028	0.061	0.128	0.205	0.316	0.596	0.774
Investments/Assets*	565,271	0.085	0.117	0.000	0.000	0.000	0.024	0.132	0.353	0.475
Property, Plant, & Equipment/Assets*	488,571	0.447	0.396	0.002	0.020	0.129	0.318	0.690	1.238	1.568
Research & Development/Assets*	571,756	0.051	0.107	0.000	0.000	0.000	0.000	0.047	0.295	0.504
Carbon Beta*	504,282	-0.001	0.525	-1.156	-0.850	-0.312	-0.026	0.263	0.983	1.529
Idiosyncratic Volatility (%)	561,671	45.197	29.198	12.386	15.471	24.769	36.973	56.487	104.937	147.465
CAPM Beta	564,329	1.002	0.373	0.208	0.393	0.767	1.007	1.232	1.610	1.941
Momentum	540,886	0.079	0.641	-0.834	-0.628	-0.218	0.030	0.267	0.879	2.041
Panel B: Emission variables										
Scope 1 Emissions (millions tons CO_2)	199,473	0.917	3.603	0.000	0.000	0.003	0.024	0.148	4.980	24.047
Scope 2 Emissions (millions tons CO_2)	199,473	0.215	0.549	0.000	0.000	0.006	0.030	0.130	1.186	3.244
Scope 1 & 2 Emissions (millions tons CO_2)	199,473	1.132	3.837	0.000	0.000	0.011	0.068	0.358	6.076	24.459
Scope 1 Emission Intensity (tons CO_2/$ mln.)	199,473	158.985	592.723	0.296	0.556	3.597	14.152	32.942	734.434	4049.417
Scope 2 Emission Intensity (tons CO_2/$ mln.)	199,473	28.355	36.187	0.668	1.127	7.546	16.161	35.973	106.015	180.598
Scope 1 & 2 Emission Intensity (tons CO_2/$ mln.)	199,473	187.340	599.493	1.984	2.133	13.034	37.577	80.377	834.414	4052.123

*Winsorized at the 2% level.

accounted for as scope 3. As our database does not contain the complete data for scope 3 emissions, we only include scope 1 and scope 2 emissions into our analyses.[12] 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 associated firm's revenues as reported by Trucost. In the remainder of 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*.

Our merged Trucost - Compustat sample contains over 17,000 firm-year observations on around 2,700 unique firms. Of these, about 10,000 firm-year observations were estimated using Trucost's proprietary mode, 3,000 observations were directly reported 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 $13.6 billion ($3.1 billion). Firms are generally more profitable (ROE of around 5%), higher-valued (Book-to-Market of 0.56), similarly leveraged (book leverage of 0.24), and similarly capital intensive (Investments-to-Assets of 0.08). In terms of sector representation, the samples are relatively similar. Financials, IT, and Industrials all represent between 17% and 15% of the sample. Health Care and Consumer Staples account for 14% and 13%. Both Energy and Materials have about 6% of observations. Consumer Staples, Utilities, and Communication Services, represent about 4% of the sample, and Real Estate represent 1%.

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.[13] 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)

[12] Our Trucost data only includes the downstream scope 3 emissions, which are 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.

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

Index as follows. We start by applying several text preprocessing steps commonly used in Natural Language Processing.[14] We then perform a Term Frequency - Inverse Document Frequency (TF-IDF) transformation to convert our collections of text articles in numerical vector form.[15] 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.[16] 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 the index equal to 100.

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 15th 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 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

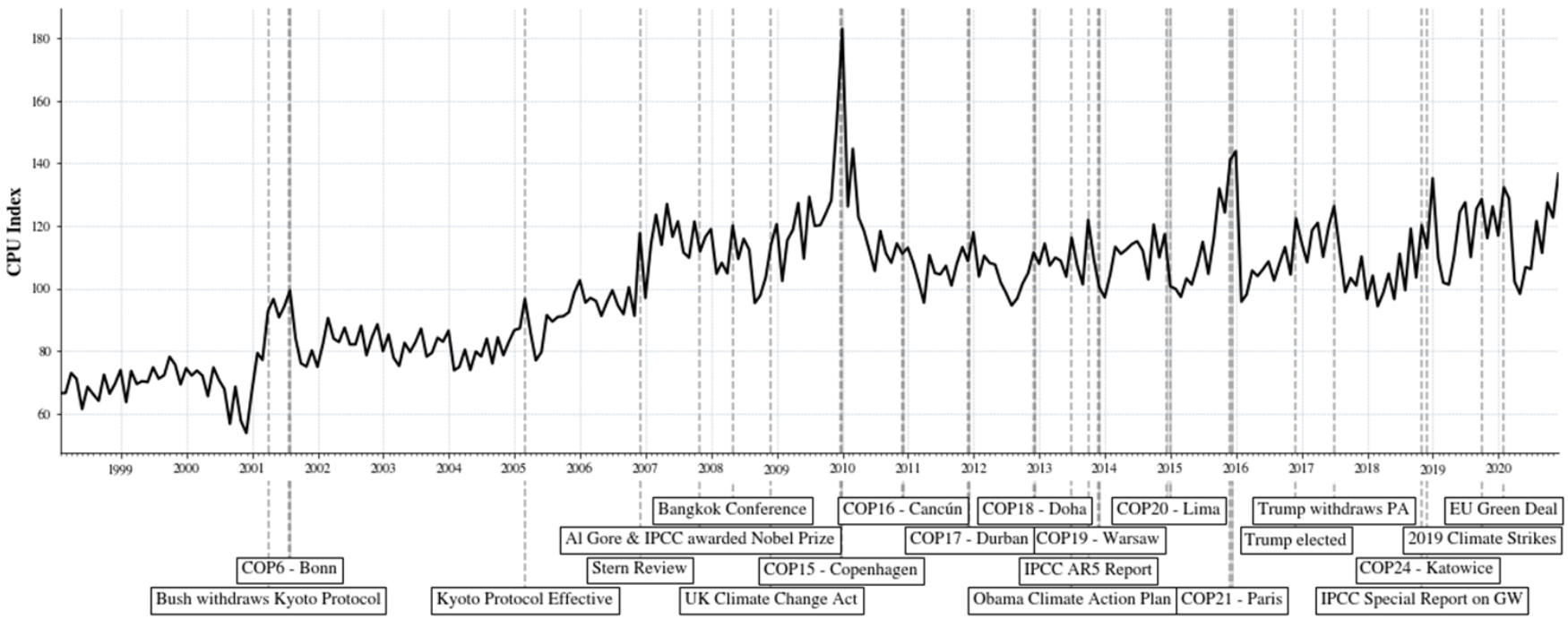
[14] These involve, in the following order: removing punctuation, tokenizing (splitting sentences into words), removing stop words, lemmatizing (reducing words to their word roots, e.g. the words 'climate' and 'climatology' both become 'climat'), and converting terms into bigrams (two-word collections of consecutive words).

