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RESEARCH

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

OPEN ACCESS

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We introduce carbon beta, a measure of climate transition risk determined by a stock's return sensitivity to a pollutive-minus-clean portfolio. Carbon beta is higher for smaller and more leveraged firms, firms with more investments and fixed assets, as well as firms with lower R&D. Carbon betas correlate with green patent issuance and other forward-looking measures of climate risk. We study the interaction of carbon beta with shocks to climate risk to judge its hedging ability: Returns to stocks with high carbon betas are lower during months with climate risk realizations.

Keywords: asset pricing; carbon risk; climate change; climate finance

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In the 2015 Paris Agreement, 197 parties committed to holding global average temperature increases to below 2 °C above pre-industrial levels. The agreement explicitly calls on the financial industry to help make finance flows "consistent with a pathway towards low carbon emissions" (United Nations 2015, 3). Yet 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 (Giglio, Kelly, and Stroebel 2021; Krueger, Sautner, and Starks 2020).

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We contribute to this discussion by introducing a market-based measure of an asset's climate risk exposure, determined by how an asset's return is correlated with a carbon risk factor. We call this measure *carbon beta*. Because it is market-based, carbon beta reflects investor expectations about future transition risks.[1] Beyond current emissions, factors such as technology, management quality, innovation capacity, competition, and financial health can affect a company's ability to manage transition risks. If market prices incorporate expectations about such aspects, then our carbon beta will reflect those. The annual direct carbon 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 80th percentile in our sample. Whereas Tesla and W&T Offshore have similar emissions, they have very different carbon betas: Tesla ranks in the bottom 5%, W&T Offshore in the top 5%. Seemingly, investor expectations of climate risk exposure can diverge even among firms with comparable emissions.

Development of scientific methods and metrics to measure exposure to climate change risk is needed.[2] One issue in this respect is that green innovation is driven by the firms in the worst-performing industries on environmental issues (Cohen, Gurun, and Nguyen 2020). Also, brown firms increase emissions much more in response to increases in the cost of capital than green firms do, as shown by Hartzmark and Shue (2023). This undermines the effectiveness of policies that exclude such stocks from investment portfolios. Carbon emissions data are most effective at identifying firms or industries that are slow to transition to a low-carbon or "green" economy but lack the ability to identify leaders in this regard (Sautner et al. 2023). 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.

We find that stocks with positive carbon betas tend to fall in value when climate concerns rise. On the contrary, negative–carbon beta assets act as "climate hedges" because they deliver high returns when climate worries increase. To study the effect of this relationship, we construct a Climate Policy Uncertainty (CPU) index based on the similarity between *Wall Street Journal* articles and climate-related texts from official sources, similar to Engle et al.'s (2020) Climate Change News Index. Our assumption is that spikes in climate-related news signal higher policy uncertainty. In months when CPU rises, firms with higher carbon betas have lower returns. A one–standard deviation increase in carbon beta corresponds to a 15-bps return decline per standard deviation shock to CPU. These findings remain robust when we use other climate news indices[3] or substitute extreme weather events for news-based shocks. This aligns with evidence that extreme temperatures hurt polluting firms' valuations by reducing earnings (Addoum, Ng, and Ortiz-Bobea 2023; Pankratz, Bauer, and Derwall 2023) and lowering investor demand for polluting stocks (Choi, Gao, and Jiang 2020). Our results support the model of Pástor, Stambaugh, and Taylor (2020), in which green (brown) stocks can temporarily outperform (underperform) when climate concerns unexpectedly rise.

We further examine the link between carbon beta and green patent output. Green innovation is concentrated in the energy sector, which paradoxically tends to perform poorly on environmental metrics (Cohen, Gurun, and Nguyen 2020). We construct data on firms' green patent output and link these to firms in our sample. We compile firms' green patent data and match them to our sample. Results show a negative, weakly significant relationship between carbon beta and green innovation, suggesting that green innovators face less climate risk. The effect is stronger among energy firms, where both climate risk and green innovation are more prevalent. By contrast, we do not observe similar patterns when using emissions or carbon intensity as indicators of climate risk. This suggests that markets incorporate green innovation into climate risk assessments, reflected in carbon betas. We also find a strong positive association between carbon beta and Morgan Stanley Capital International (MSCI) Climate Value-at-Risk, a measure constructed to capture forward-looking climate risks.

A natural question is whether the hedging benefit of carbon beta comes at the cost of lower expected returns—in other words, whether climate risk is priced. If investors dislike scenarios where the climate worsens, they should demand higher returns for high–carbon beta assets and accept lower returns for hedge assets with negative carbon betas. Consistent with theory (Pástor, Stambaugh, and Taylor 2020), our pricing tests confirm this: A one–standard deviation increase in carbon beta is linked to an annualized return increase of about

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1.15 percentage points in the most restrictive configuration of the model. 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 our findings on the risk premium with caution.

Finally, our approach requires minimal assumptions and data, enabling us to calculate carbon betas for any asset with observable returns. This includes asset classes lacking direct carbon measures (e.g., commodities) or opaque ones (e.g., hedge funds). The method is transparent, consistent across assets, and independent of voluntary emissions disclosure. We demonstrate its versatility across three asset classes: (1) US equities, as the main focus of this paper, (2) national equity indices in the Online Appendix, and (3) US corporate bonds in the Online Appendix. In principle, the approach can be applied to any asset with sufficient return history, though further applications are left for future research.[4]

Data and Methodology

Sample Construction. Returns and financial data were obtained from the intersection of the Center for Research in Security Prices (CRSP) and Compustat. All accounting variables are winsorized at 1% and 99% cutoffs to mitigate the effects of extreme values (outliers) and potential data errors. We use daily returns obtained from CRSP's daily security file to estimate capital asset pricing model (CAPM)–implied market betas and idiosyncratic return volatilities. Estimations are based on rolling windows containing three years of daily returns. We obtain data on US factor returns from Kenneth French's data library, which we use in the estimation of CAPM betas, idiosyncratic volatilities, and carbon betas.

