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

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We estimate asset-level climate transition risk exposure by regressing stock returns on a pollutive-minus-clean portfolio. This climate risk measure, 'carbon beta', is able to distinguish climate winners from losers through its forward-looking character. Furthermore, it is transparent and has high availability over time and space. Variation in carbon betas correlates with green patent issuance and other forward-looking measures of climate risk. We study the interaction of carbon beta with several proxies for realisations in climate risk in order to judge its hedging ability: 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. We find that exposure to climate transition risk is priced in the cross-section of equity returns. The 'carbon risk premium' amounts to a small but positive return of 1.15% annually for each standard deviation increase in carbon beta.

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

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1 Introduction

In the 2015 Paris Agreement, 196 parties committed to holding global average temperature increases to below 2°C above pre-industrial levels. The agreement explicitly calls on the financial industry in helping to make finance flows *'consistent with a pathway towards low carbon emissions ...'* (p. 3, United Nations, 2015). Investors are becoming increasingly aware of their role in mitigating climate change and the potentially enormous societal and economic consequences of failing to do so. As a result, asset owners and investors representing over $120 trillion in assets have signed up for the UN Principles for Responsible Investment in 2021.[1] 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 (Krueger et al., 2020; Giglio et al., 2020).

Development of scientific methods and metrics to measure climate risk exposure is urgently needed (Krueger et al., 2020; Giglio et al., 2020). One of the main issues in this respect is that green innovation is driven by the firms that belong to the worst performers on environmental issues. Cohen et al. (2020) show that the green innovation is largely driven by the energy sector, measured by both the number and quality of green patents. In addition, De Haas and Popov (2022) show that sectors with the highest carbon intensity also display the steepest subsequent decrease in carbon intensity, especially when and where the equity market development is high. Also, brown firms increase emissions much more in response to increases in cost of capital than green firms do, as shown by Hartzmark and Shue (2023). Corporate emissions, however, are best at identifying 'climate losers' (Sautner et al., 2022), that is, firms that are currently among the heaviest emitters. In this setting, 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), 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, and W&T Offshore, Inc., an independent oil and gas producer, are relatively similar, ranking close to the 80$^{\text{th}}$ percentile in our sample.

We contribute to this discussion by introducing a market-based measure of asset-level climate

[1] See UN PRI Annual Report 2021: `https://www.unpri.org/annual-report-2021/how-we-work/building-our-effectiveness/enhance-our-global-footprint`

risk exposure, determined by the extent to which an asset's price correlates with a carbon risk factor. Following the terminology of the asset pricing literature, we refer to this measure as *carbon beta*. Due to the market-based nature of our measure, carbon betas reflect market participants' expectations regarding an asset's future transition risk exposure. Besides a company's current 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 ability to deal with transition risks and reduce future greenhouse gas emissions. If market prices incorporate expectations about such aspects, then our carbon beta will reflect those too.[2] Coming back to our earlier examples, whereas the carbon emissions were comparable, the average carbon beta of Tesla is among the *bottom* 5%, while that of W&T is in the *top* 5%. Seemingly, investors can hold widely varying expectations of climate risk exposure as measured by carbon beta even for firms with similar emissions output.

Our carbon risk factor is constructed by forming a long-short portfolio. 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 whether a company is *green* or *brown*,[3] but rather that as a group, heavy emitters are more likely to be negatively affected by an accelerated low-carbon transition than light emitters are. Our carbon risk factor 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, controlling for size as in Fama and French (1993). We refer to this portfolio as the Pollutive-Minus-Clean, or *PMC*, portfolio.[4] We 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, the *carbon beta*, as a firm-level indicator of climate transition risk exposure.

Inspired by recent work by Cohen et al. (2020) we explore the relationship between our measure

[2] The distinction between greenhouse gas emissions and carbon betas is akin to the broader distinction in the asset pricing literature between characteristics and the covariance structure of returns as introduced in Daniel and Titman (1997).

[3] 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.

[4] In 5.5% of firm-month observations, firms are in the top (bottom) 30% of emissions whereas they are in the bottom (top) 30% of carbon betas. We have constructed an alternative PMC factor without such contradictory cases, and found a correlation of 99% with the original PMC factor. This confirms that the most and least pollutive firms are indeed captured by taking the portfolios of the top and bottom 30% emitters.

of climate risk and firms' green patents output. Cohen et al. (2020) find that green innovation is largely driven by firms in the Energy sector, yet paradoxically these firms are generally amongst the worst performers on environmental issues. We download all patents issued by the U.S. Patent and Trademark Office (USPTO) from 2010 to 2020 and link their patent classes to green patent classification schemes. Our results indicate a negative and statistically significant association between carbon beta and green innovation, indicating that green innovators are less exposed to climate risk. If we only include Energy firms in the analysis, the effect becomes more pronounced. We do not find similar results when focusing our analysis on carbon intensities or carbon emissions as the indicator of climate risk exposure. These findings suggest that firm differences in green innovation are taken into consideration by market participants and are therefore reflected by carbon betas, illustrating the forward-looking nature of carbon beta. In addition, we find a robust and positive association between carbon beta and MSCI Climate Value-at-Risk, which is purpose built to be forward looking.

The economic mechanism behind the carbon risk factor follows that of the Pástor et al. (2020, 2022)'s model of an ESG factor. If concerns regarding the climate unexpectedly rise, consumer demand will shift from brown products and services to greener ones. Producers of these products and services will benefit accordingly, which increases their valuation. Simultaneously, investors who care about the climate will substitute brown asset holdings for greener alternatives, either because they derive more utility from holding green assets (for example because they are publicly pressured to do so), or because they anticipate stricter environmental policies. Our proxy for the carbon risk factor is intended to capture such shifts in the valuation of brown firms relative to green firms that occur due to changing concerns around climate change. In other words, we expect carbon beta to provide hedging ability against realization of transition risk, and have an unconditional positive risk premium. We empirically test these hypotheses.

Assets with positive carbon betas tend to depreciate in value when investors become more concerned about the climate. On the contrary, negative carbon beta assets tend to appreciate in such times. These assets can be regarded as 'climate hedge' assets because they deliver high returns when climate change concerns increase. We devise several tests to uncover such an effect. To start, we construct an index similar to Engle et al. (2020)'s Climate Change News Index. Our 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 theorise 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 that in the literature on 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 with higher carbon beta have lower returns. A one standard deviation higher carbon beta leads to around a 15 bps reduction in returns, *ceteris paribus*, for each standard deviation increase in climate policy uncertainty. Based on observations that extreme temperature shocks reduce corporate earnings (Addoum et al. 2018; Pankratz et al. 2019) and disproportionably diminish the market values of pollutive firms (Choi et al. 2020), we perform similar analyses using extreme weather events in the United States. We document that during months with abnormally high temperatures, firms with high carbon betas tend to generate significantly lower returns, in both economic and statistical terms. A qualitatively similar pattern is observed in periods of extreme drought, where a one standard deviation higher carbon beta is associated with a 39 bps lower return. These results are consistent with the model of Pástor et al. (2020, 2022), implying that carbon beta is indeed functioning as a measure of climate risk. In other words, the carbon beta approach allows investors to hedge the carbon transition risk in their portfolio since it can single out climate winners next to climate losers.

A natural question that arises, is whether the hedging ability of carbon beta comes at a cost of lower unconditional expected returns, or, in other words, whether climate risk is priced in the cross-section of stock returns. If investors dislike states of the world in which the climate deteriorates, they should demand higher returns for holding high carbon beta assets that underperform in such scenarios. Likewise, they should be willing to accept lower expected returns for climate hedge assets with negative carbon betas, in return for these assets' ability to hedge climate risks. On the contrary, in times of increasing concern about the environment, assets with high carbon betas tend 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. In line with theoretical predictions by Pástor et al. (2020), our asset pricing tests confirm this to be the case. A one standard deviation increase in carbon beta tends to be associated with, ceteris paribus, an increase in annualised return by 1.15%-points.[5]

Apart from being able to distinguish transition winners from transition losers, our approach allows us to calculate carbon betas for any asset for which returns are observed. In our data sample of US equity from 2007 to 2020, we are able to calculate carbon betas for a little under 600,000 firm-month observations. Over the same sample, we have observations for emissions and emission intensities for a little over 200,000 firm-month observations. In addition, our procedure allows the estimation 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. hedge funds for which the holdings data are not publicly available). The estimation procedure is transparent and consistent across assets and asset classes and does not directly rely on the voluntary disclosure of emissions-related information. We demonstrate the flexibility of our methodology by applying it to three different asset classes: (i) U.S. equities as the core focus of our paper, (ii) national equity indices in Appendix B, and (iii) U.S. corporate bonds. Theoretically it is possible to apply our approach to any asset class with a sufficient history of returns observations, but further avenues to apply our concept are left for future research.[6]

Our paper relates to a growing literature on *climate finance*, which studies the interactions between climate change and financial markets. Addoum et al. (2018) examine the effects of extreme temperature shocks on corporate earnings and find that such shocks significantly impact earnings in over 40% of industries. Relatedly, Bansal et al. (2019) estimate stock return sensitivities to long-run temperature shocks and find that temperature-exposed stocks carry a risk premium. Pankratz et al. (2019) establish a causal negative relationship between heat exposure and firms' operating performance, and observe that financial analysts and market participants incorrectly anticipate the effects of heat on company performance. Bortolan et al. (2022) argue that variation in temperatures affects asset prices, and provide empirical evidence to back their claim. Huynh et al. (2021) observe that mutual fund managers divest from pollutive firms after they experience increased local air pollution. Hong et al. (2019) explore the stock prices of food producers and conclude that they do not efficiently reflect long-run drought risks. Engle et al. (2020) construct portfolios to hedge innovations in climate change news. We

[5]Note that whereas the hedging ability is relatively easy to identify, identification of a risk premium requires a long history of data due to the low signal-to-noise ratio in financial markets. Therefore, we interpret the findings of the risk premium with caution.

[6]The PMC index is available through the website of the authors.

adopt their methodology of quantifying climate change news. Choi et al. (2020) study how people update their beliefs about climate change during periods 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. Painter (2020) and Goldsmith-Pinkham et al. (2022) find that physical climate risks are priced in the U.S. municipal bond market. Goldstein et al. (2022) model how ESG investing affects price informativeness. One of the model's implications is that an increasing share of ESG-motivated investors leads to prices that are more reflective of ESG signals and less reflective of firm fundamentals.

Görgen et al. (2020) are 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.[7] Görgen et al. (2020)'s paper is different from ours in several ways. First, Görgen et al. (2020) primarily adopt an asset pricing perspective of the carbon risk factor as a driver of stock returns, while we focus 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. Considering the many variables available to choose from and given that ESG data are notoriously inaccurate (see, for example, Chatterji et al. (2016), Kotsantonis and Serafeim (2019), and Berg et al. (2022)) and costly to obtain, we refrain from making additional assumptions on how firms are exposed to climate risks, other than that such exposure is proxied for by carbon emissions.

Our paper fits into a relatively recent literature that examines forward-looking, firm-level mea-

[7] 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. 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).

sures of climate risk. Sautner et al. (2022) and Li et al. (2020) construct measures of corporate climate risk from textual analysis of earnings call transcripts. Both studies use a similar methodology that quantifies climate risk via the share of the earnings call conversations devoted to climate-related topics. Sautner et al. (2022) go to great lengths to validate their Climate Change Exposure. The measure indicates higher exposure for companies listed in countries with stronger climate regulations. 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 (2021) 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. (2022) 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 more emissions are associated with higher returns, yet only the indirect 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 by Monasterolo and De Angelis (2020) finds 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. (2023) 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 on greenhouse gas emissions. A long-short portfolio sorted on toxic emissions generates a return spread of 5.52% annually. 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. We utilise the Wharton Research Data Services (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.[8] To mitigate survivorship bias resulting from Compustat's data collection procedure (Banz and Breen, 1986), we only include firms after they have appeared in Compustat for two consecutive years.

We proceed by calculating several variables from the combination of fields in CRSP and Compustat. To compute book-to-market ratios, we divide the book value of equity by the market capitalisation at the end of January of the associated year. We divide the following items by total assets: book leverage; capital expenditures; property, plant, & equipment; and research & development expenses, resulting in the accounting ratios debt-to-assets, investment-to-assets, PP&E-to-assets, and R&D-to-assets. We calculate return on equity by dividing net income by total shareholder's equity. All accounting variables are winsorised at the 1% and 99% cutoff points to mitigate the effect of outliers and potential data errors. We calculate momentum by compounding a stock's return over the past 12 months, excluding the most recent month to account for short-term reversal (Jegadeesh, 1990). We utilise daily returns obtained from CRSP's daily security file to estimate CAPM-implied market betas and idiosyncratic return volatilities.

[8] 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.