[15] 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.

[16] 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°.

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 textual 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.



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 available at `https://osf.io/fd6jq/`. We cross-sectionally standardise all Sautner et al. (2021) exposure values.

2. Temperature and drought statistics. We collect monthly temperature anomalies for the United States from the U.S. Climate Reference Network.[17] A month's temperature anomaly is defined as the temperature deviation from its 30-year average reference temperature. We download the Palmer Z-Index, a derivative of the Palmer Drought Severity Index (PDSI; Palmer 1965) as a measure of drought severity.[18] The PDSI uses precipitation, temperature, and geographic data to model available quantities of water to a location of interest. As the PDSI is inaccurate over short frequencies (see, e.g. Karl (1986)), we use the Palmer Z-Index which is designed to be more responsive over short-term periods. Negative values of -4 indicate extreme drought, values between -1 to 1 indicate regular conditions, and values of +4 indicate unusually wet periods.

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 has been designed to capture forward-looking valuation assessments regarding climate risk and opportunities.[19] 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 that a company is expected to suffer (benefit) from climate change. We reverse the sign of CVaR to align it with traditional Value-at-Risk, and cross-sectionally standardise to enable comparison with other metrics.

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 through the USPTO's Bulk Data Storage System.[20] The USPTO provides text files for all patents issued in the United States from 1976 onwards. We download patent grants issued from 2010

[17] Available at: `https://www.ncdc.noaa.gov/temp-and-precip/national-temperature-index/time-series/anom-tavg/1/0`

[18] Available at: `https://www7.ncdc.noaa.gov/CDO/CDODivisionalSelect.jsp`

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

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

up to and including 2020. We rely on two techniques to link our dataset to patent issuance. First, we download a patent-to-company mapping from the Compustat Link table of WRDS' newly released US Patents (Bèta) product.[21] This patent-company linkage is available for the 2011 - 2019 period. For this period, our patent database and that of WRDS cover almost the same patents.[22] A small difference (less than 1%) in coverage is likely the result of retrospective changes in USPTO's data, or of rare errors in the automated retrieval of patent files. Second, we map the stated assignees in patent grants to the company names in our Compustat sample by applying a similar cosine similarity comparison as in section 2.3. This technique allows us to implement approximate-string matching and at the same time estimates a confidence level for the matching outcome. We only match records if the confidence level exceeds 85%. At this level, manual inspection of matching outcomes yields very little incorrect matches, yet we risk overlooking valid links. We assume, however, that such valid links are covered by WRDS's linking table. When our own matching algorithm disagrees with that of WRDS, we follow the link proposed by WRDS, as we believe the linking table by WRDS is better able to deal with company subsidiaries and name changes. For patents outside the 2011 - 2019 window, we try to extrapolate the WRDS linking table, and otherwise rely on our own linking procedure.

To identify green patent issuance, we follow guidelines by the OECD as described in Haščič and Migotto (2015). These guidelines describe the patent classifications that are related to a wide variety of green technologies, for example environmental management, water pollution abatement, waste management, climate 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.[23] 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 3,000 firms. A little under 10% of total patent issues are classified as green. Top green patent issuers, by total number of green patents, are IBM, Ford, General Electric, Intel, Apple, and Raytheon.

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

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

[23] 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 working of our carbon risk factor follows the mechanism of the Pástor et al. (2020, 2021) model for ESG risk. In this model, 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 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).[24] 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, so that the return on the PMC portfolio increases.

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 3 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.[25] As different firms operate at different levels in the value chain, downstream emissions are less comparable between

[24] Governments may, for example, tax or limit emissions, ban pollutive products, or subsidise cleaner products or services.

[25] 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.

companies. Second, scope 3 emissions data are by definition estimated rather than reported. There are considerable complexities in accurately modelling emissions associated with all activities in a company's value chain. As a result, when comparing firms' emissions, Busch et al. (2018), Berg et al. (2019), and Kalesnik et al. (2020) report much lower pairwise 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 component 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). We define breakpoints for polluting and clean firms at the 70th and 30th percentiles. For each year we form four value-weighted portfolios; Small / Polluting (SP), Big / Polluting (BP), Small / Clean (SC), and Big / Clean (BC). The return on the PMC portfolio is then given by:

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

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 rising demand 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 holds firms with 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.

3.2 Estimating Carbon Betas

To estimate carbon betas – return sensitivities to the PMC factor – we run time-series regressions of the corresponding firm's daily equity returns on the daily PMC factor, while controlling for the Fama and French (1993) three factors and the Carhart (1997) momentum factor. The regression model is

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

specified as:

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

where $R_{i,t}$ is the excess return on stock i on day t, α_i is the stock's risk-adjusted outperformance, β's denote sensitivities to the factors, $RMRF_t$, SMB_t, HML_t, UMD_t, and PMC_t are respectively the daily returns on the market, size, value, momentum, and carbon risk factors, and $\epsilon_{i,t}$ is the residual term. We use a 36-month estimation window for our regressions, which thus contains about 750 daily return observations.[26] In later tests, we cross-sectionally standardise estimates of carbon beta when we compare it to other measures of carbon risk. In all cases, we winsorize estimates at the 2% level to ensure that our results are not overly driven by outliers.

4 Results

4.1 Validation of carbon beta estimates

We start our analysis by validating our estimates of carbon risk in a multitude of ways. Our goal is to make sure 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 are correlated with corporate climate risk.