Carbon Emissions Data. We collect information on greenhouse gas emissions from S&P Trucost. We sum scope 1 and scope 2 to a combined scope 1&2 and then 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. Additional details on emissions data are provided in "Emissions Data" in Appendix A.

The CPU Index. We follow Engle et al. (2020) in creating an index for climate news risk. The index levels are based on the similarity of daily *Wall Street Journal* articles to a set of climate change terms from authoritative sources (such as assessment reports by the UN Intergovernmental Panel on Climate Change (IPCC). We refer to this index as the Climate Policy Uncertainty (CPU) index due to the similarity of our approach with that of more general Economic Policy Uncertainty (see, e.g., Baker, Bloom, and Davis 2016). We elaborate on the construction of this CPU index and its dynamics in "Climate Policy Uncertainty Index" in Appendix A.

Green Patents. We obtain US patents from the US Patent and Trademark Office's (USPTO) Bulk Data Storage System, covering all patents issued from 1976 onward.[5] We focus on patents granted between 2010 and 2020. We link patents to firms in our dataset using the Wharton Research Data Services (WRDS) Compustat Link table for US Patents (Beta) and apply string matching for unmatched cases.[6]

To identify green patents, we follow OECD guidelines (Haščič and Migotto 2015) on classifications covering technologies such as renewable energy, waste management, pollution control, and fuel efficiency. We supplement this with the International Patent Classification (IPC) Green Inventory.[7] We measure "Green Share" as the number of green patents as a percentage of all patents issued to a company (Cohen, Gurun, and Nguyen 2020). Further information on green patent data is provided in "Other Data" in Appendix A.

Our analysis uses several additional data sources for validation and robustness tests. We provide a complete overview of data sources in Appendix A. Table 1 reports descriptive statistics on our sample. Panel A of Table 1 reports descriptive statistics for our stock market sample. After merging CRSP with Compustat data and applying filters, the dataset contains more than 780,000 monthly return observations for more than 7,100 firms. Panel B of Table 1 provides statistics on emissions and intensities. A description of the variables used in our analysis is provided in Table B1 in Appendix B.

Methodology

The Pollutive-Minus-Clean Portfolio. We regard the pollutive-minus-clean (PMC) portfolio as an observable proxy for carbon risk. The PMC portfolio captures the return difference between a

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Table 1. Descriptive Statistics CRSP–Compustat–Trucost Merged

				Percentiles			
	No. Obs.	Mean	SD	5%	25%	75%	95%
A. Firm-level and market variables							
Excess Return (%)	786,481	0.676	14.712	−21.837	−6.243	6.764	23.540
Market Cap. (millions)	701,774	5,358	24,972	19	132	2,545	21,098
Book/Market	701,774	0.663	0.678	0.034	0.268	0.856	1.852
Return on Equity	788,412	−0.015	0.711	−0.934	−0.040	0.148	0.445
Debt/Assets	785,576	0.190	0.208	0.000	0.006	0.312	0.603
Investment/Assets	783,907	0.041	0.057	0.000	0.005	0.052	0.156
Property, Plant, & Equipment/Assets	701,774	0.418	0.436	0.000	0.066	0.674	1.242
Research & Development/Assets	701,774	0.049	0.119	0.000	0.000	0.037	0.261
Carbon Beta	682,022	0.052	0.557	−0.777	−0.266	0.312	1.034
Idiosyncratic Volatility (%)	765,204	40.823	21.938	15.195	23.903	52.546	85.790
CAPM Beta	765,204	0.976	0.510	0.125	0.631	1.304	1.850
Momentum	737,261	0.065	0.469	−0.621	−0.216	0.265	0.879
B. Emission variables							
Scope 1 Emissions (mlns tons CO_2)	238,902	1.558	8.921	0.000	0.003	0.128	4.692
Scope 2 Emissions (mlns tons CO_2)	238,902	0.276	0.987	0.000	0.006	0.136	1.227
Scope 1&2 Emissions (mlns tons CO_2)	238,902	1.834	9.298	0.000	0.011	0.339	6.091
Scope 1 Emission Intensity (tons CO_2/$ mln)	238,902	161.869	596.842	0.540	3.716	30.009	764.240
Scope 2 Emission Intensity (tons CO_2/$ mln)	238,902	33.099	45.600	1.127	7.822	41.608	117.576
Scope 1&2 Emission Intensity (tons CO_2/$ mln)	238,902	198.877	623.588	2.133	13.942	77.493	893.624

Notes: 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.

group of polluting firms and a group of cleaner firms. The mechanism behind our carbon risk factor follows the ESG risk model introduced in Pástor, Stambaugh, and Taylor (2020) and empirically tested in Pástor, Stambaugh, and Taylor (2022). In this model, ESG risks materialize through two channels: the customer channel and the investor channel. The same logic applies to carbon risk. When climate concerns rise unexpectedly—for example, because the forecast for global warming worsens—customer demand shifts from "brown" to "green" products. This reduces the profitability and market values of polluting firms while boosting those of cleaner firms. The second channel involves investor behavior. During climate stress, investors derive more value from sustainable assets, either because they care about the climate or because they face reputational or regulatory pressure to divest from brown assets. This leads them to shift away from polluting stocks and toward greener ones.[8] Choi, Gao, and Jiang (2020) find support for this mechanism by showing that carbon-intensive stocks underperform during unusually warm months, mainly due to retail investors selling those stocks. Investors may also anticipate stricter climate policies, as the probability of government action increases with rising environmental concerns.[9] Selling pressure and higher discount rates then push polluting firms' values down and clean firms' values up. Since the PMC portfolio is long brown and short green, both channels reduce its value during climate shocks. The reverse happens when climate concerns unexpectedly ease, making PMC returns positive.