Estimations are based on rolling windows containing three years of daily return observations. We obtain data on U.S. factor returns from Kenneth French's data library, which we use in the estimation of CAPM-betas, idiosyncratic volatilities, and carbon betas.[9]

Panel A of Table 1 reports descriptive statistics for our stock market data set. After merging CRSP with Compustat and applying our filters, the sample contains a little over 540,000 monthly return observations for over 6,300 unique firms. The average return in excess of the risk-free rate equals 0.83% per month. Moreover, the average (median) firm in our sample has a market capitalisation of about \$5.5 billion (\$495 million). Average book-to-market, book leverage, and investment-to-assets equal 0.77, 0.25, and 0.08, 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 the observations are linked to stocks in the Financial sector, 17% to IT, 15% to both Health Care and Industrials, 13% to Consumer Discretionary, around 5% to each of Energies, Materials, and Consumer Staples, 3% to both 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 private conversations with company representatives. A majority of estimations result from Trucost's proprietary model, which utilises an extensive input-output model that associates business activities with environmental impacts. Trucost reports emissions according to the standards set forth by the Greenhouse Gas Protocol.[10] The Greenhouse Gas Protocol decomposes emissions into three 'scopes'. Scope 1 emissions include the direct emissions occurring in a company's production process. Scope 2 emissions are the indirect emissions associated with the purchase of electricity, heat, or steam. All other emissions taking place in a company's value chain are accounted for

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

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 in our analyses.[11] We sum scope 1 and scope 2 to a combined scope 1 & 2, and calculate emission intensities for the combined and separate scope 1 & 2 emissions by dividing each of the total emissions by 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*. The descriptive statistics of the emissions and intensities are given in Panel B of Table 1.

[11] 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.

Table 1: Descriptive Statistics CRSP - Compustat - Trucost Merged

The table reports descriptive statistics on the variables used in our analysis. *Panel A* reports company and market variables. *Panel B* reports emissions variables. Our sample consists of the intersection between CRSP and S&P Capital IQ Compustat (and S&P Trucost for *Panel B*). The sample period extends from January 2007 to end of December 2020.

				Percentiles						
	N.o. Obs.	Mean	SD	1%	5%	25%	Median	75%	95%	99%
Panel A: Firm-level and market variables										
Excess Return (%)	786,481	0.676	14.712	-39.801	-21.837	-6.243	0.359	6.764	23.540	51.866
Market Cap. (millions)	701,774	5,358	24,972	7	19	132	592	2,545	21,098	88,765
Book/Market*	701,774	0.663	0.678	-0.617	0.034	0.268	0.509	0.856	1.852	4.152
Return on Equity*	788,412	-0.015	0.711	-3.970	-0.934	-0.040	0.073	0.148	0.445	3.209
Debt/Assets*	785,576	0.190	0.208	0.000	0.000	0.006	0.124	0.312	0.603	0.901
Investment/Assets*	783,907	0.041	0.057	0.000	0.000	0.005	0.021	0.052	0.156	0.324
Property, Plant, & Equipment/Assets*	701,774	0.418	0.436	0.000	0.000	0.066	0.268	0.674	1.242	1.936
Research & Development/Assets*	701,774	0.049	0.119	0.000	0.000	0.000	0.000	0.037	0.261	0.672
Carbon Beta	682,022	0.052	0.557	-1.197	-0.777	-0.266	0.013	0.312	1.034	1.830
Idiosyncratic Volatility (%)	765,204	40.823	21.938	11.855	15.195	23.903	35.437	52.546	85.790	110.428
CAPM Beta	765,204	0.976	0.510	-0.127	0.125	0.631	0.976	1.304	1.850	2.303
Momentum	737,261	0.065	0.469	-0.831	-0.621	-0.216	0.031	0.265	0.879	2.033
Panel B: Emission variables										
Scope 1 Emissions (millions tons CO_2)	238,902	1.558	8.921	0.000	0.000	0.003	0.020	0.128	4.692	40.364
Scope 2 Emissions (millions tons CO_2)	238,902	0.276	0.987	0.000	0.000	0.006	0.032	0.136	1.227	4.600
Scope 1 & 2 Emissions (millions tons CO_2)	238,902	1.834	9.298	0.000	0.000	0.011	0.065	0.339	6.091	42.451
Scope 1 Emission Intensity (tons CO_2/$ million)	238,902	161.869	596.842	0.234	0.540	3.716	13.580	30.009	764.240	4303.386
Scope 2 Emission Intensity (tons CO_2/$ million)	238,902	33.099	45.600	0.929	1.127	7.822	17.611	41.608	117.576	285.483
Scope 1 & 2 Emission Intensity (tons CO_2/$ million)	238,902	198.877	623.588	1.731	2.133	13.942	38.246	77.493	893.624	4447.235

*Winsorised at the 2% level.

2.3 Climate Policy Uncertainty Index

We follow Engle et al. (2020) in creating an index for climate news risk. The index levels are determined by the textual similarity of news articles in the Wall Street Journal with a corpus of climate change terms constructed from authoritative sources. We theorise that periods of high climate change news are indicative of increased uncertainty around climate change regulation. Following similarly constructed indices for Economic Policy Uncertainty (see Baker et al. 2016), we refer to this index as the Climate Policy Uncertainty (CPU) index.

The CPU index is constructed as follows. First, we collect documents on climate change. 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. 2022; Li et al. 2020), we extend the climate change corpus with articles in the 'climate change' category on Wikipedia.[12] We assume that the writing in Wikipedia articles is more representative of the language used in newspapers than the writing in official reports on climate change. We refer to the collection of texts from the IPCC reports and the Wikipedia articles as the *climate change corpus*, denoted by $\mathbb{C}_{CC}$. 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 CPU index as follows. We start by applying several text preprocessing steps commonly used in Natural Language Processing.[13] We then perform a term frequency - inverse document frequency (TF-IDF) transformation to convert our collection of text articles into numerical vector form.[14] We apply the same TF-IDF transformation to the climate change corpus $\mathbb{C}_{CC}$ and each day's collection of news article texts $\mathbb{C}_{WSJ,t}$, yielding TF-IDF vectors denoted by $\boldsymbol{v}_{CC}$ and $\boldsymbol{v}_{WSJ,t}$. Finally, for each day we compare $\boldsymbol{v}_{WSJ,t}$ with $\boldsymbol{v}_{CC}$ by cosine similarity.[15] The intuition behind this approach is that when news articles use climate change terms in similar proportions as the texts related to climate change, the index indicates a high level of climate

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

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

[14] The TF-IDF algorithm converts words, in our case bigrams, into scores determined by the word's frequency within a document, penalised by its frequency across documents. Hence, a word occurring often in one document but rarely in other documents receives a high score, as it is regarded as being informative for that certain document.

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

change news risk (Engle et al., 2020)[16]. We lower the frequency of our measure from daily to monthly by taking monthly averages of daily index levels. For ease of interpretability, we scale index values such that the mean of the index equals 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 (COP) was held in Copenhagen. COP15 was one of the first 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. 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 various additional sources. In this section, we briefly describe the datasets used, the data collection procedure, and the purpose of collecting the data.

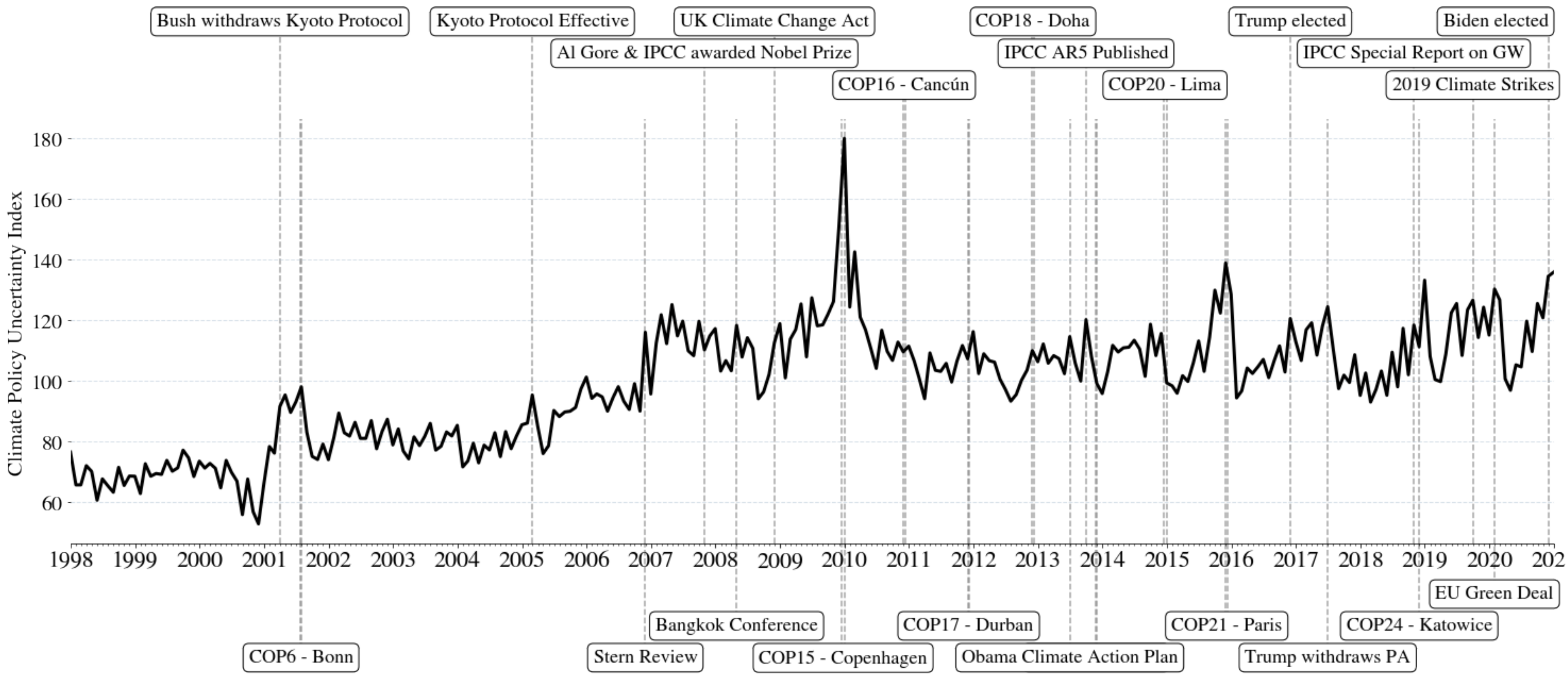
1. Sautner et al. (2022) Firm-Level Climate Change Exposure. We compare our estimates of carbon beta with Sautner et al. (2022) Climate Change Exposures (hereafter SvLVZ CCEs). This measure is determined by the extent to which climate change-related words are used by the company's management and analysts during earnings calls. Besides general Climate Change Exposure, Sautner et al. (2022) determine separate vocabularies for risks, opportunities, and regulations related to climate change.[17] We use the three components, as well as general climate change exposure in our analysis. We cross-sectionally standardise all SvLVZ CCE exposure values to make their scales comparable.

2. Temperature and drought statistics. We collect monthly temperature anomalies for the

[16] The construction of our Climate Policy Uncertainty index closely follows that of the Engle et al. (2020) Climate Change News Index. The difference mainly lies in the composition of our climate change corpus. First, our climate change corpus only includes the 5 Assessment Reports by the IPCC, while Engle et al. (2020)'s CCNI also incorporates various reports from other authoritative sources. Second, our corpus includes all Wikipedia articles on climate change. The correlation (in levels) between the CPU index and CCNI is about 75%.

[17] The data are available at `https://osf.io/fd6jq/`

Figure 1: Climate Policy Uncertainty Index
The figure plots the Wall Street Journal-based Climate Policy Uncertainty (CPU) index over time alongside various events related to climate policy. The CPU index is defined as the textual similarity between daily articles published in the Wall Street Journal and a corpus of documents on climate change.



United States from the U.S. Climate Reference Network.[18] 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.[19] 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 on a monthly frequency. 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 and MSCI Emissions Data. We obtain Climate-Value-at-Risk (CVaR) data from MSCI for about 2,200 firms in our sample. CVaR has been designed to capture firm-specific forward-looking valuation assessments regarding climate risk and opportunities.[20] The measure includes a wide array of information, including - but not limited to - corporate emissions data, green patent issuance, exposure to physical climate risks, green revenues, and modeled outcomes in different policy and technology scenarios. Values for CVaR are bounded by -100 and 100, where -100 (100) indicates that a company is expected to be harmed by (benefit from) climate change. We reverse the sign of CVaR to align it with traditional Value-at-Risk, and cross-sectionally standardise it to enable comparison with other metrics. In additional robustness checks, we base the construction of the PMC portfolio on MSCI's corporate emissions data rather than Trucost's.