[26] We have considered several alternative estimation procedures. In unreported robustness checks, we have further included the Fama and French (2015) profitability and investments factors, performed the regression on monthly instead of daily return observations, utilised an industry-neutral carbon risk factor, and considered a carbon risk factor based on carbon intensities. Our validation results remained qualitatively similar.

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.

We also exploit international variation in carbon betas. Next, we perform a firm-level comparison of carbon betas with alternative measures of climate risk, amongst which the Sautner et al. (2021)'s measure constructed from analyst earnings calls and MSCI's Climate-Value-at-Risk measure.

4.1.1 Sector and Headquartered State 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 3a 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 much lower exposure towards climate risks (not reported). Note that in later regression specifications, we often include industry fixed effects, so that we only exploit variation in carbon betas *within* industries, rather than the variation *across* industries reported in Figure 3a. We believe this is a conservative approach, as we control for any unobserved industry effect and are able to circumvent the effect of potential industry biases in the definition of the carbon risk factor.

We estimate a similar regression as in Equation (3) but now turn our analysis to company headquartered states as indicated by Compustat. Figure 3b presents our results. Particularly in Texas, Oklahoma, and New Mexico, we average carbon betas are high. This is likely the result of the large concentration of Oil & Gas firms operating in this region. In California, to the contrary, carbon betas are on average negative. This likely stems from the state's dominant Technology sector. Overall, geographic variation in carbon betas seems to align with common sense, yet seems driven mostly by industry effects. As mentioned previously, we include industry fixed effects in most regressions so as to make sure that these effects do not corroborate our results.

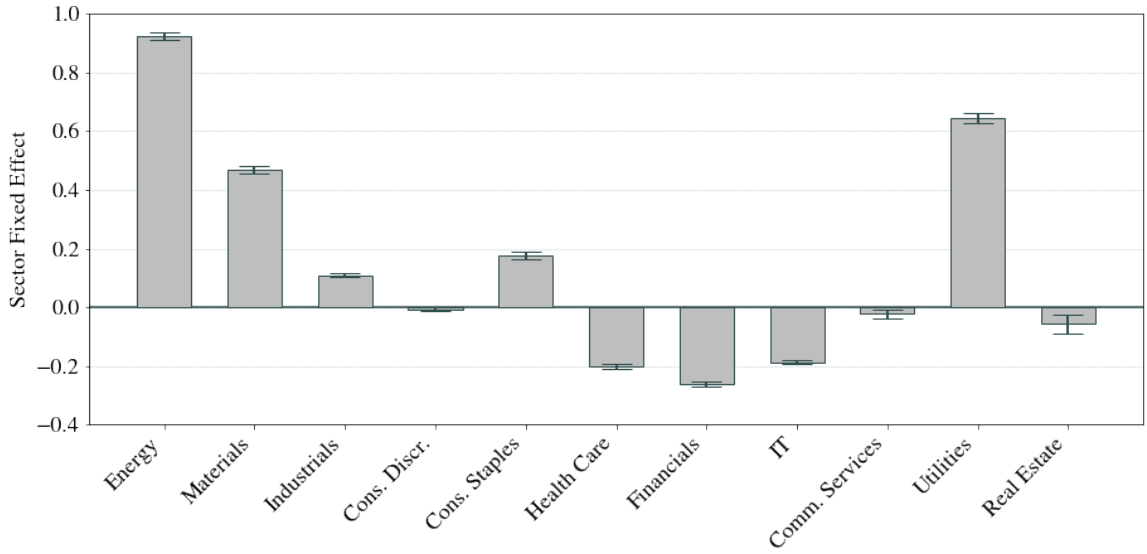
4.1.2 Country Variation in Carbon Beta

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. 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 their U.S. factor equivalents.

Figure 4 shows the coefficients from regressing international carbon betas on their respective country dummies, a similar specification 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 pollutive as a large part of its fossil resources are found in oil sands.

Figure 3: Industry Sector and Geographic Variation in Carbon Beta
The figure displays the coefficients estimated by regressing Carbon Beta on two-digit GICS Industry Sector fixed effects (Panel A) and headquarter state fixed effects (Panel B). The sample period is January 2007 to December 2020. 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) Headquarter State Fixed Effects

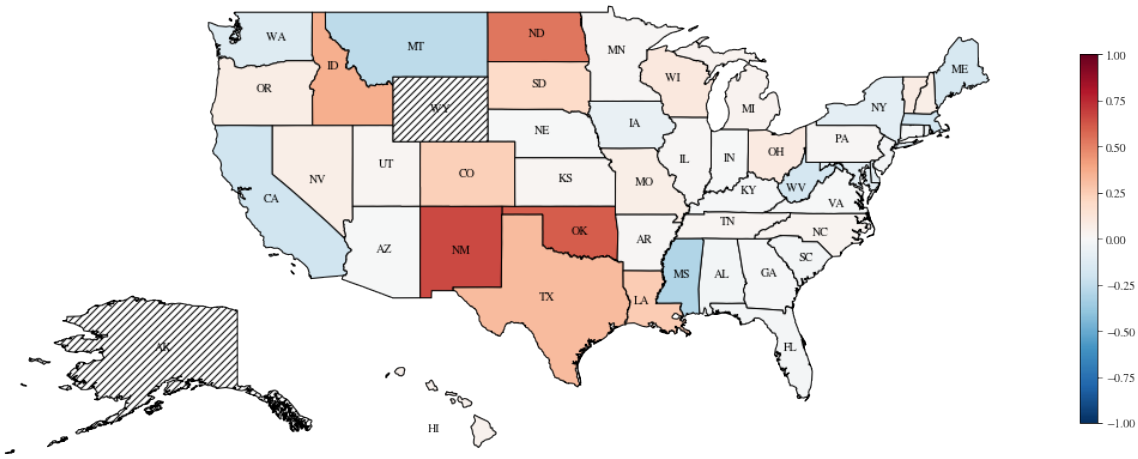
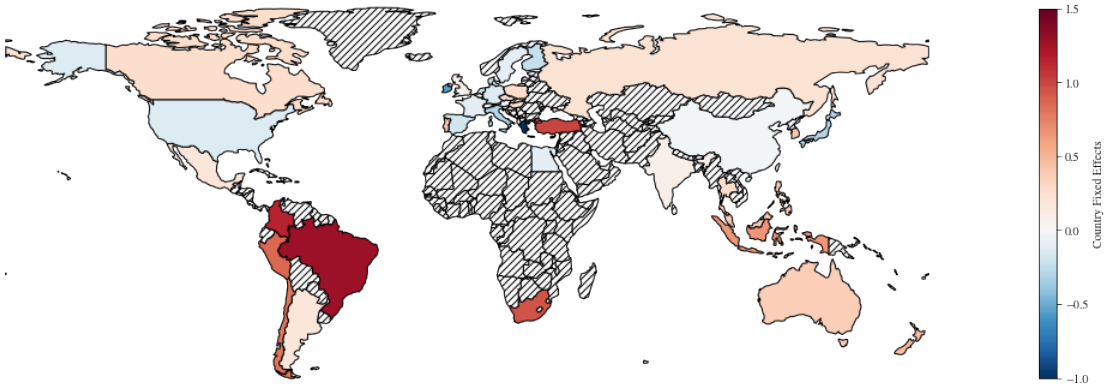