We similarly construct the PMC portfolio as the Fama and French (1993) High-Minus-Low (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. 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

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polluting and clean firms at the 70th and 30th percentiles. For each year, we form four value-weighted portfolios: small/polluting (SP), big/polluting (BP), small/clean (SC), and big/clean (BC). The return on PMC is then given by:

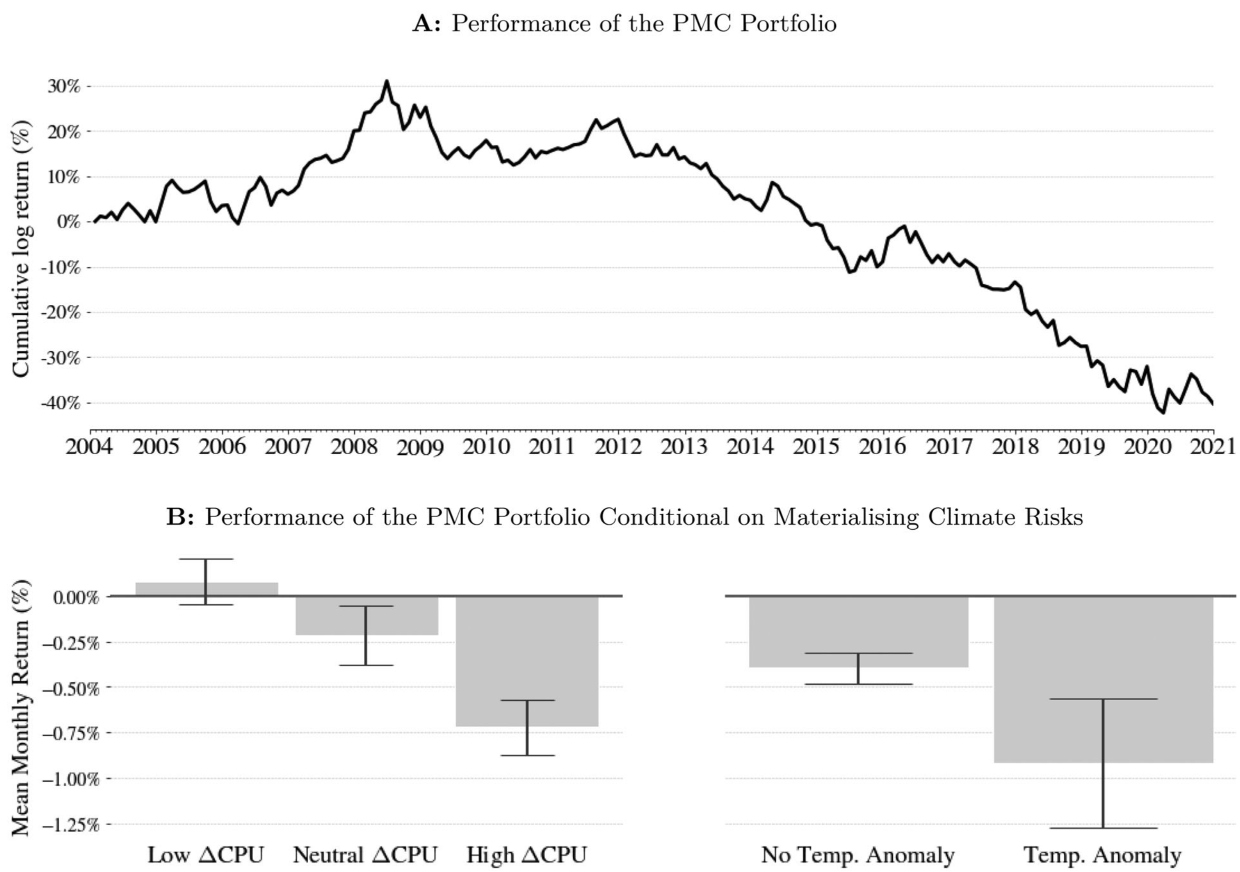
$$r_{PMC,t} = \frac{r_{SP,t} + r_{BP,t}}{2} - \frac{r_{SC,t} + r_{BC,t}}{2}, \qquad (1)$$

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 SP, BP, SC, and BC portfolios on day t. Panel A of Figure 1 displays the cumulative log return on the PMC portfolio.

The mean return on PMC was 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 1 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 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

Figure 1. Performance of the PMC Portfolio



Notes: The figure in panel A plots the cumulative log return on the PMC 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 "The Pollutive-Minus-Clean Portfolio." The figure in panel B plots the performance of the PMC portfolio conditional on two proxies for materializing climate risks: Terciles of monthly innovations in the CPU index and the 10% of months with the highest temperature deviations from long-term averages.

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Table 2. Factor Return Descriptive Statistics

			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

Notes: 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 5% and 1% level, respectively.

robustness of our factor construction choices, we alternatively construct PMC portfolios on other sorting variables besides Trucost's reported and estimated emissions. Figure B1 and Table B2 in Appendix B report evidence that portfolios constructed by (1) using only reported emissions; (2) using only estimated emissions; (3) using emissions intensities; and (4) using emissions provided by MSCI yield relatively similar portfolio returns, both unconditional as well as during episodes of materialising climate risks.

Estimating Carbon Betas. To estimate carbon betas—that is, 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:

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

where $R_{i,t}$ is the return on stock i on day t in excess of the risk-free rate; 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 error 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.[10] Betas are estimated at the end of each month and assigned to the subsequent month to ensure they are free from look-ahead bias. In later tests, we cross-sectionally standardize estimates of carbon beta when comparing them to other measures of carbon risk. In all cases, we winsorize estimates at the 1% and 99% levels to mitigate the impact of outliers.[11]

Results

Summary of Validation Exercises. To verify that our carbon beta estimates truly capture climate risk and are not just artifacts of industry effects or spurious correlations, we run a series of validation tests. Our aim is to check whether variation in carbon betas aligns with insights from earlier studies and with common views on climate exposure. We start by comparing carbon betas across industries.