4. MSCI Country Indices. For tests on international carbon betas, we download daily returns on 48 national equity indices from Refinitiv (formerly Thomson Reuters) Eikon. All index prices are denominated in U.S. dollars. We collect data from January 2015 to December 2020. We use national equity indices to estimate carbon betas on the country level, which we use for our validation tests in Appendix 5.

5. Green Patents. Following Cohen et al. (2020), we download U.S. patents through the U.S. Patent and Trademark Office's (USPTO) Bulk Data Storage System.[21] The USPTO provides text files for all patents issued in the United States from 1976 onwards. We download patents

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

[19] https://www.ncei.noaa.gov/access/monitoring/historical-palmers/

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

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

granted from 2010 up to and including 2020. We rely on two techniques to link patent issuance to our dataset. First, we download the patent-to-company mapping from the Compustat Link table of WRDS' newly released US Patents (Beta) product.[22] 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.[23] A small difference (less than 1%) in patent coverage is likely the result of retrospective changes in USPTO's data or an occasional error in our or WRDS's retrieval of patent files. Second, we map the stated assignees in patent grants to the company names in our Compustat sample by applying an approximate-string matching algorithm based on a cosine similarity comparison utilised in section 2.3. We only match records if the confidence level exceeds 85%. At this level, manual inspection of matching outcomes yields very few incorrect matches, yet this conservative approach comes with the risk of overlooking valid links. We assume, however, that such valid links are covered by WRDS's linking table. When our 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 first extrapolate the WRDS linking table and otherwise rely on our linking procedure. To check the robustness of our green patent construction procedure, we also download information on green patent shares from MSCI.

To identify green patent issuance, we follow guidelines by the OECD as described by 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.[24] In our analyses, we 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 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 the total number of green patents, are IBM, Ford, General Electric, Intel, Apple, and Raytheon.

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

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

[24] 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 carbon risk. The PMC portfolio captures differences in the returns to a portfolio of polluting firms relative to the returns to a portfolio of cleaner firms. The working of our carbon risk factor follows the mechanism of the Pástor et al. (2020, 2022) 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 occurs for clean companies. The second channel involves investors' preferences. Investors derive more utility from sustainable investments in times of climate stress, either because they 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. Their findings are 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 Pástor and Veronesi (2013) for political risk in general). Selling pressure and increased 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 in response to a climate shock. The opposite occurs when concerns regarding climate change unexpectedly lessen so that the return on the PMC portfolio becomes positive.

We similarly construct the PMC portfolio as the Fama and French (1993) HML portfolio. PMC is a self-financing portfolio that 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 & 2 emissions, which include both estimated and reported emissions. We do not consider scope 3 emissions for several reasons. First, our data only includes downstream scope 3 emissions, which measures the 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 companies. Second, scope 3 emissions data are by definition estimated rather than reported. There are considerable complexities in accurately modeling 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. (2022), and Kalesnik et al. (2022) report much lower pairwise correlations for scope 3 emissions than for scope 1 & 2 emissions. Third, because scope 3 emissions are double-counted for firms active in the same value chains (see Kalesnik et al. 2022), 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 70^{th} and 30^{th} 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 PMC 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 PMC factor on day 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 on day t. Figure 2 displays the cumulative log return on the PMC portfolio.

The mean return on PMC has been substantially negative over the 2007 to 2021 period. Returns to the PMC portfolio are significantly lower in months where climate policy uncertainty increases and in months that have abnormally high temperatures, as Panel B of Figure 2 shows. Table 2 compares the PMC factor to the Fama and French (1993) factors and the Carhart (1997) momentum factor.

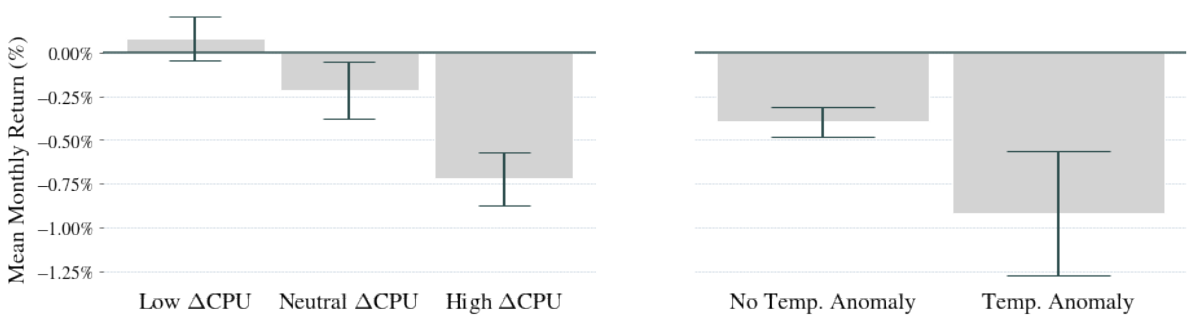
Returns to the PMC portfolio are negatively correlated with the market factor, indicating that the pollutive leg on average holds firms with lower systematic risk. The PMC portfolio correlates positively with value. This is expected, as the most pollutive firms tend to be value firms, while

[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.

Figure 2: Performance of the PMC Portfolio
The figure in (a) 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 described in Section 3.1. The figure in (b) plots the performance of the PMC portfolio conditional on two proxies for materialising climate risks: Terciles of month-to-month changes in the Climate Policy Uncertainty index introduced in Section 2.3 and the 10% of months with the highest temperature deviations from long-term averages (see Section 2.4).

(A) Performance of the PMC Portfolio

(B) Performance of the PMC Portfolio Conditional on Materialising Climate Risks



cleaner firms tend to be growth firms. The procedure we follow to ensure size neutrality seems to work, as indicated by the insignificant association between the carbon risk and size factors. To verify the robustness of some of our portfolio construction choices, we alternatively construct PMC portfolios on other sorting variables besides Trucost's reported and estimated emissions. Figures A1 and A2 and Table A4 in Appendix A report evidence that portfolios constructed by (i) using only reported emissions; (ii) using only estimated emissions; (iii) using emissions intensities; and (iv) using emissions provided by MSCI yield relatively similar portfolio returns.

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

3.2 Estimating Carbon Betas

To estimate carbon betas – i.e. return sensitivities to the PMC factor – we run time-series regressions of the corresponding firm's daily stock returns on PMC while controlling for the Fama and French (1993) market, size, and, value factors and the Carhart (1997) momentum factor. We estimate:

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

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. Our interest lies in β_i^{PMC}, which denotes the stock i's carbon beta. We use a 36-month estimation window, which thus contains about 750 daily return observations.[26] In later tests, we cross-sectionally standardise estimates of carbon beta when comparing them to other measures of carbon risk. In all cases, we winsorise estimates at the 1% and 99% levels to mitigate the impact of outliers.[27]

[26] Besides considering several alternative carbon risk factor definitions (as shown in Figure A1 and Table A4 in Appendix A), 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 remain qualitatively similar.

[27] Our results are virtually unaffected by omitting to winsorise and by increasing the extent of winsorisation to 2% and 98% cutoff points.

4 Results

4.1 Summary of validation exercises

To verify that our estimates of climate risk exposure align with expectations, are not overly governed by industry effects, or are driven by spurious correlations, we subject firm-level estimates of carbon betas to a battery of validation tests. The goal of these exercises 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 exposures. We first compare carbon betas across industry sectors.

Figure 3: Industry Sector 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 are estimated with the specification in Equation (12). The 95% confidence intervals are based on robust standard errors adjusted for clustering at the firm level.

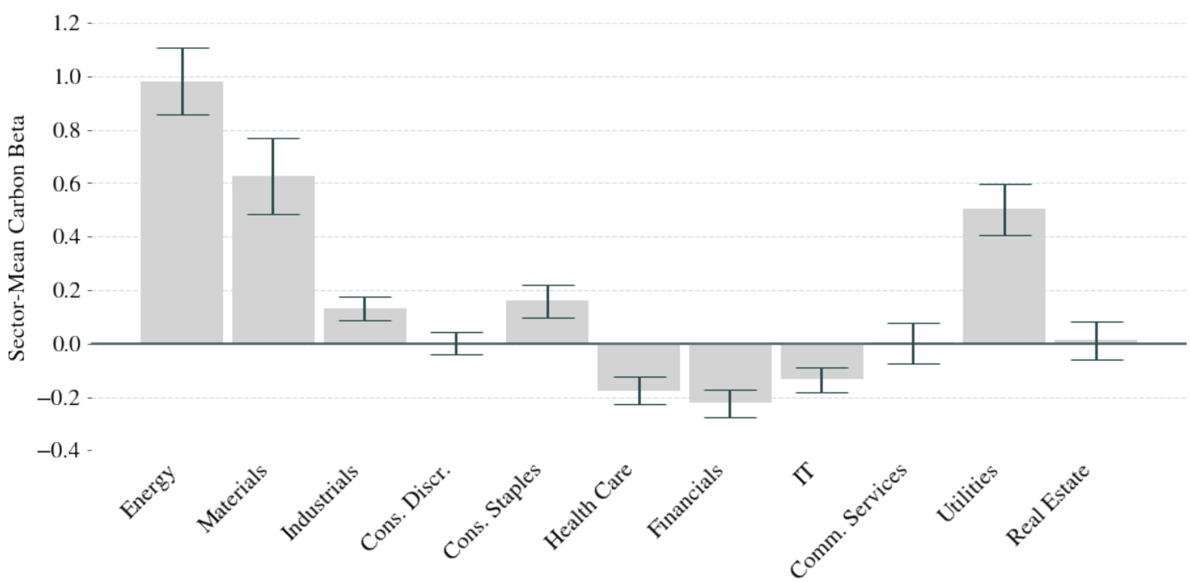


Figure 3 shows that we find the highest carbon betas in the Energy, Materials, and Utilities sectors. These sectors are collectively responsible for over 70% of scope 1 & 2 emissions in our sample, so their high loadings on the carbon risk factor are expected. On the contrary, we observe that firms in the IT, Financial, and Health Care sectors tend to exhibit the lowest average carbon betas. The negative carbon betas of the stocks in these industries indicate a tendency for high stock returns in times of increasing climate concerns. Continuing our validation tests, we investigate how firm characteristics correlate with estimates of 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 largely turn out to be true.

Then, we investigate how firm characteristics correlate with corporate climate risk exposure. Firm characteristics are known to be related to climate risk exposure, see, for example, Bolton and Kacperczyk (2021a), Hsu et al. (2023), Sautner et al. (2022), and Li et al. (2020). We make several 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. Larger firms can also exert greater lobbying power, leaving them less exposed to potentially adverse effects of climate regulation. On the contrary, we expect that firms holding more physical assets are vulnerable to rising costs of climate regulation via the greenhouse gas emissions and energy requirements of their assets (see Sautner et al. 2022 and Li et al. 2020 for empirical evidence). Many studies report lower firm valuations as a result of higher climate risk 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 at greater transition risk. The opposite holds for firms that actively invest in research & development. 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. (2022) find firm-level climate risks to be negatively correlated with R&D expenses relative to assets. To test our expectations, we estimate via panel regression:

$$CB_{i,t} = \lambda X_{i,t-1} + c_i + \mu_t + \epsilon_{i,t}, \tag{3}$$

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.

Table 3 reports our estimates. 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 0.22 to 0.50 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

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 (3). 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.)	-0.023***	-0.197***	-0.052***	-0.127***
	(0.005)	(0.012)	(0.004)	(0.011)
Book/Market	0.124***	0.100***	0.078***	0.051*
	(0.014)	(0.033)	(0.013)	(0.027)
Return on Equity	-0.013	-0.024*	-0.012*	-0.012
	(0.009)	(0.013)	(0.007)	(0.011)
Debt/Assets	0.368***	0.310***	0.164***	0.166***
	(0.044)	(0.067)	(0.035)	(0.053)
Investment/Assets	2.944***	3.138***	1.136***	1.100***
	(0.237)	(0.493)	(0.169)	(0.289)
Property, Plant, & Equipment/Assets	0.740***	0.524***	0.183***	0.151***
	(0.032)	(0.058)	(0.025)	(0.040)
Research & Development/Assets	-0.886***	-1.244***	-0.526***	-1.171***
	(0.076)	(0.144)	(0.077)	(0.147)
ln(Emissions)†	-	0.510***	-	0.266***
	-	(0.025)	-	(0.025)
Year - Month FE	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes
N.o. Obs.	595,293	200,917	595,202	200,917
R^2-Adj.	0.243	0.472	0.421	0.608

†Indicates a cross-sectionally standardised variable.

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 only be attributed to general differences in leverage and carbon betas across sectors. All in all, our results are in line with the hypotheses derived from the existing literature.