Figure 4: International Variation in Carbon Beta
The figure displays the coefficients estimated by regressing international Carbon Beta on country fixed effects. Returns are based on each countries respective MSCI country index. The sample period is January 2014 to December 2020. Data comes from Refinitiv (formerly Thomson Reuters) Eikon.



4.1.3 Carbon Beta and Firm Characteristics

In this section, we investigate how firm characteristics correlate with corporate climate risk exposure. Firm characteristics are known to affect climate risk exposure, see, for example, Bolton and Kacperczyk (2021a), Hsu et al. (2019), Sautner et al. (2021), and Li et al. (2020). We make a number of predictions based on economic theory and related research. First, we expect larger firms to be better equipped at dealing with transition risks as they are more diversified across operating activities.[27] Larger firms can also exert greater lobbying power, leaving them less exposed to potentially adverse effects of climate regulation. To the contrary, we expect that firms holding more physical assets, are vulnerable to rising of costs of climate regulation via the greenhouse gas emissions and energy requirements of their assets (see Sautner et al. 2021 and Li et al. 2020 for empirical evidence). Many studies report lower firm valuations as a result of higher climate risks exposure (for example, Bolton and Kacperczyk 2021a, Matsumura et al. 2014, and Li et al. 2020). Moreover, it is more difficult for capital-constrained firms to make investments in low-carbon technologies. A reduced ability to adapt leaves these firms with greater transition risk exposure. The opposite holds for firms that actively invest in research & technology. Such firms will either have better low-carbon technologies available, or are better able to capitalise on such technologies as they become available in the future. Indeed, Sautner et al. (2021) find firm-level climate risks to be negatively correlated with R&D expenses relative to assets.

To test our expectations, we estimate via cross-sectional regression:

[27] Bolton and Kacperczyk (2021a), for example, find company size and emission intensity to be negatively correlated.

$$CB_{i,t} = \lambda X_{i,t-1} + c_i + \mu_t + \epsilon_{i,t}, \tag{4}$$

where $CB_{i,t}$ is a firm i's carbon beta at month t, $X_{i,t}$ is a vector of lagged firm characteristics that includes the natural logarithm of the firm's market capitalisation, its book-to-market ratio, return on equity, book leverage, investments-to-assets, PP&E-to-assets, and R&D-to-assets, c_i is an optional sector (two-digit GICS) fixed effect, and μ_t is a year-month fixed effect. We cluster standard errors by firms, as residuals within firms are correlated over time. We optionally include sector fixed effects to control for variation that can be attributed to sector differences. Our model includes time fixed effects so as to exploit the cross-sectional variation in carbon beta estimates and to help mitigate omitted variable bias by controlling for unobserved effects that vary over time but not over firms.

Table 3 reports our estimates. When the regression specification includes sector fixed effects, as in columns (3) and (4), identification only comes from the cross-section of firms active in the same sector. Negative correlates of climate risk exposure are company size (market capitalisation), profitability (return-on-equity), and innovation (R&D-to-assets). For company size, we find a positive coefficient in column (1), yet this specification omits corporate emissions as a control variable and thereby fails to control for the indirect effect of corporate emissions on transition exposure via company size. The positive association also turns negative after we account for industry-specific differences in company size and carbon beta, indicating that within industry sectors, larger firms have lower carbon betas. We find capital intensity (proxied for by investments-to-assets and PP&E-to-assets) and corporate greenhouse gas emissions to be positively associated with carbon beta. The association between emissions and carbon beta is economically sizeable, as a standard deviation increase in the log-transformed emissions variable tends to be associated with a 0.23 to 0.48 standard deviation increase in carbon beta, depending on whether or not sector effects are considered. Our results for book-to-market and book leverage are mixed. Columns (1) and (3) report a positive relationship between the book-to-market ratio and our measure, suggesting that firms exposed to climate risk trade at lower valuations. Yet this does not survive the addition of corporate emissions as a control variable in (2), and therefore merely reflects a tendency of emission-heavy firms to trade at lower valuations. However in specification (4), which controls for industry differences, book-to-market remains to hold explanatory value beyond the effect of corporate emissions. We find a negative association between book leverage and carbon beta in columns (1) and (2), yet it disappears after the inclusion of sector fixed effects in columns (3) and (4), suggesting it can be attributed to general differences in leverage and carbon betas across sectors.