As shown in Figure 2, Energy, Materials, and Utilities firms have the highest carbon betas. These sectors account for more than 70% of scope 1&2 emissions in our sample, so high loadings are expected. In contrast, IT, Financials, and Health Care firms show the lowest carbon betas. Their negative values indicate that stocks in these industries tend to perform well when the PMC factor underperforms. However, large differences in carbon beta can still arise within industries. To provide an example, NextEra Energy Inc., a leading renewable energy firm, has a carbon beta of −0.18 at the end of 2020, while the industry average for the Energy sector is considerable higher. Texas Pacific Land Corporation, a company with very few operations other than leasing out land for oil exploration, has very limited emissions (scoring among the lowest 30%) but a considerably high carbon beta at 0.52. We further test how firm characteristics relate to carbon beta. Theory and prior research suggest that smaller, more capital-intensive, lower-valued, less profitable, and less innovative firms should face

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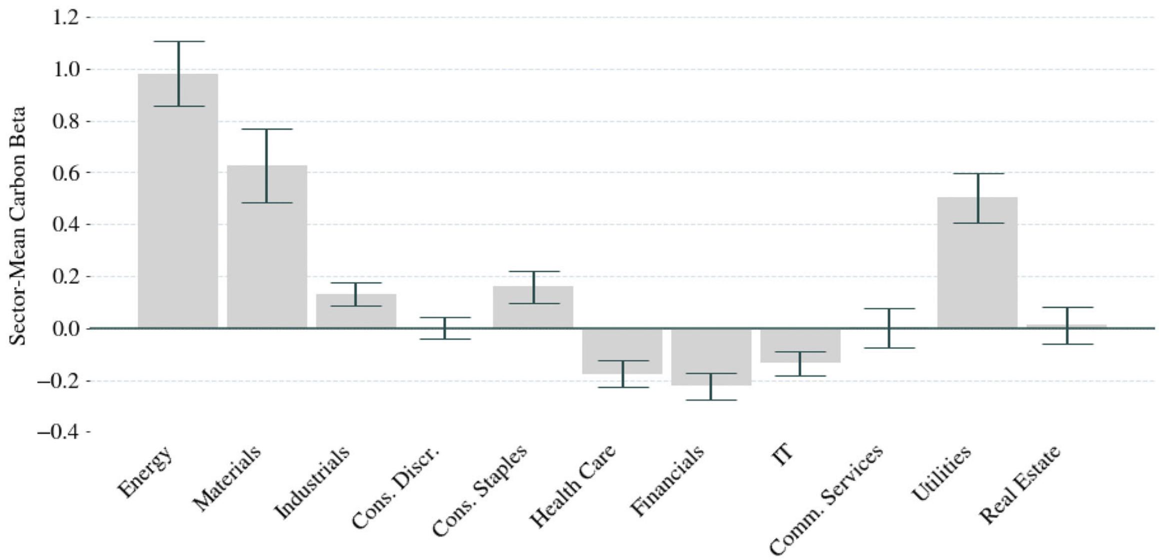
Figure 2. Industry Sector Variation in Carbon Beta



Notes: The figure displays the coefficients estimated by regressing carbon beta on two-digit GICS industry sector fixed effects. The sample period is January 2007 to December 2020. The coefficients are estimated with the specification in Equation (9). The 95% confidence intervals are based on robust standard errors adjusted for clustering at the firm level.

higher transition risks (see, e.g., Bolton and Kacperczyk 2021; Hsu, Li, and Tsou 2023; Li et al. 2024; Sautner et al. 2023).

In more detail: Larger firms are typically better positioned to manage transition risk because they are diversified and can exert lobbying power. By contrast, firms with heavy physical assets are more exposed, since their operations carry higher emissions and energy needs. Research also shows that higher climate risk exposure is linked to lower valuations. Capital-constrained firms, in particular, struggle to invest in low-carbon technologies, leaving them more vulnerable. On the other hand, firms that invest in R&D are better able to develop or adopt clean technologies, reducing their exposure. Indeed, earlier studies find a negative relationship between R&D intensity and climate risk (Bolton and Kacperczyk 2021; Sautner et al. 2023).

To test these ideas, we estimate the following panel regression:

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

where $CB_{i,t}$ is firm i's carbon beta in month t and $X_{i,t}$ includes lagged firm characteristics: log of market capitalization, book-to-market ratio, return on equity, leverage, investments-to-assets, PP&E-to-assets, and R&D-to-assets. We include a year-month fixed effect, μ_t, and optionally include a sector fixed effect, c_i. Standard errors are clustered at the firm level.

Table 3 reports our estimates. Our predictions are largely supported by our empirical results. We find that larger, more profitable, and more innovative firms (measured by R&D-to-assets) are less exposed to climate risk. By contrast, firms with higher capital intensity (investments-to-assets and PP&E-to-assets), greater leverage, and higher greenhouse gas emissions show higher carbon betas. The emissions link is economically meaningful: A one-standard deviation increase in log emissions corresponds to a 0.27- to 0.51-standard deviation increase in carbon beta, depending on whether sector effects are included. Columns 2 and 3 suggest that lower return on equity is linked to higher carbon beta, but this effect disappears once emissions are controlled for, showing that it mainly reflects the lower profitability of emission-heavy firms. The positive relation with leverage indicates that financially constrained firms face higher transition risk. Overall, these results align with prior research and expectations.