Next, we turn to comparisons of carbon beta with alternative measures of climate risk. Correlation Table 4 reveals robust associations with emissions, emission intensities, Sautner et al. (2022) Climate Change Exposures, MSCI Climate-Values-at-Risk, and MSCI Green Scores. These associations go in a direction that is *ex-ante* in line with expectations. Appendix B describes our validation tests in greater detail and provides additional validation efforts.

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. SvLVZ CCE is the Sautner et al. 2022 Climate Change Exposure measure. 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(Emissions)	Emissions Intensity	SvLVZ CCE	CVaR
Carbon Beta	1.00	-	-	-	-
ln(Emissions)	0.49^{***}	1.00	-	-	-
Emissions Intensity	0.34^{***}	0.48^{***}	1.00	-	-
SvLVZ CCE	0.19^{***}	0.24^{***}	0.50^{***}	1.00	-
CVaR	0.36^{***}	0.44^{***}	0.41^{***}	-0.03	1.00

4.2 Capturing forward-looking aspects of carbon risks

4.2.1 Green Innovation

Cohen et al. (2020) report a striking disconnect: firms operating in the Energy sectors are responsible for a large share of greenhouse gasses and are amongst the worst performers on environmental issues, yet they are the most active in patenting low-carbon technologies. As ‘green innovators’ are likely to be less exposed to climate-related risks and might even benefit from a low-carbon transition, we expect carbon beta to partially pick up differences in green innovation output. Especially in the Energy sector, we expect this result to appear, as here the ‘ESG-innovation disconnect’ is most pronounced. To test whether active issuers of green patents have lower carbon beta, we exploit the main measure of green innovation used by Cohen et al. (2020): *Green Share*, determined by the number of green patents granted to a company at time t as a fraction of total patents granted to that company. Specifically, we estimate:

$$S_{i,t} = \sigma GreenShare_{i,t} + \lambda X_{i,t-1} + c_i + \mu_t + \epsilon_{it}, \tag{4}$$

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 5 reports our estimates for the specification in Equation (4).

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 small yet statistically significant negative relationship 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 effect 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 7% 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 important 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 0.3 of 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. As a robustness check, we repeat the analysis using MSCI Green Patent Share as the measure of green innovation. Table A3 in Appendix A presents the results. Here, the coefficient on green innovation for all sectors is not significant at the 10% level. When focusing

Table 5: Carbon Beta and Green Innovation
This table reports the coefficients obtained from estimating regression Equation (4). Green Share (%) is the measure of green patent innovation from Cohen et al. (2020). We collect data on U.S. patents issuance from the U.S. Patent and Trademark Office's Bulk Data Storage System. The data are from December 2010 to 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†	Emissions Intensity†	ln(Emissions)†
Green Share (%)	-0.071*	-0.344**	-0.161	0.297
	(0.041)	(0.148)	(0.274)	(0.264)
ln(Market Cap.)	-0.044***	0.006	0.086**	0.413***
	(0.006)	(0.028)	(0.039)	(0.028)
Book/Market	0.109***	0.065	0.158	0.200***
	(0.027)	(0.082)	(0.122)	(0.076)
Return on Equity	-0.003	0.009	-0.032	0.002
	(0.010)	(0.050)	(0.050)	(0.037)
Debt/Assets	0.187***	0.708**	0.600	0.688**
	(0.054)	(0.302)	(0.475)	(0.276)
Investment/Assets	0.078	1.263	-1.639*	-1.161**
	(0.330)	(0.849)	(0.869)	(0.497)
Property, Plant, & Equipment/Assets	0.380***	0.636***	0.509***	0.246***
	(0.045)	(0.141)	(0.147)	(0.092)
Research & Development/Assets	-0.686***	-1.712*	-4.136	-6.527
	(0.104)	(1.043)	(6.582)	(6.580)
Year-Month	Yes	Yes	Yes	Yes
Industry FE	Yes	No	No	No
Sectors	All	Energy	Energy	Energy
N.o. Obs.	223,659	12,660	6,859	6,859
R^2-Adj.	0.432	0.342	0.136	0.726

†Indicates a cross-sectionally standardised variable.

the analysis only on the Energy sector, we do however find the same pattern. That is, within the energy sector, firms that are more active in patenting green technologies have lower carbon betas yet are not significantly different in terms of emissions or emission intensities. Coupled with Cohen et al. (2020)'s observation that much of green innovation is driven by the Energy sector, our findings hold important implications for investors. Our results suggest that divestment from the Energy sector also cuts funding to green innovators, while a divestment strategy that targets high-carbon beta firms operating in the Energy sector still allocates to those firms most productive in researching low-carbon innovation.

4.2.2 Unobserved Factors of Forward-Looking Climate Risk

Climate-Value-at-Risk (CVaR) is a measure developed by MSCI that incorporates forward-looking and corporate valuation assessments of the impact of climate change and related policies on asset prices. MSCI includes a wide variety of aspects in the estimation of CVaR. Firm emissions and green patent innovations are its main determinants. The measure also incorporates various proxies for physical climate risks, transition scenario analyses, low-carbon revenues, and abatement policies. The objective of our analysis is to investigate whether or not carbon betas correlate with forward-looking aspects of carbon risk as modeled by CVaR. We are specifically interested in the components of CVaR unrelated to emissions and green innovation. To achieve this objective, we estimate:

$$CVaR_{it} = \alpha + \sigma GreenShare_{it} + \lambda ln(Emissions)_{it} + \gamma CB_{it} + c_i + \mu_t + \epsilon_{it}, \tag{5}$$

where $CVaR_{it}$ is MSCI's Climate-Value-at-Risk; $GreenShare_{it}$ is a firm's share of green patents relative to 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. Note that we make use of the information provided by MSCI rather than our manually collected data on green innovation. We do so because the measure of green innovation provided by MSCI is used as one of the inputs to the estimation of CVaR, and thus is most suited for orthogonalising CVaR to green innovation.

Regression estimates are presented in Table 6.

The specification in column (1) does not include sector-fixed effects while the specification in

Table 6: Carbon Beta and Unobserved Climate Risk Factors
This table reports the coefficients obtained from estimating regression Equation (5). 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†	0.209***	0.077***
	(0.030)	(0.028)
MSCI S1&2 Emissions†	0.353***	0.281***
	(0.032)	(0.038)
MSCI Green Patent Share†	-0.191***	-0.191***
	(0.073)	(0.070)
Year - Month FE	Yes	Yes
Industry FE	No	Yes
N.o. Obs	167,055	167,055
R^2	0.261	0.317

†Indicates a sectionally standardised variable.

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 association between components of CVaR unrelated to emissions characteristics and green innovation and between carbon beta. Even while controlling for industry effects, the coefficient on carbon beta remains statistically significant, indicating that the information captured by carbon beta does not only vary at the industry level and must thus partly be firm-specific. As column (2) in Table 6 reports, increasing carbon beta by one standard deviation, while keeping emissions, green innovation, and industry membership constant, is associated with about a 7.7% standard deviation increase in CVaR. This indicates that carbon beta correlates with factors included in CVaR other than emissions and green innovation, for example, exposure to low-carbon technologies, exposure to carbon abatement policies, or green revenues.

4.3 Carbon Beta and Hedging of Climate Risk

In this section, we investigate equity return dynamics during times in which climate change risks materialise. We evaluate two proxies for aggregate climate risk realization. First, we consider shocks to an index that captures how frequently climate change is reported in the news, where we assume such shocks coincide with uncertainty regarding future climate policies. Second, we consider extreme weather events in the contiguous United States. Research shows that during extreme weather events, investors become more concerned about climate change (Alekseev et al., 2022; Huynh 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 risk on stock returns. Specifically, we seek to answer the question of how market responses to materialising climate risks are different for firms with high versus low carbon betas.

To answer this question, we adopt the framework of Daniel and Titman (1997) and Bolton and Kacperczyk (2021a,b). We utilise specifications of the form:

$$R_{i,t} = \beta CB_{i,t-1} + \lambda X_{i,t-1} + c_i + \mu_t + \epsilon_{i,t}, \tag{6}$$

where $R_{i,t}$ is firm i's excess stock return in month t, $CB_{i,t-1}$ is the carbon beta at the end of month *t-1*, $X_{i,t-1}$ is a vector of lagged control variables including the natural logarithm of firm i's market capitalisation, its book-to-market, return on equity, book leverage, investment-to-assets, PP&E-to-assets, and stock i's CAPM beta, idiosyncratic volatility, and momentum, c_i is a sector fixed effect, and μ_t is a time fixed effect. Alternatively, we replace $CB_{i,t-1}$ with other measures of climate risk, in which case we cross-sectionally standardise both measures to enable comparison. We include industry sector and time-fixed effects to mitigate possible bias resulting from unobserved effects that vary across sectors respectively in time. Robust standard errors are clustered at the firm level to adjust for possible serial correlation of residuals within firms.

4.3.1 Carbon Beta and Climate Policy Uncertainty

As a first proxy for realisations in climate risks, we utilise the Climate Policy Uncertainty index. We study the effects of innovations in the CPU index and its interaction with carbon beta on stock returns. Our specification is the following variation on Equation (6):

$$R_{i,t} = \beta CB_{i,t-1} + \gamma\, CB_{i,t-1} \times \Delta CPU_t + \lambda X_{i,t-1} + c_i + \mu_t + \epsilon_{i,t}, \tag{7}$$

where $R_{i,t}$ is the excess return on the 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 CPU index from month *t-1* to month t, $X_{i,t-1}$ is a vector of lagged control variables including the natural logarithm of firm i's market capitalisation, its book-to-market, return on equity, book leverage, investment-to-assets, PP&E-to-assets, and stock i's CAPM beta, idiosyncratic volatility, and momentum, c_i is a sector effect, and μ_t is a year-month effect. The regression does not include a main effect for ΔCPU_t, as it is subsumed by the year-month fixed effect. We are primarily interested in γ, as it signifies the incremental monthly return associated with a one standard deviation increase in carbon beta for each standard deviation with which the CPU index increases. We estimate similar regression models where we replace carbon beta and its interaction term with standardised log-transformed scope 1&2 emissions or standardised emission intensities to uncover any potential differences in market responses to CPU shocks. Table 7 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 15 bps (equivalent to 1.80% annualised) for each standard deviation with which the CPU index increases. To provide a more precise comparison with emissions intensities and emissions, column (2) reports regression estimates for the subsample of observations that have available emissions data. Within this smaller subsample, the coefficient roughly halves, but the effect remains economically meaningful and statistically significant at the 1% level. Turning to column (3), we repeat the analysis for emissions and emissions intensities instead of carbon betas. We do not find a similar effect when interacting innovations in the CPU with companies' emissions intensities. Column (4), on the contrary, does reveal a similar pattern for emissions. The effect however is subsumed by the inclusion of the carbon beta interaction in column (5), in which the interaction effect of carbon beta remains statistically significant. Our findings suggest that carbon betas are able to sort stocks according to their exposure to climate policy uncertainty. The evidence is

Table 7: Carbon Beta, Climate Policy Uncertainty, and Stock Returns
This table reports the full set of coefficients obtained from estimating Equation (7). The sample period is from January 2007 to December 2020. ΔCPU is the monthly percentage change in the Climate Policy Uncertainty index, as defined in Section 2.3. 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)*				
	(1)	(2)	(3)	(4)	(5)
Carbon Beta† × ΔCPU†	-0.150***	-0.072***	-	-	-0.058*
	(0.019)	(0.025)	-	-	(0.029)
Carbon Beta†	0.037	0.045	-	-	0.014
	(0.028)	(0.047)	-	-	(0.047)
Emissions Intensity† × ΔCPU†	-	-	-0.026	-	0.012
	-	-	(0.018)	-	(0.022)
Emissions Intensity†	-	-	-0.052*	-	-0.112***
	-	-	(0.031)	-	(0.038)
ln(Emissions)† × ΔCPU†	-	-	-	-0.064**	-0.040
	-	-	-	(0.028)	(0.037)
ln(Emissions)†	-	-	-	0.181**	0.245***
	-	-	-	(0.081)	(0.092)
ln(Market Cap.)	-0.014	0.062***	0.064***	-0.003	-0.019
	(0.013)	(0.023)	(0.023)	(0.035)	(0.038)
Book/Market	0.130***	-0.175	-0.161	-0.239*	-0.253**
	(0.046)	(0.120)	(0.119)	(0.126)	(0.127)
Return on Equity	0.143***	0.109	0.109	0.100	0.096
	(0.042)	(0.076)	(0.076)	(0.076)	(0.076)
Debt/Assets	0.149	0.291	0.314	0.219	0.193
	(0.111)	(0.202)	(0.203)	(0.201)	(0.201)
Investment/Assets	-1.645***	-1.139	-1.145	-0.888	-0.942
	(0.596)	(1.217)	(1.206)	(1.211)	(1.202)
Property, Plant, & Equipment/Assets	0.075	-0.145	-0.108	-0.242*	-0.237*
	(0.073)	(0.133)	(0.135)	(0.138)	(0.138)
CAPM Beta	0.153***	-0.481***	-0.491***	-0.494***	-0.495***
	(0.044)	(0.111)	(0.109)	(0.109)	(0.112)
Idio. Volatility	-1.520***	3.918***	3.930***	3.905***	3.951***
	(0.189)	(0.540)	(0.538)	(0.539)	(0.537)
Momentum	0.296***	-0.086	-0.088	-0.091	-0.093
	(0.054)	(0.112)	(0.112)	(0.112)	(0.112)
Year - Month FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
N.o. Obs.	593,367	200,309	200,309	200,309	200,309
R^2-Adj.	0.175	0.253	0.253	0.253	0.253

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

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, to the extent that such realisations are reflected by our CPU index.