Table 3: Carbon Beta and Firm Characteristics
This table reports the regression coefficients obtained from regressing monthly, firm-level estimates of Carbon Beta on firm characteristics. The regression equation is given by Equation (4). Firm-specific characteristics are derived from Compustat data. Corporate greenhouse gas emissions are obtained from Trucost. 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)
ln(Market Cap.)	0.012**	-0.149***	-0.018***	-0.079***
	(0.006)	(0.013)	(0.005)	(0.012)
Book/Market	0.074***	0.020	0.048***	0.041**
	(0.011)	(0.026)	(0.009)	(0.020)
Return on Equity	-0.175***	-0.154***	-0.081***	-0.051*
	(0.019)	(0.035)	(0.017)	(0.029)
Debt/Assets	-0.315***	-0.384***	-0.010	0.010
	(0.057)	(0.085)	(0.048)	(0.065)
Investment/Assets	0.205**	-0.148	0.466***	0.506***
	(0.088)	(0.154)	(0.072)	(0.116)
Property, Plant, & Equipment/Assets	0.833***	0.658***	0.222***	0.184***
	(0.035)	(0.060)	(0.025)	(0.039)
Research & Development/Assets	-1.945***	-2.157***	-0.954***	-1.538***
	(0.107)	(0.201)	(0.103)	(0.179)
ln(Scope 1 & 2 Emission)†	-	0.501***	-	0.230***
	-	(0.030)	-	(0.028)
Year - Month FE	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes
N.o. Obs.	391,646	151,646	391,646	151,646
R^2-Adj.	0.193	0.427	0.382	0.595

†Indicates a cross-sectionally standardised variable.

4.1.4 Covariation with Alternative Measures of Climate Risk

We now compare carbon betas with alternative firm-level measures of climate risk by pairwise correlation. Here we consider the natural logarithm of firm emissions, emission intensity, the Sautner et al. (2021) measure of corporate Climate Change Exposure (CCE), and MSCI's Climate-Value-at-Risk (CVaR). We standardise all measures of corporate climate risks to enable a better comparison. 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 correlation coefficients of carbon beta with the log of emissions and of carbon beta with emission intensities are close, at 53% respectively 40%. This suggests that while there is different information hiding 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 scores on the forward-oriented CVaR and Sautner et al. (2021) measures 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 firm-level climate risk. We explore the relationship between our measure and CVaR in deeper ways in section 4.3.2.

Table 4: Correlations Between 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)	0.53***	1.00	-	-	-
S1&2 Intensity	0.40***	0.51***	1.00	-	-
Sautner et al. 2021 CCE	0.22***	0.22***	0.45***	1.00	-
MSCI CVaR	0.34***	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 Climate Change Exposures, where we exploit that Sautner et al. (2021)'s measure is decomposed into three components: exposures to regulatory, climate opportunities, and physical risk. This allows us to test which of these three aspects of climate change risks are captured by carbon beta. All CCEs are available for download at `https://osf.io/fd6jq/`. We estimate a similar model as in Equation (4), yet we alternatively include the main CCE, each of its three components, and all three of the components. In our regressions, we standardise the CCEs for reasons of comparability and interpretability. We again cluster standard errors at the firm level to account for serial correlation in our variables. Table 5 reveals that carbon betas are positively related to CCE and all of its three components. A standard deviation increase in CCE tends to be associated with about 22% of a standard deviation increase in carbon beta. We observe effects of similar magnitudes for the subcomponents measuring exposures related to regulatory risks and climate opportunities. Interesting to note is the positive sign on the latter subcomponent's coefficient: this indicates that the firms whose carbon beta is *higher* are also the firms with which analysts more frequently discuss climate change opportunities. This finding might seem counter-intuitive, but could suggest that today's major emitters have an important role to play in enabling low-carbon technologies. Sautner et al. (2021) observe a similar pattern when comparing $CCE_{Opportunities}$ with *ISS Carbon Risk Ratings*. Our results for the component of CCE measuring physical climate risks are somewhat of an exception. Although the coefficient reported in column (4) is statistically significant

at the 1% level, its magnitude is much smaller compared to the coefficients on overall CCE and the other components. The R^2 reported in column (4) also reveals that physical climate change exposure is of no 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, rather much more driven by geographic vulnerabilities. Hence, our approach is unlikely to pick up differences in physical climate risk exposure, and our analysis confirms that carbon betas are 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 the Sautner et al. (2021) Climate Change Exposure defined as the extent to which a company's earnings analyst calls are devoted to discussing 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†	0.222***	-	-	-	-
	(0.012)	-	-	-	-
CCE$_{Regulatory}$†	-	0.163***	-	-	0.113***
	-	(0.010)	-	-	(0.010)
CCE$_{Opportunities}$†	-	-	0.179***	-	0.119***
	-	-	(0.013)	-	(0.011)
CCE$_{Physical}$†	-	-	-	0.050***	0.032***
	-	-	-	(0.007)	(0.006)
N.o. Obs.	312,753	312,753	312,753	183,148	183,148
R^2-Adj.	0.048	0.031	0.026	0.000	0.038

†Indicates a cross-sectionally standardised variable.

4.2 Carbon Beta and Realisations of Climate Risk

In this section we investigate firm return dynamics during times in which climate change risks partly materialise. We evaluate two proxies for materialising climate risk. 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 become more concerned about climate change (Alekseev et al., 2021; Huyhn et al., 2021; Choi et al., 2020; Bansal et al., 2016). Our interest lies specifically in the interaction effect between carbon beta and the proxy for materialising climate on stock returns. That is, we seek to answer the question: How are market responses to materialising climate change different for firms with higher versus lower

carbon beta?

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 (e.g. Baker et al. 2016), we refer to this index as the Climate Policy Uncertainty index.

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:

$$R_{i,t} = \alpha + \beta CB_{i,t-1} + \gamma\, CB_{i,t-1} \times \Delta CPU_t + \theta\, \Delta CPU_t + \lambda X_{i,t-1} + c_i + \mu_t + \epsilon_{i,t}, \tag{5}$$

where $R_{i,t}$ is the excess return on company i's stock in month t, $CB_{i,t-1}$ denotes the stock i's carbon beta at the end of month *t-1*, ΔCPU_t is the standardised percentage change in the Climate Policy Uncertainty index from month *t-1* to month t, $X_{i,t-1}$ is a vector of lagged control variables including company size, book-to-market, return on equity, book leverage, investment-to-assets, PP&E-to-assets and stock i's CAPM beta, idiosyncratic volatility, and 12-month-minus-1-month momentum, c_i is the sector effect, and μ_t is the year-month effect. We are primarily interested in γ, as it tells us the incremental monthly return associated with a one standard deviation higher carbon beta for each standard deviation with which the CPU index increases. We estimate similar regressions models where we replace carbon beta and the interaction term with standardised log-transformed scope 1&2 emissions or standardised emission intensities to compare any potential differences in market responses to shocks in the CPU index.