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Table 3. Carbon Beta and Firm Characteristics

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
No. Obs.	595,293	200,917	595,202	200,917
R^2 Adj.	0.243	0.472	0.421	0.608

Notes: 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. FE = fixed effects. * and ** denote statistical significance at the 5% and 1% level, respectively. †Indicates a cross-sectionally standardized variable.

Table 4. Correlations Between Carbon Beta and Alternative Measures of Climate Risk

	Carbon Beta	ln (Emissions)	Emissions Intensity	SLVZ20 CCE	CVaR
Carbon Beta	1.00	–	–	–	–
ln(Emissions)	0.49**	1.00	–	–	–
Emissions Intensity	0.34**	0.48**	1.00	–	–
SLVZ20 CCE	0.19**	0.24**	0.50**	1.00	–
CVaR	0.36**	0.44**	0.41**	−0.03	1.00

Notes: 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. SLVZ20 CCE is the Sautner et al. (2023) Climate Change Exposure measure. CVaR is the MSCI Climate-Value-at-Risk measure. Emissions and emission intensity data are from Trucost. The data collection procedure is described in detail in Appendix A. * and ** denote statistical significance at the 5% and 1% level, respectively.

We then compare carbon beta with alternative measures of climate risk. Table 4 shows strong correlations with emissions, emission intensity, the Sautner et al. (2023) Climate Change Exposures (CCE), MSCI Climate Value-at-Risk, and MSCI Green Scores, all consistent with expectations. Table 5 breaks down the CCE link: Carbon beta is most strongly related to the "regulatory" and "climate

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Table 5. Carbon Beta and Sautner et al. (2023) Climate Change Exposures

	Carbon Beta†				
Dependent variable:	(1)	(2)	(3)	(4)	(5)
CCE†	0.205**	–	–	–	–
	(0.012)	–	–	–	–
CCE Regulatory†	–	0.158**	–	–	0.112**
	–	(0.009)	–	–	(0.009)
CCE Opportunities†	–	–	0.159**	–	0.114**
	–	–	(0.012)	–	(0.011)
CCE Physical†	–	–	–	0.044**	0.027**
	–	–	–	(0.006)	(0.005)
No. Obs.	350,339	350,339	350,339	350,339	350,339
R^2 Adj.	0.043	0.026	0.026	0.002	0.038

Notes: 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. (2023) 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 standardized. Standard errors are clustered at the firm level. * and ** denote statistical significance at the 5% and 1% level, respectively. †Indicates a cross-sectionally standardized variable.

technologies" subscores, which are both transition risk measures. The correlation with physical CCE is positive and significant but only about one-quarter the size of the transition CCEs.

Additional validation results are reported in the Online Appendix.

Capturing Forward-Looking Aspects of Carbon Risks

Green Innovation. Cohen, Gurun, and Nguyen (2020) report a striking paradox: Energy firms are heavy emitters and poor environmental performers, yet they are also the most active in patenting low-carbon technologies. Since "green innovators" are likely less exposed to climate risk and may benefit from the transition, we test whether carbon beta reflects differences in green patenting activity. We use *Green Share*, defined as the fraction of a firm's patents that are green, as our measure of innovation (Cohen, Gurun, and Nguyen 2020). Specifically, we estimate:

$$S_{i,t} = \sigma \text{ Green Share}_{i,t} + \lambda X_{i,t-1} + c_i + \mu_t + \epsilon_{i,t}, \qquad (4)$$

where S_{it} is either firm i's cross-sectionally standardized carbon beta, scope 1&2 emissions intensity, or the natural logarithm of total scope 1&2 emissions in month t; $X_{i,t-1}$ includes the same lagged firm characteristics of Equation (3); c_i is an optional sector fixed effect; and μ_t is a time fixed effect.

Table 6 reports the results. Across all sectors, we find a small negative relationship (−0.071, $P = .08$). Within the Energy sector, however, the effect is much stronger and significant: a one-unit increase in green share reduces carbon beta by roughly 34% of a standard deviation ($P = .04$), as column 2 in Table 6 reports.

When we repeat the test using emissions intensity or total emissions as dependent variables, no significant effect emerges. As a robustness check, we substitute MSCI's Green Patent Share measure. Our results are consistent using this measure. The link between green innovation and lower carbon betas remains strongest within the Energy sector.

Taken together, these findings have important implications. Broad divestment from Energy stocks may also reduce capital available to leading green innovators. In contrast, targeting high–carbon beta firms within the Energy sector still allows investors to back those most engaged in developing low-carbon technologies.

Unobserved Factors of Forward-Looking Climate Risk. Climate-Value-at-Risk (CVaR), developed by MSCI, measures how climate change and related policies may affect asset prices. It combines forward-looking assessments with firm valuation metrics. Key inputs include firm emissions and green patenting, but MSCI also incorporates proxies

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Table 6. Carbon Beta and Green Innovation

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)
PP&E/Assets	0.380**	0.636**	0.509**	0.246**
	(0.045)	(0.141)	(0.147)	(0.092)
R&D/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
No. Obs.	223,659	12,660	6,859	6,859
R^2 Adj.	0.432	0.342	0.136	0.726

Notes: This table reports the coefficients obtained from estimating regression Equation (4). Green Share (%) is the measure of green patent innovation from Cohen, Gurun, and Nguyen (2020). We collect data on US patents issuance from the US Patent and Trademark Office's Bulk Data Storage System. In the first column, we regress carbon betas on green shares across all firms in our sample, while in subsequent columns we only consider firms categorized in the Energy sector (2-digit GICS equal to 10). The data are from December 2010 to December 2020. Standard errors are clustered at the firm level. FE = fixed effects. * and ** denote statistical significance at the 5% and 1% level, respectively. †Indicates a cross-sectionally standardized variable.

for physical risks, transition scenarios, low-carbon revenues, and abatement policies.