4.3.2 Stock Returns and Extreme Weather Events

Bansal et al. (2016) and Choi et al. (2020) theorise and empirically validate that pollutive firms tend to exhibit poorer returns during 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 90^{th} percentile of past 30-year observations to classify months in which temperatures are abnormally high. Our second test focuses on drought events. We utilise values of the Palmer Z-Index (Palmer, 1965) below the 10^{th} percentile of past 30-year observations to classify periods of extreme drought. The 10^{th} percentile equates to a Z-Index of just below -2 in our sample, which according to Palmer (1965) indicates moderate drought conditions. We estimate the model:

$$R_{i,t} = \beta CB_{i,t-1} + \phi EW_t \times CB_{i,t-1} + \lambda X_{i,t-1} + c_i + \mu_t + \epsilon_{i,t}, \tag{8}$$

where $R_{i,t}$ is firm i's excess stock return in month t, EW_t is an extreme weather dummy equal to 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 the natural logarithm of firms i's market capitalisation, 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 year-month fixed effect. Our coefficient of interest is ϕ, which can be interpreted as the additional return associated with a one standard deviation increase in carbon beta, ceteris paribus, in times of an extreme weather event. The regression does not include a main effect for EW_t is it is subsumed by the year-month fixed effect μ_t.[28]

[28] Note that the EW dummy is subsetted by t only, and not by i, meaning that our identification relies on shocks to aggregated temperatures and droughts for the (contiguous) United States. Such shocks could affect shareholders' perception of climate change, and thus could lead to a reallocation of their investment portfolios. As an alternative empirical strategy, we could utilise local variation in extreme weather events (that is, an $EW_{i,t}$ dummy). We however do not opt for this approach, for two reasons. First, it is not trivial to clearly identify where a firms' shareholders are located. Second, we want to minimise the possibility that our results are driven by changes to firms' fundamentals induced by the extreme weather shock. Our approach mitigates this issue since firm fundamentals are stronger influenced by local shocks than by US-wide shocks.

We find that firms with higher carbon betas experience lower returns during abnormally warm months. The results are presented in Table 8. We repeat the analysis for two alternative firm-level indicators of carbon risk: Scope 1 & 2 emissions intensity and the natural logarithm of Scope 1 & 2 emissions. These variables do not show a similar pattern in extreme temperature months. In months with temperature anomalies above the 90^{th} percentile, a standard deviation increase in carbon beta tends to be associated with about a 33 bps lower monthly excess return. In Table 9, we turn our attention to drought spells. Again, we find that carbon beta is the only proxy that shows a significantly negative interaction effect with equity returns.

These findings can be explained in several ways. For one, investors might regard extreme weather events as realisations of climate risk, and therefore buy stocks that they deem a 'hedge' against such risk. Here, negative carbon betas proxy for such hedging potential. Second, 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 to a changing climate. This could follow a similar mechanism as in Huynh 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. A potential third explanation is that extreme weather directly affects the earnings of high carbon beta companies more so than the earnings of lower carbon beta companies. In all three cases, however, climate beta functions as an indicator for which firms suffer most from such adverse climate events. Carbon beta is consistently better at providing this hedging ability than both emissions and intensities.

4.4 Pricing of Carbon Risk

In this section, we provide evidence on the asset-pricing implications of climate transition 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 the 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 an optional vector of lagged control variables

Table 8: Carbon Beta, Extreme Temperature, and Stock Returns
This table reports the full set of coefficients obtained from estimating regression Equation (8). The sample period is from January 2007 to December 2020. *Temp.Anomaly* is a dummy variable equal to 1 if the associated month's temperature anomaly is above the 90^{th} percentile and 0 otherwise. 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 excess return* ($\times$100)				
	(1)	(2)	(3)	(4)	(5)
Carbon Beta† × Temp. Anomaly	-0.330***	-0.315***	-	-	-0.352***
	(0.070)	(0.098)	-	-	(0.114)
Carbon Beta†	0.069**	0.083*	-	-	0.057
	(0.028)	(0.048)	-	-	(0.049)
Emissions Intensity† × Temp. Anomaly	-	-	-0.052	-	0.062
	-	-	(0.067)	-	(0.073)
Emissions Intensity†	-	-	-0.045	-	-0.119***
	-	-	(0.029)	-	(0.037)
ln(Emissions)† × Temp. Anomaly	-	-	-	-0.105	0.046
	-	-	-	(0.085)	(0.106)
ln(Emissions)†	-	-	-	0.192**	0.236**
	-	-	-	(0.081)	(0.093)
ln(Market Cap.)	-0.013	0.064***	0.065***	-0.001	-0.017
	(0.013)	(0.023)	(0.023)	(0.035)	(0.038)
Book/Market	0.132***	-0.169	-0.161	-0.238*	-0.245*
	(0.046)	(0.120)	(0.119)	(0.126)	(0.127)
Return on Equity	0.143***	0.109	0.109	0.100	0.097
	(0.042)	(0.076)	(0.076)	(0.076)	(0.076)
Debt/Assets	0.154	0.296	0.314	0.222	0.198
	(0.111)	(0.202)	(0.203)	(0.201)	(0.201)
Investment/Assets	-1.682***	-1.152	-1.140	-0.877	-0.967
	(0.596)	(1.217)	(1.208)	(1.213)	(1.203)
Property, Plant, & Equipment/Assets	0.082	-0.139	-0.109	-0.242*	-0.229*
	(0.073)	(0.133)	(0.135)	(0.138)	(0.137)
CAPM Beta	0.152***	-0.485***	-0.492***	-0.493***	-0.501***
	(0.044)	(0.111)	(0.109)	(0.109)	(0.111)
Idio. Volatility	-1.514***	3.942***	3.933***	3.912***	3.978***
	(0.189)	(0.539)	(0.538)	(0.539)	(0.535)
Momentum	0.298***	-0.088	-0.088	-0.091	-0.094
	(0.054)	(0.112)	(0.112)	(0.112)	(0.112)
Year - Month FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
N.o. Obs.	593,367	200,309	200,309	200,309	200,309
R^2-Adj.	0.175	0.253	0.253	0.253	0.253

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

Table 9: Carbon Beta, Extreme Drought, and Stock Returns
This table reports the full set of coefficients obtained from estimating regression Equation (8). The sample period is from January 2007 to December 2020. *Drought* is a dummy variable equal to 1 if the associated month's Palmer Z-Index is below the 10^{th} percentile and 0 otherwise. 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 excess return (×100)*				
	(1)	(2)	(3)	(4)	(5)
Carbon Beta† × Drought	-0.393***	-0.310***	-	-	-0.445***
	(0.069)	(0.112)	-	-	(0.132)
Carbon Beta†	0.066**	0.064	-	-	0.042
	(0.028)	(0.047)	-	-	(0.047)
Emissions Intensity† × Drought	-	-	-0.077	-	-0.068
	-	-	(0.093)	-	(0.102)
Emissions Intensity†	-	-	-0.047	-	-0.108***
	-	-	(0.031)	-	(0.038)
ln(Emissions)† × Drought	-	-	-	0.063	0.337**
	-	-	-	(0.107)	(0.142)
ln(Emissions)†	-	-	-	0.177**	0.220**
	-	-	-	(0.083)	(0.094)
ln(Market Cap.)	-0.014	0.062***	0.064***	-0.003	-0.019
	(0.013)	(0.023)	(0.023)	(0.035)	(0.038)
Book/Market	0.128***	-0.181	-0.161	-0.240*	-0.258**
	(0.046)	(0.120)	(0.119)	(0.126)	(0.127)
Return on Equity	0.142***	0.106	0.109	0.100	0.095
	(0.042)	(0.076)	(0.076)	(0.076)	(0.076)
Debt/Assets	0.149	0.290	0.314	0.218	0.192
	(0.111)	(0.202)	(0.203)	(0.201)	(0.201)
Investment/Assets	-1.678***	-1.169	-1.147	-0.885	-0.987
	(0.596)	(1.216)	(1.206)	(1.211)	(1.201)
Property, Plant, & Equipment/Assets	0.076	-0.142	-0.108	-0.243*	-0.232*
	(0.073)	(0.133)	(0.135)	(0.138)	(0.138)
CAPM Beta	0.151***	-0.484***	-0.493***	-0.493***	-0.491***
	(0.044)	(0.111)	(0.109)	(0.109)	(0.112)
Idio. Volatility	-1.523***	3.908***	3.931***	3.906***	3.932***
	(0.189)	(0.540)	(0.538)	(0.539)	(0.536)
Momentum	0.294***	-0.091	-0.087	-0.091	-0.098
	(0.054)	(0.112)	(0.112)	(0.112)	(0.112)
Industry FE	Yes	Yes	Yes	Yes	Yes
Year - Month FE	Yes	Yes	Yes	Yes	Yes
N.o. Obs.	593,367	200,309	200,309	200,309	200,309
R^2-Adj.	0.175	0.253	0.253	0.253	0.254

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

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 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. As carbon betas are estimated imprecisely – due to estimation errors – their use as explanatory variables creates an errors-in-variables (EIV) problem. This biases the estimated coefficient toward zero. If the 'true' carbon premium would be positive, then it would be underestimated by regression Equation (9). We employ Jegadeesh et al. (2019)'s approach to correct this issue. Jegadeesh et al. (2019) propose an instrumental variable methodology that adjusts for the EIV bias by estimating betas on disjoint sample periods. In practice, this amounts to estimating carbon betas separately using only the (daily) returns in odd or even months. As the measurement errors are thus by definition uncorrelated, the EIV bias is then resolved by a two-stage least-squares regression estimation where the prior month beta is used as an instrument. The procedure is outlined in detail in Appendix C. 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 "carbon risk discount" is consistent with the underperformance of the PMC portfolio displayed in Figure 2. Including control variables in column (2) takes away some of the negative coefficient suggesting that the negative premium observed in column (1) is partly driven by factors attributable to characteristics that were negatively rewarded over the sample period and positively correlated with carbon beta, or *vice versa*. Our analysis also reveals that the perceived underperformance of high carbon beta firms is driven by an industry effect: firms with high (low) carbon betas tend to operate in sectors that have shown below (above) average returns over the sample period. Including industry fixed effects to correct for this pattern, as column (3) does, turns the carbon risk premium insignificant from zero. We believe that both controlling for additional factors and including industry-fixed effects results in the most credible and precise identification of a carbon risk premium. The coefficients estimated according to this specification, reported in column (4) of the Table, uncover that a standard deviation increase in carbon beta tends to be associated with an additional 9.6 bps monthly return, *ceteris paribus*, or about 1.15% annualised. Table C1 in Appendix C presents the results without the application of Jegadeesh et al. (2019)'s correction. In this case, the (underestimated) carbon risk premium equals about

Table 10: Pricing of Carbon Risk with Errors-in-Variables Correction
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 optionally 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. We use Jegadeesh et al. (2019)'s IV-estimation methodology to account for errors-in-variables (see Appendix C for details). Standard errors are clustered at the firm level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable:	*Monthly excess return (×100)*			
	(1)	(2)	(3)	(4)
Carbon Beta†	-0.137***	-0.043**	-0.010	0.096***
	(0.019)	(0.021)	(0.026)	(0.027)
ln(Market Cap.)	-	-0.014	-	-0.017
	-	(0.012)	-	(0.012)
Book/Market	-	-0.342***	-	-0.167***
	-	(0.050)	-	(0.054)
Return on Equity	-	0.095**	-	0.120**
	-	(0.047)	-	(0.047)
Debt/Assets	-	-0.007	-	0.126
	-	(0.098)	-	(0.105)
Investment/Assets	-	-1.851***	-	-1.137**
	-	(0.536)	-	(0.560)
Property, Plant, & Equipment/Assets	-	0.005	-	-0.046
	-	(0.061)	-	(0.069)
CAPM Beta	-	0.277***	-	0.301***
	-	(0.045)	-	(0.048)
Idio. Volatility	-	-0.807***	-	-1.148***
	-	(0.230)	-	(0.246)
Momentum	-	0.287***	-	0.244***
	-	(0.059)	-	(0.059)
Industry FE	No	No	Yes	Yes
Year - Month FE	Yes	Yes	Yes	Yes
N.o. Obs.	427,876	427,955	427,876	427,876
R^2-Adj.	0.229	0.230	0.230	0.230

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

5.6 bps a month, or 0.6% annualised, suggesting the size of the EIV bias amounts to about half of the carbon risk premium. All in all, we find a small positive risk premium, although the sign and size does depend on the exact specification of the model. Given that the time-span of our data sample is relatively short for asset-pricing tests, this is not surprising.