Table 6 reports our findings. Our results show that in months where the CPU index increases (decreases), stocks with higher carbon betas tend to have lower (higher) returns. This finding is economically sizeable: for two firms that differ only by a one standard deviation difference in carbon beta, the firm with the higher carbon beta will tend to underperform the other firm by 11bps (equivalent to 1.32%-points annualised) for each standard deviation with which the CPU index increases. Interestingly, markets react strikingly asymmetrically to upward versus downward shocks to Climate Policy Uncertainty. Column (2) shows that the interaction effect becomes more negative when conditioning on increases instead of decreases in policy uncertainty. That is, in months where the CPU

index spikes upward, the returns to high carbon beta firms tend to decrease much more than they increase from an equivalently large downward shock. This might suggest that investors respond more firmly to increases in policy uncertainty. It could also suggest that our index does a better job at capturing increases in policy uncertainty than it does at capturing decreases. Such a hypothesis could be plausible given that our index is constructed from news sources, as it could be the case that news are quickly reported around events deemed relevant for climate policy, but that reporting already diminishes even while policy risks have not yet disappeared. Turning to columns (4) and (5), we repeat the analysis for emissions and emissions intensities instead of carbon betas. We do not find any similar effects when interacting innovations in the CPU with companies' emissions or emissions intensities. Our findings seem to suggest that carbon betas are better able to sort stocks according to their climate-change-related risk exposure. The evidence is also consistent with an explanation of carbon betas being able to identify 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. In our first test, we use temperature anomaly observations from the U.S. Climate Reference Network above the 90th percentile of past 30-year observations to classify months in which temperatures are abnormally high. In our second test, we use values of the Palmer Z-Index (Palmer, 1965) below the 10th percentile of past 30-year observations to classify periods of high temperatures and extreme drought. In our sample period, the 10th percentile equates to a Z-Index of just below -2, which according to Palmer (1965) indicates moderate drought conditions. We estimate the model:

$$R_{i,t} = \sigma EW_t + \eta CB_{i,t-1} + \phi EW_t \times CB_{i,t-1} + \lambda X_{i,t-1} + c_i + \mu_t + \epsilon_{i,t}, \tag{6}$$

where $R_{i,t}$ is firm i's excess stock return in month t, EW_t is an extreme weather dummy equalling 1 if the temperature anomaly or drought severity of month t ranks among the 10% most extreme months, $CB_{i,t-1}$ is the carbon beta at the end of month *t-1*, $X_{i,t-1}$ is a vector of lagged control variables including company size, book-to-market, return on equity, book leverage, investment-to-assets, PP&E-to-assets and stock i's CAPM beta, idiosyncratic volatility, and 12-month-minus-1-month momentum, c_i is a sector fixed effect, and μ_t is a time fixed effect. Our coefficient of interest is ϕ, which can be interpreted as the additional return in times of an extreme weather event associated

Table 6: Carbon Beta × Climate Policy Uncertainty and Stock Returns
This table reports the coefficients obtained from estimating regression Equation (5). The sample period is from January 2007 to December 2020. ΔCPU is the monthly percentage change in the Climate Policy Uncertainty index, defined in Section 2.3. The regression additionally includes the firm's natural logarithm of market capitalisation, book-to-market ratio, return on equity, book leverage, investment-to-assets, PP&E-to-assets, CAPM beta, idiosyncratic volatility, and 12-month momentum as control variables. All regressions include sector and year-month fixed effects. 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)*				
		$\Delta CPU \geq 0$	$\Delta CPU < 0$		
	(1)	(2)	(3)	(4)	(5)
Carbon Beta† × ΔCPU†	-0.109***	-0.485***	-0.119*	-	-
	(0.026)	(0.070)	(0.068)	-	-
Carbon Beta†	0.100***	0.460***	0.022	-	-
	(0.037)	(0.073)	(0.074)	-	-
Scope 1 & 2 Intensity† × ΔCPU†	-	-	-	-0.019	-
	-	-	-	(0.018)	-
Scope 1 & 2 Intensity†	-	-	-	-0.090***	-
	-	-	-	(0.026)	-
ln(Scope 1 & 2 Emissions)† × ΔCPU†	-	-	-	-	-0.029
	-	-	-	-	(0.030)
ln(Scope 1 & 2 Emissions)†	-	-	-	-	-0.116**
	-	-	-	-	(0.058)
Controls	Yes	Yes	Yes	Yes	Yes
Year - Month FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
N.o. Obs.	216,740	110,089	106,651	143,442	143,442
R^2-Adj.	0.264	0.283	0.243	0.283	0.283

†Indicates a standardised variable. Firm-level variables are cross-sectionally standardised.

with a one standard deviation increase in carbon beta.

We find that firms with higher carbon betas experience lower returns during abnormally warm months.[28] The results are presented in Panel A of Table 7. We perform the same analysis for two alternative firm-level indicators of carbon risk, namely Scope 1 & 2 emissions intensity and the natural logarithm of Scope 1 & 2 emissions. Both variables exhibit a similar return tendency in extreme temperature months. These results confirm 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. In months with temperature anomalies above the 90th percentile, a standard deviation increase in carbon beta tends to be associated with a 36bps lower monthly excess return, *ceteris paribus*. We find a market response similar in magnitude for the standardised logarithm of total emissions. For standardised emission intensities, the effect is smaller, amounting to an approximately 12bps reduction in return for each standard deviation increase in intensities.