Our goal is to test whether carbon beta correlates with forward-looking aspects of CVaR beyond emissions and green innovation. To do so, we regress CVaR on emissions, green share, carbon beta, and optional industry fixed effects. We use MSCI's own green innovation data, since they are directly included in their CVaR model. Our regression specification includes green share and emissions because we are primarily interested in the association between carbon beta and the component of CVaR that is unrelated to emissions and green innovation, that is, inputs of the measure related to forward-looking climate risks.

$$\text{CVaR}_{i,t} = \alpha + \sigma \text{ Green Share}_{i,t} + \lambda \ \ln(\text{Emissions})_{i,t} + \gamma CB_{i,t} + c_i + \mu_t + \epsilon_{i,t}, \tag{5}$$

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

Results are reported in Table 7. As expected, emissions are positively and green innovation negatively associated with CVaR, reflecting MSCI's construction of the measure. Importantly, carbon beta is consistently positive and statistically significant. Even after controlling for industry effects, a one–standard deviation increase in carbon beta corresponds to a 7.7%–standard deviation increase in CVaR.

This result confirms that carbon beta captures information beyond emissions and green innovation. Specifically, it appears to align with other CVaR components such as exposure to low-carbon technologies, sensitivity to abatement policies, or dependence on green revenues. In other words,

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carbon beta provides a complementary market-based signal of transition risk that overlaps with but also extends beyond MSCI's model inputs.

Table 7. Carbon Beta and Unobserved Climate Risk Factors

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
No. Obs.	167,055	167,055
R^2	0.261	0.317

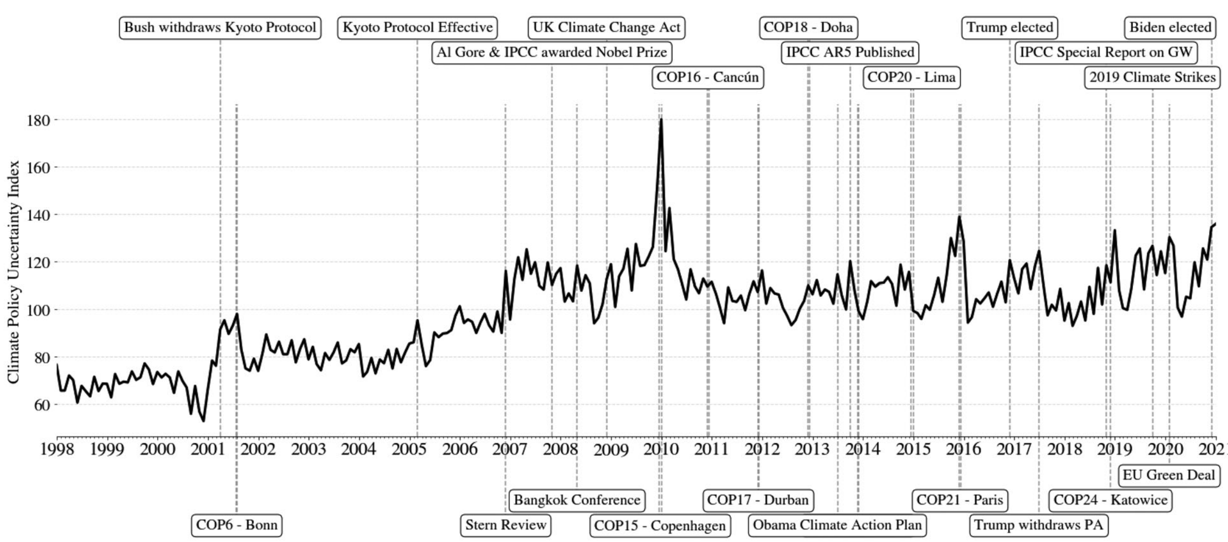
Notes: This table reports the coefficients obtained from estimating regression Equation (5). MSCI CVaR is MSCI's Climate-Value-at-Risk. Standard errors are clustered at the firm level. Specification (1) does not control for industry fixed effects, while specification (2) does. FE = fixed effects. * and ** denote statistical significance at the 5% and 1% level, respectively. †Indicates a cross-sectionally standardized variable.

Carbon Beta and Hedging of Climate Shocks.

In this section, we study how equity returns behave when climate risks materialize. We use two proxies for aggregate climate shocks. The first is news-based and captures attention to climate change through the CPU index, which we treat as indicative of heightened uncertainty about future climate policies. The second concerns extreme weather events, such as episodes of unusual heat, storms, or droughts in the United States. We expect that these events have only limited direct consequences for high–carbon beta stocks; however, prior research shows that such events increase investor concerns about climate change (Alekseev et al. 2022; Bansal, Kiku, and Ochoa 2016; Choi, Gao, and Jiang 2020; Huynh, Li, and Xia 2025). Our focus is on the interaction between a firm's carbon beta and these proxies of realized climate risk. Put simply, we ask: Do stocks with high carbon betas react differently to climate shocks than those with low carbon betas?

As a first proxy for realized climate risks, we use the CPU index. Figure 3 plots the CPU index over time. As can be seen, the CPU index spikes when climate-related events occur. The index peaks in December 2009, during the 15th Conference of the Parties (COP) in Copenhagen. COP15 was one of the first international conferences to bring climate

Figure 3. CPU Index



Notes: The figure plots *The Wall Street Journal*–based 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.

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change to the highest political level. The Copenhagen Accord—which expressed clear political intent to limit carbon emissions and respond to climate change—resulted from this conference. The CPU index reached its second-highest level in November and December 2015, during COP21 in Paris, where the Paris Agreement was negotiated. Around the end of 2019, the index remained high, coinciding with mass climate protests and the Climate Action Summit in New York.