4.5 Corporate Bond Carbon Betas

In this section, we apply the concept of carbon beta to a sample of corporate bonds. Our data collection and estimation procedure follows Huynh and Xia (2021), who estimate bond returns sensitivities to the Engle et al. (2020) Climate Change News Index. We download data on corporate bond prices for the period January 2012 to December 2021 from the FINRA's Trade Reporting and Compliance Engine (TRACE) Enhanced database. We follow the procedure of Dick-Nielsen (2009, 2014) to clean prices in TRACE. Observations in TRACE are merged with Mergent's Fixed Income Securities Database (FISD) to obtain the characteristics of the bonds and issuers in our sample. We also map S&P's credit ratings[29] from Compustat's Capital IQ to our data. Following Bai et al. (2019), we eliminate trades reported in: (1) bonds other than corporate bonds, (2) convertible bonds, (3) bonds with reported prices below $5 or above $1000, (4) bonds with floating coupon rates, (5) and bonds with maturities shorter than 1 year. We exclude the least liquid bonds from our sample by requiring bonds to be traded on at least 50% of trading days. Finally, we merge corporate emissions data from Trucost on 6-digit CUSIP numbers. We calculate the monthly corporate bond return as of month t as in Lin et al. (2011):

$$R_{i,t} = \frac{(P_{i,t} + AI_{i,t}) + C_{i,t} - (P_{i,t-1} + AI_{i,t-1})}{(P_{i,t-1} + AI_{i,t-1})}, \tag{10}$$

where $P_{i,t}$ is the volume-weighted average of intraday transaction prices of bond i on the last trading day of month t, $AI_{i,t}$ is accrued interest, and $C_{i,t}$ is the coupon payment.

We construct the pollutive-minus-clean (PMC) portfolio similarly as in our main analysis; by going long the bonds that are in the top 30% of emissions, offset by a short position in the 30% of emissions.

To estimate carbon betas for corporate bonds, we adjust the factor model of Huynh and Xia

[29] Converted to numerical scale as follows: `AAA` $\rightarrow$ 1, `AA+` $\rightarrow$ 2, ... , `C` $\rightarrow$ 19, `D` $\rightarrow$ 20.

(2021):

$$
\begin{aligned}
R^e_{i,t} = \alpha_i + \beta_i^{PMC} PMC_t + \beta_i^{MKT} MKT_t + \beta_i^{TRM} TRM_t + \beta_i^{DEF} DEF_t + \beta_i^{TED} TED_t \\
+ \beta_i^{ILLIQ} ILLIQ_t + \epsilon_{i,t},
\end{aligned}
\tag{11}
$$

where $R^e_{i,t}$ is the return on bond i as of month t calculated in (10), in excess of the 1-month T-Bill rate, α_i is the bond's risk-adjusted outperformance, β's denote sensitivities to the factors, MKT_t is the aggregate bond market return, TRM_t is the term spread of Welch and Goyal (2008),[30] DEF_t is the default spread of Welch and Goyal (2008),[30] TED_t is the TED spread,[31] $ILLIQ_t$ is the Dick-Nielsen et al. (2012) bond market illiquidity series,[32] and $\epsilon_{i,t}$ is the residual term. Our interest lies in β_i^{PMC}, which denotes the bond i's carbon beta.

Figure 4 presents mean bond carbon betas by issuer GICS industry. We obtain a pattern that is similar to the sectoral distribution of carbon betas in equity securities: the highest exposures are found in the Energy and Materials sectors, while the lowest are found in the Financials sector. Figure 5 provides empirical evidence on the relationship between climate risk exposures with credit ratings and bond maturities. We expect that bonds of lower-rated issuers have higher transition risk exposure, as such firms have greater difficulty in meeting the investments required for a low-carbon transition. This is also consistent with our findings on the firm-level drivers of carbon beta in the equity market. Bonds rated investment grade - that is, bonds with a credit rating of `BBB` or above - indeed have lower climate risk exposures than bonds with lower ratings. Regarding bond climate betas and maturities, we expect that longer-dated bonds hold larger climate risk exposures, as the impact of low-carbon transition shifts likely has larger effects in the distant future than in the near future. In line with this hypothesis, we find a strong positive association between bond maturities and bond carbon betas.

[30] Available at Amit Goyal's website: `https://sites.google.com/view/agoyal145`
[31] Obtained from Federal Reserve Bank of Saint Louis: `https://fred.stlouisfed.org/series/TEDRATE`
[32] Available at Peter Feldhütter's website: `https://feldhutter.com/`

Figure 4: Corporate Bond Carbon Beta by Issuer Industry
The figure displays the coefficients estimated by regressing corporate bond carbon betas on issuer two-digit GICS Industry Sectors. The sample period is January 2012 to December 2021. The 95% confidence intervals are based on robust standard errors adjusted for clustering at the bond level.

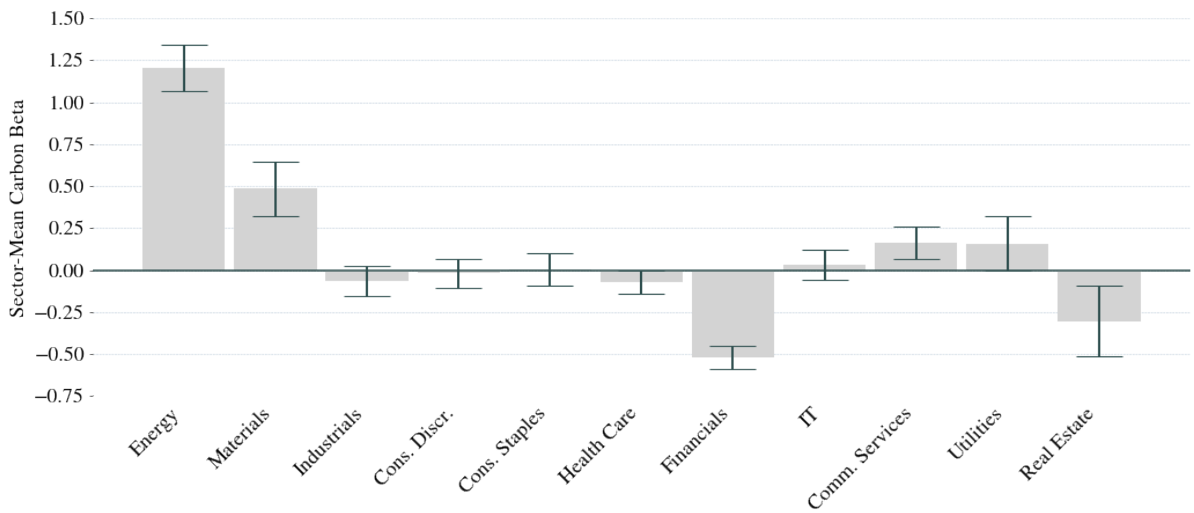
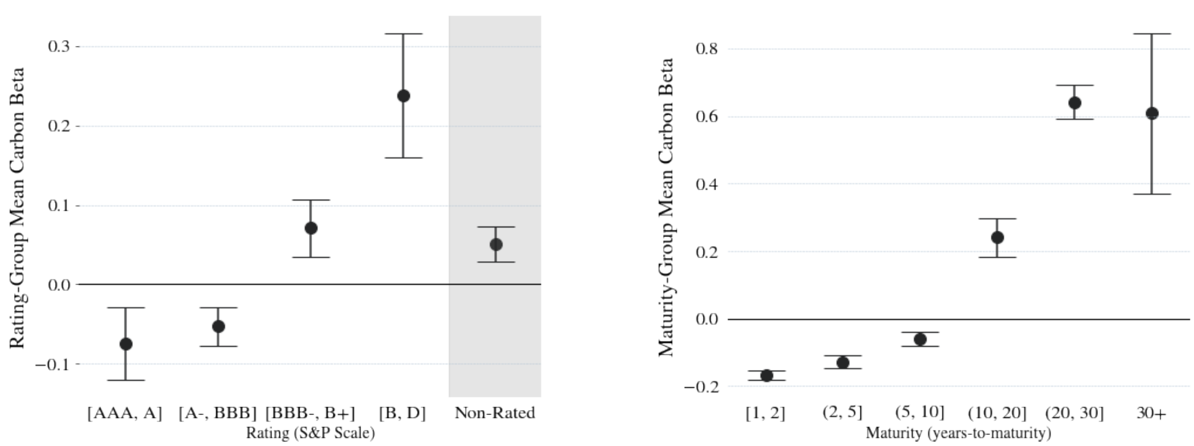


Figure 5: Corporate Bond Carbon Beta by Rating Group and Maturity Group
The figures display the coefficients estimated from regressing corporate bond carbon betas on groups formed on bond credit rating and bond maturities. The sample period is January 2012 to December 2021. The 95% confidence intervals are based on robust standard errors adjusted for clustering at the bond level.



5 Conclusion

Research shows that green innovation is, for a large extent, driven by the current climate laggards. Therefore, we propose a forward-looking measure of climate transition 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. Regressing individual stock returns on the PMC portfolio's returns and the Fama and French (1993) and Carhart (1997) factors, we regard the loadings on the PMC portfolio as the firm-level exposure to climate transition risk: Carbon beta.

Our approach is complementary to conventional approaches that measure climate risk exposure. The measure reflects the market's consensus view on a company's climate transition 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. Regression of carbon beta on firm characteristics indeed shows that variation in carbon beta aligns with our expectations. Larger, innovative, and profitable firms have lower climate risk exposure, whereas capital-intensive and carbon-intensive firms have higher climate risk exposure.

Our measure is robustly associated with green innovation, illustrating its forward-looking character. Subsequent comparisons of carbon beta estimates with alternative (commercial) measures of climate risk at the firm level also reveal robust positive associations. 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 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 return patterns for months with abnormally high temperatures, and for months that are exceptionally dry in precipitation.

Finally, the methodology covers a large universe of assets for which a sufficient history of returns is observed. Our framework is not limited to a specific asset class either.

Whereas we rely on carbon emissions as the basis for construction of the PMC factor, with a relatively short history, alternative proxies for a carbon risk factor could be informative too. One could use the price of emission allowances, for example, now that emissions trading schemes are becoming 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 to create climate-aware investment strategies. Carbon beta can be employed as an indicator of 'climate hedge' potential and used for the construction of hedge portfolios with high returns in periods of climate stress, against a small risk premium. Furthermore, most investors can utilise our approach as it is transparent, accessible, and easily replicated. Carbon betas could thus be used by investors investing in products for which emission data is not available and for whom it is too costly to make use of commercial alternatives, e.g. small retail investors or low-cost ETF providers. Our methodology might also be valuable to academics in assessing the asset pricing implications of climate risk, as our approach yields a cross-sectionally 'rich' dataset. Lastly, regulators and policymakers could use carbon beta to identify highly exposed firms 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 policymakers could employ our framework as a tool to disentangle 'green innovators' from otherwise pollutive firms.

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Appendix A: Additional Tables and Figures

Table A1: Variable Definitions

This table reports on the data sources and definitions of the variables used in our main analyses.