Turning to drought spells, carbon beta is the only proxy that shows a significantly negative interaction effect with returns. 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. This could follow a similar mechanism as in Huyhn et al. (2021), who find that fund managers divest from carbon-intense investments after they experience local air pollution. In our case, carbon beta might partially capture 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 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

4.3.1 Green Innovation

Cohen et al. (2020) report a striking disconnect: firms operating in the Energy sectors are responsible

[28] Generally, the interaction effect becomes stronger (more negative) when increasing the threshold for an 'extreme' temperature event further above the 90th 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). The sample period is from January 2007 to December 2020. *TempAnomaly* is a dummy variable equal to 1 if the associated month's temperature anomaly is above the 90th percentile and 0 otherwise. *Drought* is a dummy variable equal to 1 if the associated month's Palmer Z-Index is below the 10th percentile and 0 otherwise. The regression additionally includes the firm's natural logarithm of market capitalisation, book-to-market ratio, return on equity, book leverage, investment-to-assets, PP&E-to-assets, CAPM beta, idiosyncratic volatility, and 12-month momentum as control variables. All regressions include sector and year-month fixed effects. 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† × Temp Anomaly	-0.359***	-	-
	(0.099)	-	-
Carbon Beta†	0.185***	-	-
	(0.047)	-	-
Scope 1 & 2 Intensity† × Temp Anomaly	-	-0.117*	-
	-	(0.062)	-
Scope 1 & 2 Intensity†	-	-0.075***	-
	-	(0.026)	-
ln(Scope 1 & 2 Emissions)† × Temp anomaly	-	-	-0.311***
	-	-	(0.103)
ln(Scope 1 & 2 Emissions)†	-	-	-0.092
	-	-	(0.059)
Controls	Yes	Yes	Yes
Year - Month FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
N.o. Obs.	143,486	143,486	143,486
R^2-Adj.	0.289	0.289	0.289
Panel B: Returns during drought spells			
Carbon Beta† × Drought	-0.226**	-	-
	(0.099)	-	-
Carbon Beta†	0.167***	-	-
	(0.046)	-	-
Scope 1 & 2 Intensity† × Drought	-	-0.064	-
	-	(0.067)	-
Scope 1 & 2 Intensity†	-	-0.084***	-
	-	(0.027)	-
ln(Scope 1 & 2 Emissions)† × Drought	-	-	0.233**
	-	-	(0.113)
ln(Scope 1 & 2 Emissions)†	-	-	-0.138**
	-	-	(0.059)
Controls	Yes	Yes	Yes
Year - Month FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
N.o. Obs.	143,486	143,486	143,486
R^2-Adj.	0.290	0.290	0.290

†Indicates a cross-sectionally standardised variable.

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 whether firms with higher carbon betas are less active in issuing green patents, we exploit the main measure of green innovation used by Cohen et al. (2020): *Green Share*, determined by the number of patents issued to a company classified as green at time t as a fraction of total patents issued. Specifically, we estimate:

$$S_{i,t} = \sigma GreenShare_{i,t} + \lambda X_{i,t-1} + c_i + \mu_t + \epsilon_{it}, \tag{7}$$

where S_{it} is either firm i's cross-sectionally standardised carbon beta, scope 1 & 2 emissions intensity, or the natural logarithm of total scope 1 & 2 emissions in month t; $X_{i,t-1}$ is a vector of lagged firm characteristics that includes the natural logarithm of the firm's market capitalisation, its book-to-market ratio, return on equity, book leverage, investments-to-assets, PP&E-to-assets, and R&D-to-assets; c_i is an optional sector fixed effect; and μ_t is a time fixed effect.

Table 8 reports our regression results for the specification in Equation (7). In column (1), we regress carbon beta on green innovation and firm-level control variables using our complete sample. In this sample, which includes firms in sectors other than the Energy sector, an economically weak yet statistically significant negative relation is observed between green innovation and carbon beta. That is, firms that are more active in issuing green patents tend to have lower climate risk exposure as indicated by carbon beta. The effects is small however, as a unit (theoretically, the maximum increase possible in green innovation) increase in green innovation is only associated with a reduction of about 8% of a cross-sectional standard deviation in carbon beta. In column (2), we focus our analysis on the Energy sector, where we expect green patenting to be most relevant based on Cohen et al. (2020)'s findings. The negative relationship between carbon beta and green innovation is much more pronounced within the Energy sector. A unit increase in green share is associated with about half a standard deviation reduction in carbon beta. Moving to emission intensity in column (3) and the natural logarithm of emissions as the dependent variable in column (4), we do not find a similar effect for green innovation. Although the coefficient lacks statistical significance, our evidence points toward a positive relationship between total emissions and green innovation, suggesting that emission-heavy firms drive green innovation. Were this indeed the case, this finding could hold important implications for investors, as it suggests that divestment from heavy polluters implicitly

Table 8: Carbon Beta and Green Innovation
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 Bulk Data Storage System. The data are from January 2010 to end of December 2020. 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†	S1&2 Intensity†	ln(S1&2 Emissions)†
Green Share (%)	-0.079*	-0.482**	-0.256	0.050
	(0.044)	(0.208)	(0.336)	(0.259)
ln(Market Cap.)	-0.026***	0.068**	0.119*	0.404***
	(0.007)	(0.034)	(0.064)	(0.037)
Book/Market	0.073***	0.084	-0.171	0.269***
	(0.020)	(0.059)	(0.126)	(0.083)
Return on Equity	-0.075***	-0.147**	0.241	0.024
	(0.023)	(0.067)	(0.253)	(0.114)
Debt/Assets	-0.019	0.002	0.926	1.551**
	(0.066)	(0.357)	(0.748)	(0.729)
Investment/Assets	0.590***	0.382	-3.033	-1.227
	(0.108)	(0.691)	(2.112)	(1.361)
PP&E/Assets	0.306***	0.456***	0.795*	0.281
	(0.041)	(0.156)	(0.448)	(0.193)
R&D/Assets	-1.041***	-9.441***	10.233	-4.809
	(0.136)	(3.540)	(8.719)	(6.475)
Year - Month FE	Yes	Yes	Yes	Yes
Industry FE	Yes	No	No	No
Sectors	All	Energy	Energy	Energy
N.o. Obs.	194,792	8,736	4,695	4,695
R^2-Adj.	0.386	0.340	0.293	0.688

†Indicates a cross-sectionally standardised variable.

also cuts investment in low-carbon innovation.