We study how carbon beta interacts with changes in the CPU index to affect stock returns. Our specification follows the framework of Daniel and Titman (1997), Bolton and Kacperczyk (2021), and Bolton and Kacperczyk (2023):

$$R^e_{i,t} = \beta\ CB_{i,t-1} + \gamma\ CB_{i,t-1} \times \Delta CPU_t + \lambda\ X_{i,t-1} + c_i + \mu_t + \epsilon_{i,t}, \tag{6}$$

where $R^e_{i,t}$ is firm i's excess monthly return, $CB_{i,t-1}$ is its lagged carbon beta, ΔCPU_t is the standardized monthly change in the CPU index, and $X_{i,t-1}$ includes firm-level controls (size, book-to-market, return on equity, leverage, investment-to-assets, PP&E-to-assets, CAPM beta, idiosyncratic volatility, and momentum). Our focus is on the coefficient γ, which captures how stocks with higher carbon betas perform when climate policy uncertainty rises. We estimate similar regression models where we replace carbon beta and its interaction term with standardized log-transformed scope 1&2 emissions or standardized emission intensities to uncover any potential differences in market responses to CPU shocks between these measures.

Table 8 shows that when the CPU index increases, stocks with higher carbon betas earn lower returns. The effect is economically meaningful: For two otherwise identical firms, a carbon beta that is one standard deviation higher implies underperformance of about 14 bps per month (1.7% annualized) when CPU rises by one standard deviation. In the smaller subsample with emissions data available, the coefficient roughly halves but remains statistically significant at the 1% level. This finding suggests that smaller firms for whom emissions data are less likely to be available are potentially more exposed to climate shocks. When repeating the analysis with emissions and emission intensities instead of carbon betas, results are weaker. Emission intensities show no effect, and emissions show a similar but clearly weaker pattern.[12]

To ensure that our findings are not driven by the choice of climate news index, we further validate our results with alternative climate news indices: the Climate Change News Index (Engle et al. 2020), the Media Climate Change Concerns index (Ardia et al. 2023), and the Climate Policy textual factor (Faccini, Matin, and Skiadopoulos 2023). The results are reported in Table B3 in Appendix B. Despite low correlation across these measures, all show a similar pattern. Stocks with higher carbon betas underperform when climate attention rises according to all four proxies.

Bansal, Kiku, and Ochoa (2016) and Choi, Gao, and Jiang (2020) show empirically that pollutive firms deliver weaker returns during extreme weather. We test this mechanism by examining two types of weather-related events. First, we classify months as "temperature anomalies" when average temperature exceed the corresponding month's 90th percentile determined over the past 30 years. Second, we define droughts as months when the Palmer Z-index falls below the 10th percentile, equivalent to moderate drought conditions, according to Palmer (1965).

We adopt a similar specification as Equation (6), where we now substitute for EW, which defines an extreme weather month determined by a temperature anomaly in our first test and a drought period in our second test.

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

where $R_{i,t}$ is firm i's excess stock return in month t and 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. All other variables are as in Equation (6). Our coefficient of interest, ϕ, measures the additional return impact of carbon beta during extreme weather. Year-month fixed effects are included to absorb the main effect of weather shocks.

Results are reported in Tables B4 and B5. We find that firms with higher carbon betas earn significantly lower returns during abnormally warm months, while emissions and emission intensity show no similar effect. A one–standard deviation increase in carbon beta is associated with roughly 32 bps lower monthly excess return when temperatures are unusually high. A similar negative effect appears for droughts. Again, this pattern only arises for carbon beta.

These results can be explained in several ways. Investors may view extreme weather as realizations

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Table 8. Carbon Beta, Climate Policy Uncertainty, and Stock Returns

	Monthly Excess Return (×100)			
Dependent variable:	(1)	(2)	(3)	(4)
Carbon Beta† × Δ CPU†	−0.143**	−0.066**	–	–
	(0.019)	(0.025)	–	–
Carbon Beta†	0.043	0.058	–	–
	(0.028)	(0.046)	–	–
Emissions Intensity† × Δ CPU†	–	–	−0.026	–
	–	–	(0.018)	–
Emissions Intensity†	–	–	−0.053	–
	–	–	(0.031)	–
ln(Emissions)† × Δ CPU†	–	–	–	−0.064*
	–	–	–	(0.028)
ln(Emissions)†	–	–	–	0.177*
	–	–	–	(0.080)
ln(Market Cap.)	−0.014	0.062**	0.064**	−0.002
	(0.013)	(0.023)	(0.022)	(0.035)
Book/Market	0.130**	−0.180	−0.162	−0.239
	(0.046)	(0.121)	(0.119)	(0.125)
Return on Equity	0.143**	0.108	0.109	0.100
	(0.042)	(0.076)	(0.076)	(0.076)
Debt/Assets	0.148	0.286	0.314	0.219
	(0.111)	(0.202)	(0.203)	(0.201)
Investment/Assets	−1.660**	−1.167	−1.160	−0.907
	(0.596)	(1.213)	(1.205)	(1.210)
PP&E/Assets	0.074	−0.157	−0.113	−0.250
	(0.073)	(0.134)	(0.135)	(0.138)
CAPM Beta	0.154**	−0.478**	−0.493**	−0.494**
	(0.044)	(0.111)	(0.109)	(0.109)
Idio. Volatility	−1.522**	3.921**	3.935**	3.908**
	(0.189)	(0.539)	(0.537)	(0.538)
Momentum	0.297**	−0.087	−0.088	−0.091
	(0.054)	(0.112)	(0.112)	(0.112)
Year-Month FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
No. Obs.	593,367	200,309	200,309	200,309
R^2 Adj.	0.175	0.254	0.254	0.254

Notes: This table reports the full set of coefficients obtained from estimating Equation (6). The sample period is from January 2007 to December 2020. Δ*CPU* is the monthly percentage change in the Climate Policy Uncertainty index, as defined in "Sample Construction." All regressions include sector and year-month fixed effects. Standard errors are clustered at the firm level. FE = fixed effects. * and ** denote statistical significance at the 5% and 1% level, respectively. †Indicates a standardized variable. Firm-level variables are cross-sectionally standardized.

of climate risk, reallocating into firms with negative carbon betas that act as hedges. Alternatively, extreme weather may heighten investor awareness of climate change, prompting them to sell perceived "brown" assets, similar to fund manager divestment after local air pollution shocks (Huynh, Li, and Xia 2025). A third explanation is that extreme weather more directly hurts the earnings of high-carbon beta firms. In all cases, carbon beta consistently outperforms emissions and intensities as a predictor of which firms suffer most during climate shocks.