Variable	Description	Source*
Excess Return$_{i,t}$	Return for stock i in month t in excess of the 1-month Treasury bill rate, winsorised at 0.5% and 99.5% cut-off points.	CRSP + KFDL
ln(Market Cap.)$_{i,t-1}$	Natural logarithm of market capitalisation (in millions of US\$), where market capitalisation is defined as shares outstanding multiplied by share price at the end of month *t-1*.	CRSP
B/M$_{i,t-1}$	Book to market ratio is the book value of equity at the end of June of previous year divided by market capitalisation at the end of month *t-1*, winsorised at 1% and 99% cut-off points.	CCM
ROE$_{i,t-1}$	Return on equity is net income divided by total shareholders' equity at the end of June in year of previous year, winsorised at 1% and 99% cut-off points.	CS
Debt/Assets$_{i,t-1}$	Total long-term and short-term debt divided by total assets at the end of June of previous year, winsorised at 1% and 99% cut-off points.	CS
Invest./Assets$_{i,t-1}$	Investment to assets is capital expenditures divided by total assets at the end of June of previous year, winsorised at 1% and 99% cut-off points.	CS
PP&E/Assets$_{i,t-1}$	Property, Plant & Equipment divided by total assets at the end of June of previous year, winsorised at 1% and 99% cut-off points.	CS
R&D/Assets$_{i,t-1}$	Annual Research & Development expenses divided by total assets at the end of June of previous year, winsorised at 1% and 99% cut-off points.	CS
Carbon Beta$_{i,t-1}$	Estimated coefficient from regressing daily returns on PMC portfolio while controlling for Fama and French (1993) three factors and Carhart (1997) momentum. For month t, we use Carbon Betas at end-of-month *t-1* winsorised at 1% and 99% cut-off points.	AC
Idio. Volatility$_{i,t-1}$	Idiosyncratic volatility is the annualised standard deviation of residuals of a 1-year rolling window regression of stock i's daily returns on the Fama and French (1993) market factor. For month t, we use idiosyncratic volatilities at end-of-month *t-1* winsorised at 1% and 99% cut-off points.	AC + CRSP + KFDL
CAPM Beta$_{i,t-1}$	Market beta is obtained by 1-year rolling window regression of stock i's daily returns on the Fama and French (1993) market factor. For month t, we use market betas at end-of-month *t-1* winsorised at 1% and 99% cut-off points.	AC + CRSP + KFDL
Momentum$_{i,t}$	Cumulative return over the past 12 months excluding the most recent month.	AC + CRSP
ln(Emissions)$_{i,t}$	Natural logarithm of combined Scope 1 and Scope 2 emissions of year *t-1* (in millions of tonnes of CO_2-equivalent), winsorised from above at 99% cut-off point.	TC
Emissions Intensity$_{i,t}$	Combined Scope 1 and Scope 2 emissions (in millions of tonnes of CO_2-equivalent) scaled by annual revenues of year *t-1*, winsorised from above at 99% cut-off point.	TC
CCE$_{i,t}$	Climate Change Exposure is defined as the extent to which managers and analysts discuss climate change related topics during quarterly earnings calls. The measure is also available in individual pillars that measure exposure related to climate regulations, climate opportunities, and physical risks. We normalise the measure for easy of comparability.	Sautner et al. (2022)
CVaR$_{i,t}$	Climate-Value-at-Risk measures firm-specific forward-looking valuation assessments regarding climate risks and opportunities. We normalise and invert the measure so that its interpretation is equivalent to conventional VaR.	MSCI
CPU$_t$	Climate Policy Uncertainty is defined by the textual similarity between articles published in the Wall Street Journal on day t and a corpus of climate change documents. A high CPU on day t indicates that climate change is frequently discussed on that particular day. We aggregate daily values over the past month to match the granularity of our data set.	AC + WSJ
Temperature Anom$_t$	Temperature Anomaly is a dummy variable equal to 1 if month t's Temperature Anomaly (deviation from 30-year reference temperature) is in the top 10% of extreme values and otherwise equal to 0.	AC + NOAA
Drought$_t$	Dummy variable equal to 1 if month t's Palmer Z-Index (Palmer, 1965) is in the top 10% of extreme values and otherwise equal to 0.	AC + NOAA
Green Patent Share$_{i,t}$	The fraction of firm i's patents issued at and before month t that are classified as green according to the OECD green patent taxonomy (Haščič and Migotto, 2015).	AC + USPTO

*KFDL = Kenneth French's Data Library, CCM = CRSP-Compustat Merged, CS = S&P CapitalIQ Compustat, AC = Authors' Calculations, TC = S&P Trucost, WSJ = Wall Street Journal News Archive, USPTO = US Patent and Trademark Office Bulk Data Storage System

Table A2: Descriptive Statistics on Top and Bottom Subindustries by Carbon Beta
This table reports the mean and median carbon beta of the top and bottom 15 GICS-subindustries by median carbon beta. The table also reports the number of firms by subindustry and the number of return and carbon beta observations by subindustry. The sample period is from January 2007 to December 2020.

Sub-Industry	**Mean**	**Median**	**N. Firms**	**N. Obs.**
Panel A: Top 15 sub-industries by mean carbon beta				
Silver	1.51	1.46	7	983
Gold	1.28	1.21	67	5507
Oil & Gas Drilling	1.18	1.27	32	2931
Oil & Gas Exploration & Production	1.14	1.13	266	23578
Precious Metals & Minerals	1.08	1.16	10	774
Copper	1.02	1.04	5	624
Coal & Consumable Fuels	0.93	0.89	36	3486
Oil & Gas Equipment & Services	0.90	0.87	119	10272
Steel	0.80	0.77	58	5624
Integrated Oil & Gas	0.79	0.71	24	3191
Aluminum	0.77	0.72	12	866
Diversified Metals & Mining	0.73	0.74	38	2935
Oil & Gas Refining & Marketing	0.69	0.68	49	4574
Oil & Gas Storage & Transportation	0.60	0.58	158	13309
Independent Power Producers & Energy Traders	0.58	0.55	22	1540
Panel B: Bottom 15 sub-industries by mean carbon beta				
Financial Exchanges & Data	-0.42	-0.41	16	2563
Investment Banking & Brokerage	-0.40	-0.42	67	6084
Other Diversified Financial Services	-0.38	-0.28	6	490
Internet Services & Infrastructure	-0.35	-0.39	27	2293
Biotechnology	-0.34	-0.29	561	34386
Systems Software	-0.34	-0.33	105	7676
Regional Banks	-0.33	-0.29	618	58638
Life & Health Insurance	-0.29	-0.26	41	4516
Consumer Finance	-0.28	-0.30	68	5762
Highways & Railtracks	-0.26	-0.24	2	66
Interactive Media & Services	-0.24	-0.25	60	5012
Insurance Brokers	-0.23	-0.23	21	1651
Semiconductors	-0.21	-0.23	182	17002
Application Software	-0.20	-0.21	325	23816
Life Sciences Tools & Services	-0.19	-0.20	91	7269

Table A3: Carbon Beta and MSCI Green Patent Share
This table reports the coefficients obtained from estimating regression Equation (4). Here, Green Share MSCI (%) is a measure of green patent innovation constructed and provided by MSCI. 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)†
MSCI Green Patent Share†	0.020	-0.231***	0.362	0.130***
	(0.021)	(0.089)	(0.269)	(0.046)
ln(Market Cap.)	-0.026***	-0.007	-0.190	0.418***
	(0.008)	(0.035)	(0.124)	(0.053)
Book/Market	0.126***	0.207	-0.155	0.395***
	(0.039)	(0.128)	(0.280)	(0.107)
Return on Equity	-0.004	-0.090*	0.666	0.189
	(0.013)	(0.055)	(0.481)	(0.140)
Debt/Assets	0.141**	0.245	1.345	0.676
	(0.066)	(0.410)	(0.841)	(0.429)
Investment/Assets	-0.283	1.081	-5.444**	-2.492***
	(0.403)	(1.384)	(2.473)	(0.761)
Property, Plant, & Equipment/Assets	0.392***	0.481**	1.009**	0.202
	(0.051)	(0.199)	(0.499)	(0.167)
Research & Development/Assets	-0.984***	0.583	-20.170	-16.644
	(0.141)	(1.622)	(17.600)	(12.999)
Year-Month FE	Yes	Yes	Yes	Yes
Industry FE	Yes	No	No	No
Sectors	All	Energy	Energy	Energy
N.o. Obs.	150,576	6,539	4,423	4,423
R^2-Adj.	0.487	0.340	0.227	0.665

†Indicates a cross-sectionally standardised variable.

Figure A1: Alternative PMC Portfolio Construction
The figure displays PMC portfolios that were constructed in different ways. The baseline PMC as used in the paper is compared to alternative constructions based on estimated emissions (PMC Estimated), reported emissions (PMC Reported), emission intensities (PMC Intensity), and emissions provided by MSCI (PMC MSCI) instead of by Trucost.

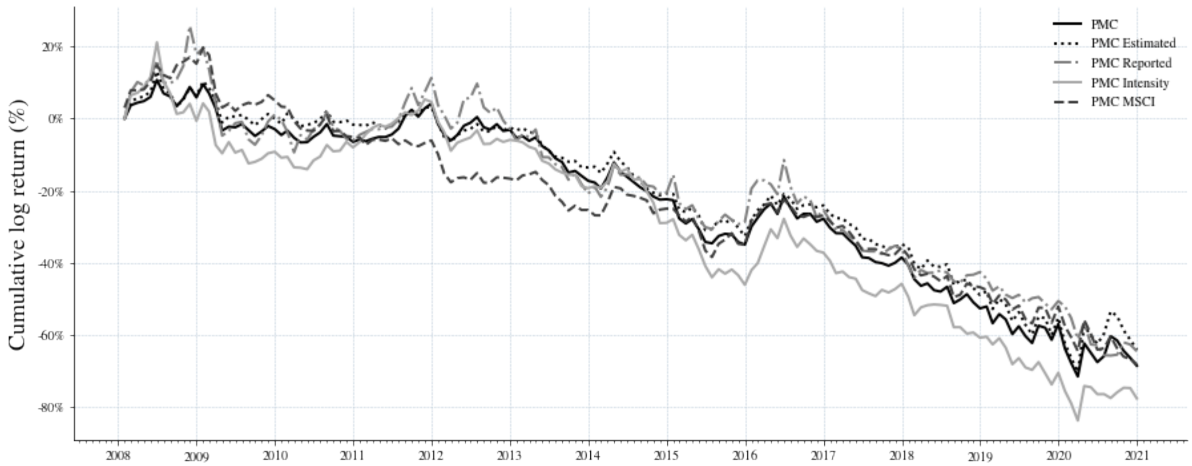
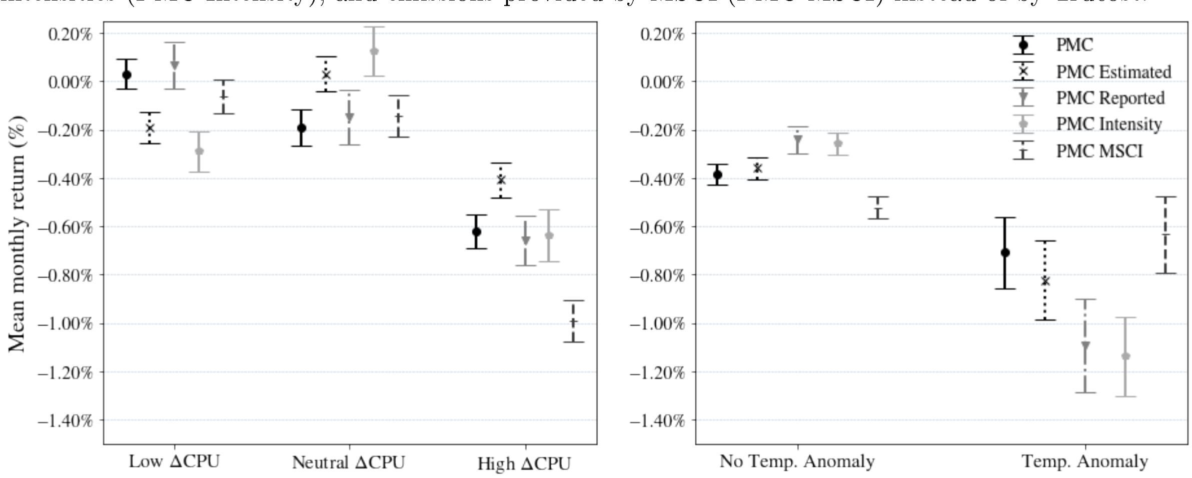


Table A4: Correlations Between Alternative PMC Portfolios
The table reports pairwise correlation coefficients between alternatively constructed PMC portfolios. PMC is the pollutive-minus-clean portfolios as employed in the paper.

	PMC	$\text{PMC}_{\text{Estimated}}$	$\text{PMC}_{\text{Reported}}$	$\text{PMC}_{\text{Intensity}}$	PMC_{MSCI}
PMC	1.00	-	-	-	
$\text{PMC}_{\text{Estimated}}$	0.95	1.00	-	-	-
$\text{PMC}_{\text{Reported}}$	0.73	0.59	1.00	-	-
$\text{PMC}_{\text{Intensity}}$	0.79	0.79	0.68	1.00	-
PMC_{MSCI}	0.85	0.83	0.63	0.72	1.00

Figure A2: Returns to Alternative PMC Portfolios Conditional on CPU and Temperature Anomalies
The figure reports the mean monthly returns of various PMC portfolio definitions during various regimes of Climate Policy Uncertainty (low change in CPU, neutral change in CPU, high change in CPU) and Temperature Anomalies. The baseline PMC as used in the paper is compared to alternative constructions based on estimated emissions (PMC Estimated), reported emissions (PMC Reported), emission intensities (PMC Intensity), and emissions provided by MSCI (PMC MSCI) instead of by Trucost.