4.3.2 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. Firm emissions and green patent innovations are the 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 modeled by CVaR that are unrelated to emissions and green innovation. To do so, we estimate:

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

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 by construction, as emissions and green innovation are used in the evaluation of CVaR by MSCI. 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 the information 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)
Carbon beta	0.057***	0.017**
	(0.010)	(0.008)
ln(Emissions)	0.037***	0.032***
	(0.005)	(0.005)
Green Share (%)	-0.343***	-0.323***
	(0.109)	(0.103)
Year - Month FE	Yes	Yes
Industry FE	No	Yes
N.o. Obs.	97,103	97,103
R^2-Adj.	0.245	0.336

4.4 Pricing of Carbon Risk

In this section, we provide preliminary evidence on the pricing of carbon risk exposures as proxied for by carbon beta. We employ a similar specification as in our other return regressions:

$$R_{i,t} = \alpha + \theta CB_{i,t-1} + \lambda X_{i,t-1} + c_i + \mu_t + \epsilon_{i,t}, \tag{9}$$

where $R_{i,t}$ is the excess return on company i's stock in month t, $CB_{i,t-1}$ denotes the stock i's carbon beta at the end of month *t-1*, $X_{i,t-1}$ is a optional vector of lagged control variables including company size, book-to-market, return on equity, book leverage, investment-to-assets, PP&E-to-assets and stock i's CAPM beta, idiosyncratic volatility, and 12-month-minus-1-month momentum, c_i is the sector effect, and μ_t is the year-month effect. We are interested in θ, the carbon risk premium, which can be interpreted as the additional return associated with a one standard deviation increase in carbon beta.

Table 10 reports our results. In column (1), where we do not additionally control for other factors known to affect returns and exclude industry fixed effects, the carbon risk premium shows negative. This suggest that higher carbon beta is associated with lower returns. The inclusion of control variables in column (2) however turns the premium insignificant, suggesting that the negative premium observed in column (1) can be attributed to characteristics that are negatively rewarded over the

sample period and positively correlated with carbon beta, or *vice versa*. The results in column (3) also reveal that the perceived underperformance of high carbon beta firms is primarily an industry effect: firms with high (low) carbon betas tend to operate in sectors that have shown low (high) realised returns over the sample period. Turning the analysis to *within*-sector differences, as the inclusion of industry fixed effects enforces, shows the opposite effect. Controlling for additional factors increases the carbon risk premium slightly more in column (4), where it amounts to about 8.4bps per month, or about 1% per year, for each standard deviation increase in carbon beta. We further find positive return premia, in line with expectations, on book/market, book leverage, CAPM beta, and idiosyncratic volatility. For market capitalisation, we find the opposite of a size effect, perhaps related to our sample period. Surprisingly, for momentum we do not find a positive return premium. However, other papers considering a similar period observe a similar pattern, see, for example Bolton and Kacperczyk (2021a) and Sautner et al. (2021).

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' concerns 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 formed 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 portfolio's returns and the four Carhart (1997) factors, we regard the loadings on PMC as our firm-level measure of climate risk.

Our approach holds several advantages over conventional approaches that assess asset-level climate risks. First, our measure covers a vastly larger number of securities than commercially available alternatives, does not suffer from any selection effects, and is available at virtually no cost. Our framework is not limited to a specific asset class either. The concept is applicable to any asset for which a sufficient return history can be observed. Second, the 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 by regressing carbon beta on firm characteristics, showing that variation in carbon beta aligns with our expectations. For example, larger, innovative, and profitable firms have lower climate risk exposure, while capital intensive and

Table 10: Pricing of Carbon Risks

This table reports the regression coefficients obtained from regressing monthly excess returns on estimates of carbon beta. The sample period is from January 2007 to December 2020. The regression additionally includes the natural logarithm of market capitalisation, book-to-market ratio, return on equity, book leverage, investments-to-assets, PP&E-to-assets, CAPM beta, idiosyncratic volatility, and 12-month momentum as control variables. Regressions contain year-month fixed effects and optionally include sector fixed effects. Standard errors are clustered at the year-month level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable: Monthly excess return (×100)			
	(1)	(2)	(3)	(4)
Carbon Beta	-0.083***	-0.020	0.063*	0.084**
	(0.024)	(0.029)	(0.037)	(0.039)
ln(Market Cap.)	-	0.088***	-	0.104***
	-	(0.017)	-	(0.019)
Book/Market	-	0.279***	-	0.315***
	-	(0.079)	-	(0.080)
Return on Equity	-	0.033	-	0.056
	-	(0.136)	-	(0.138)
Debt/Assets	-	0.765***	-	0.749***
	-	(0.159)	-	(0.161)
Investment/Assets	-	-0.364*	-	-0.441*
	-	(0.205)	-	(0.235)
Property, Plant, & Equipment/Assets	-	-0.237***	-	-0.069
	-	(0.070)	-	(0.076)
CAPM Beta	-	0.086	-	0.159*
	-	(0.071)	-	(0.082)
Idiosyncratic Volatility	-	2.620***	-	2.758***
	-	(0.317)	-	(0.339)
Momentum	-	-0.109	-	-0.123
	-	(0.076)	-	(0.076)
Year - Month FE	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes
N.o. Obs.	216,873	216,873	216,873	216,873
R^2-Adj.	0.233	0.234	0.233	0.234

† Indicates a cross-sectionally standardised variable.

carbon intensive firms have higher climate risk exposure. Our subsequent comparison of carbon beta estimates with alternative (commercial) measures of climate risk at the firm-level reveals robust positive associations. Finally, our concept enables an intuitive distinction between assets that are most *at risk* from a low-carbon transition and assets that are well-posed to benefit from such a shift. We show in related analyses that returns between low- and high carbon beta firms differ markedly in months in which climate shocks materialise. 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.

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 early 2000's, our proxy for the carbon risk factor only covers a limited history. To mitigate this issue, alternative proxies could be considered for a carbon risk factor. 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 climate risk factors could be evaluated, perhaps based on textual information 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.[29] 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. Carbon beta can also be employed as an indicator of 'climate hedge' potential, used for the construction of hedge portfolios with high returns in periods of climate stress. Our methodology might be valuable to academics in assessing the asset pricing implications of climate risk, as our approach yields a cross-sectionally "richer" dataset. Lastly, regulators and policy makers could use carbon beta to identify firms that are highly exposed to carbon risk. Our empirical results indicate that carbon betas capture green innovation, in particular in the emission-intensive Energies sector. As such, regulators and policy makers could use carbon beta as a tool to disentangle 'green innovators' from otherwise pollutive firms.

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

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