Appendix B: Validation of Carbon Betas

In our validation test, we first compare estimates of carbon beta across sectors, headquartered states, and countries. We then run panel regressions to uncover how firm characteristics are correlated with corporate climate risk. Next, we perform a firm-level comparison of carbon betas with alternative measures of climate risk, amongst which the Sautner et al. (2022)'s measure constructed from analyst earnings calls and MSCI's Climate-Value-at-Risk measure.

B1 Sector, Headquartered State, and Country Variation in Carbon Betas

In this section, we first seek to analyse how carbon beta is associated with variation in industry sector membership. To do so, we estimate:

$$CB_{it} = \sum_{k=1}^{11} \mathbb{I}[k_i = k] + \epsilon_{it}, \tag{12}$$

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 3 reports the estimated coefficients from regressing individual stock's carbon betas on their respective industry dummies. The figure 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 mean carbon betas. These findings are in line with commonly held beliefs about sectors' relative carbon risk exposure. While the figure shows differences in the carbon risk exposure across sectors, the variation of carbon betas within specific sectors 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 to climate risks (not reported). Note that in later regression specifications, we include industry fixed effects, so that we only exploit variation in carbon betas *within* industries, rather than the variation *across* industries reported in Figure 3. We believe this is a conservative approach, as we control for any unobserved industry effect and can circumvent the effect of potential industry biases in the definition of the carbon risk factor.

We now modify Equation (12) to regress on headquarter state dummies. The regression coefficients can be interpreted as average carbon betas by headquarter state. Figure A3A presents our results. Particularly in Texas, Oklahoma, and New Mexico, average carbon betas are high. This is likely the result of the large concentration of oil and gas firms operating in this region. In California, on the contrary, carbon betas are on average negative. This might stem from the state's dominant Technology sector. Overall, geographic variation in carbon betas seems to align with prior expectations, yet is strongly driven by industry effects. As mentioned earlier, we include industry dummies in most regressions to make sure that such effects do not confound our results.

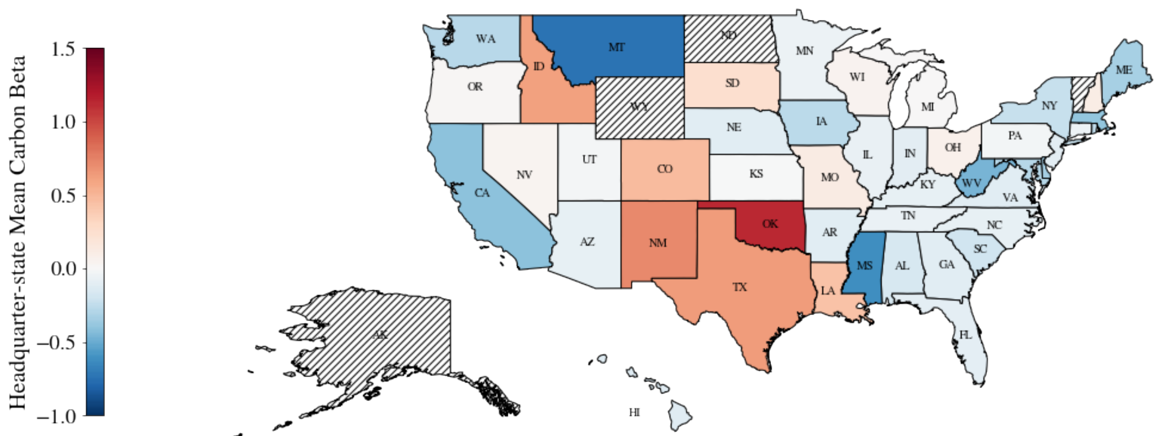
Lastly, we investigate how carbon betas vary over countries. We exploit international variation in a sample of carbon betas estimated from the returns of different MSCI Country indices. The estimation of carbon betas is based on a sample of 48 different MSCI country indices. We estimate carbon betas 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. We again estimate a modified version of Equation (12) that includes country-fixed effects. Figure A3 shows the coefficients from regressing international carbon betas on their respective country dummies, a similar specification as in Equation (12). 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 in 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 at the forefront of regulating climate change. The difference between the U.S. and Canada is also striking. While both nations have a large oil and 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.

B2 Covariation with Alternative Measures of Climate Risk

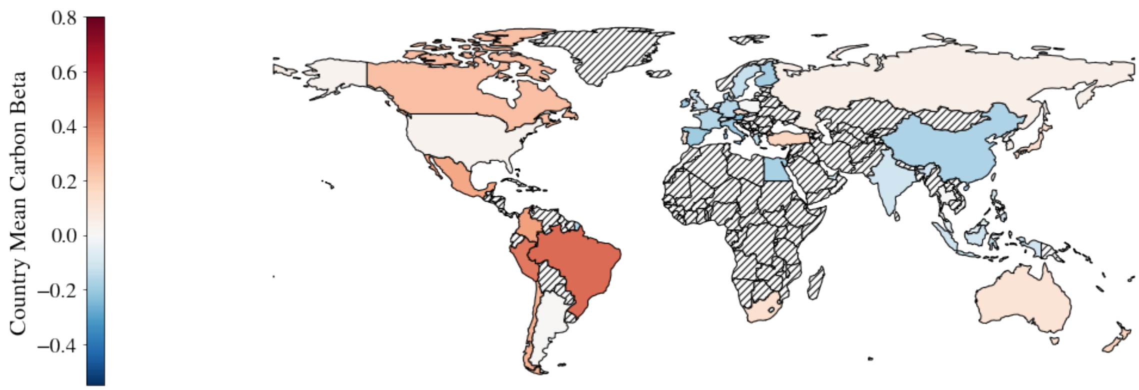
We now compare carbon betas with alternative firm-level measures of climate risk. Here we consider the natural logarithm of firm emissions, emission intensity, the Sautner et al. (2022)

Figure A3: Geographic Variation in Carbon Beta
The figure displays the coefficients estimated by regressing Carbon Beta on U.S. headquarter state fixed effects (Panel A) and international country fixed effects (Panel B). In Panel B, returns are based on each country's respective MSCI country index. The sample period is January 2015 to December 2020. Data comes from Refinitiv (formerly Thomson Reuters) Eikon.

(A) Headquarter State Fixed Effects



(B) Country Fixed Effects



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 comparison. Table 4 reveals robust correlations between carbon beta and each of the four alternative measures. The correlation coefficients are highly significant and their signs are in line with expectations. It is interesting to note 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 carbon beta with emission intensities are close, at 51% respectively 40%. This suggests that while there is different information contained in emissions and intensities, there is still a large overlap between the information in emissions and emissions intensities deemed relevant to carbon beta. Moreover, the robust associations between carbon beta and the scores on the forward-oriented CVaR and Sautner et al. (2022) 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 more detail in Section 4.2.2.

We now conduct a more detailed comparison between estimates of carbon beta and the Sautner et al. (2022)'s Climate Change Exposures, where we exploit that Sautner et al. (2022)'s measure is decomposed into three components: exposure to regulatory risks, climate opportunities, and physical risks. This allows us to analyse which aspects of climate risk are captured by carbon beta. We estimate a similar model as in Equation (3), 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 A5 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 23% 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 counterintuitive but suggests that today's major emitters have an important role to play in enabling low-carbon technologies. Sautner et al. (2022) observe the same 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 than the overall CCE coefficients and other components. The adjusted R-squared reported in column (4) also reveals that physical climate change exposure is of little help in explaining variation in carbon beta. This finding does not come as a surprise to us. Physical climate risks are more idiosyncratic 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 A5: Carbon Beta and the Sautner et al. (2022) Climate Change Exposures

This table reports the full set of coefficients obtained from estimating a similar model as in Equation (3). The sample period is from January 2007 to December 2020. CCE is the Sautner et al. (2022) 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 (3). 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†	0.205***	-	-	-	-
	(0.012)	-	-	-	-
$\text{CCE}_{\text{Regulatory}}{}^{\dagger}$	-	0.158***	-	-	0.112***
	-	(0.009)	-	-	(0.009)
$\text{CCE}_{\text{Opportunities}}{}^{\dagger}$	-	-	0.159***	-	0.114***
	-	-	(0.012)	-	(0.011)
$\text{CCE}_{\text{Physical}}{}^{\dagger}$	-	-	-	0.044***	0.027***
	-	-	-	(0.006)	(0.005)
N.o. Obs.	350,339	350,339	350,339	350,339	350,339
R^2-Adj.	0.043	0.026	0.026	0.002	0.038

†Indicates a cross-sectionally standardised variable.

Appendix C: Errors-in-Variables Adjustment

Carbon betas – like all regression coefficients – are subject to estimation error. The use of carbon beta as an explanatory variable leads to an errors-in-variables (EIV) problem: when explanatory variables are subject to measurement error, regression coefficients are biased towards zero. This 'attenuation bias' thus overestimates the 'true' coefficient when it is negative and underestimates it when it is positive. We employ the instrumental variable (IV) approach of Jegadeesh et al. (2019) to resolve these EIV-induced problems. Jegadeesh et al. (2019) propose a framework in which the betas are estimated on two disjoint sets. Similar to Jegadeesh et al. (2019), we implement this by estimating carbon betas in even months separately from carbon betas in odd months. In even (odd) months, we only use the daily returns in previous even (odd) months in the estimation window.[33] The estimator of Jegadeesh et al. (2019) is defined as:

$$\hat{\lambda}_{IV} = (X_{IV} X'_{EV})^{-1}(X_{IV} R') \tag{13}$$

where X_{IV} is the matrix of instrumental variables with odd-month (even-month) estimated carbon betas in even (odd) months, X_{EV} is the matrix of explanatory variables with even-month (odd-month) estimated carbon betas in even (odd) months, and R is a vector of stock returns in excess of the risk-free rate. Note that the matrices X_{IV} and X_{EV} contain estimated (carbon) betas, firm characteristics, and market variables, so that $\hat{\lambda}_{IV}$ is a vector of both estimated risk premia and characteristics premia.

The estimator can be decomposed into two parts by expressing it as a two-stage least squares regression. In the first stage, the explanatory variables are regressed on the instrumental variables:

$$\hat{\delta} = (X_{IV} X'_{IV})^{-1}(X_{IV} X'_{EV}) \tag{14}$$

Whereas in the second stage, the OLS estimator is pre-multiplied by the inverse of scaling matrix $\hat{\delta}$:

[33] This effectively halves the estimation window, from around 750 daily observations to around 375. While this increases estimation errors, Jegadeesh et al. (2019) show in simulation exercises that this does not lead to large deviations from the true coefficients.

$$\hat{\lambda}_{IV} = \hat{\delta}^{-1}((X_{IV}X'_{IV})^{-1}(X_{IV}R')), \tag{15}$$

By estimating betas on disjoint samples, the measurement error is uncorrelated. This property allows the IV estimation methodology to yield unbiased estimates of the true risk premia. Jegadeesh et al. (2019) point out that the diagonal elements in $\hat{\delta}$ are smaller than 1 and equal to the ratio of the variance in the beta divided by the sum of the variance in beta and in measurement error. Hence, the inverse of $\hat{\delta}$ effectively scales up the OLS coefficients and thereby alleviates the attenuation bias. As the standard errors are scaled by the same constants, there is no effect on the t-statistics.

Table C1: Pricing of Carbon Risk without Errors-in-Variables Correction
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 optionally 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 firm 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†	-0.084***	-0.017	0.007	0.056**
	(0.018)	(0.021)	(0.026)	(0.026)
ln(Market Cap.)	-	-0.014	-	-0.019
	-	(0.011)	-	(0.012)
Book/Market	-	-0.348***	-	-0.156***
	-	(0.050)	-	(0.053)
Return on Equity	-	0.088*	-	0.115**
	-	(0.047)	-	(0.047)
Debt/Assets	-	-0.043	-	0.117
	-	(0.097)	-	(0.104)
Investment/Assets	-	-1.866***	-	-1.068*
	-	(0.530)	-	(0.552)
Property, Plant, & Equipment/Assets	-	0.010	-	-0.033
	-	(0.060)	-	(0.068)
CAPM Beta	-	0.263***	-	0.271***
	-	(0.044)	-	(0.047)
Idio. Volatility	-	-0.805***	-	-1.136***
	-	(0.226)	-	(0.243)
Momentum	-	0.302***	-	0.257***
	-	(0.059)	-	(0.059)
Industry FE	No	No	Yes	Yes
Year - Month FE	Yes	Yes	Yes	Yes
N.o. Obs.	437,847	437,847	437,847	437,847
R^2-Adj.	0.227	0.227	0.227	0.228

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