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:

$$R_{i,t} = \alpha + \theta CB_{i,t-1} + \lambda X_{i,t-1} + c_i + \mu_t + \epsilon_{i,t}, \qquad (8)$$

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 including company size, book-to-market, return on equity,

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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 (8). We employ the approach of Jegadeesh et al. (2019) 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 further outlined in the Online Appendix. Table 9 reports our results.

We find rather mixed evidence on the existence of a carbon premium. The carbon risk premium shows negative in column 1 of Table 9, where we do not additionally control for other factors known to affect returns and exclude industry fixed effect. This "carbon risk discount" is consistent with the underperformance of the PMC portfolio displayed in Figure 1. Including control variables in column 2 takes away some of the negative coefficient suggesting that the negative premium observed in

Table 9. Pricing of Carbon Risk with Errors-in-Variables Correction

	Monthly Excess Return (×100)			
Dependent Variable:	(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
No. Obs.	427,876	427,955	427,876	427,876
R^2 Adj.	0.229	0.230	0.230	0.230

Notes: 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 capitalization, 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 Instrumental Variables (IV)-estimation methodology to account for errors-in-variables (see text for details). Standard errors are clustered at the firm level. FE = fixed effects. * and ** denote statistical significance at the 5% and 1% level, respectively. †Indicates a standardized variable. Firm-level variables are cross-sectionally standardized.

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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 precise identification, although considerable uncertainty arounds its quantification remains, also in part due to the relatively short sample duration that we employ. The coefficients estimated according to this specification, reported in column 4 of Table 9, 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% annualized. Table IA3 in the Online Appendix presents the results without the application of Jegadeesh et al.'s (2019) correction. In this case, the (underestimated) carbon risk premium equals about 5.6 bps per month, or 0.6% annualized, suggesting the size of the EIV bias amounts to about half of the carbon risk premium. All in all, we find a small risk premium, although the sign and size are sensitive to the specification of the model.

Conclusion

We propose a forward-looking measure of climate transition risk based on how much an asset's return correlates with a carbon risk factor. This carbon risk factor aims to capture unexpected shifts in consumer and investor concerns about climate change. As our candidate factor, we propose the PMC portfolio: a self-financing portfolio that is long the 30% of stocks with the highest carbon emissions and short the 30% with the lowest emissions. By regressing individual stock returns on the PMC portfolio's returns and the standard Fama and French (1993) and Carhart (1997) factors, we treat the loading on the PMC portfolio as the firm-level exposure to transition risk: carbon beta.

Our approach complements conventional ways of measuring climate risk exposure. The measure reflects the market's consensus on a company's transition risk and can capture any factor investors consider relevant, such as clean technology adoption, innovation, management quality, industry competition, or financial strength. Indeed, regressions of carbon beta on firm characteristics show that larger, innovative, and profitable firms face lower transition risk, while capital-intensive and carbon-heavy firms face higher risk. In extensive validation tests, we also confirm that carbon beta is positively associated with forward-looking measures of climate transition risk obtained from MSCI and analyst conference calls derived by Sautner et al. (2023).

Carbon beta is also linked to green innovation, underscoring its forward-looking nature. Our framework provides an intuitive way to distinguish between firms most exposed to a low-carbon transition and those positioned to benefit. We find that returns differ sharply between high- and low-carbon beta firms in months when climate shocks occur. In particular, when policy uncertainty spikes, low-carbon beta assets outperform. Similar patterns hold in months with unusually high temperatures or severe droughts.

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. Recent examples include Jung, Engle, and Berner (2025a) and Jung et al. (2025b), who apply similar concepts to those developed in this paper to estimate respectively transition risk of the financial sector and physical climate risk exposures of US insurance companies.

Although we rely on carbon emissions to construct the PMC factor, alternative proxies could be valuable, for example, the price of emissions allowances, which are increasingly traded, or weather-linked securities and certain commodities. Even non-tradable proxies could be used, such as indices based on climate-related text analysis similar to the CPU index.

Investors can use this framework to build climate-aware strategies. Carbon beta can signal "climate hedge" potential, enabling hedge portfolios that perform well in periods of climate stress. The approach is transparent, accessible, and easy to replicate. It can be applied by investors who lack emissions data or cannot afford commercial products, such as retail investors or low-cost ETF providers. Academics may find it useful for studying climate risk in asset pricing, given its ability to generate a large, cross-sectional dataset. Regulators and policymakers could also use carbon beta to

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flag firms with high transition risk. Our results show that carbon betas capture green innovation—especially in emission-intensive energy firms—making the framework a potential tool to separate genuine green innovators from otherwise pollutive firms.

Editor's Note

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Notes

1. Emissions are more directly related to transition risk rather than physical risks. Physical risks are typically measured using geographic information as physical risks are tied to a location. Emissions are not tied to a location, but are an aggregate firm characteristic, such that the carbon beta proxies for the risk a firm is exposed to that governments, investors, or clients transition away from carbon heavy firms.
2. See, for example, Krueger, Sautner, and Starks (2020) and Giglio, Kelly, and Stroebel (2021).
3. Based on work by Engle et al. (2020), Ardia et al. (2023), and Faccini, Matin, and Skiadopoulos (2023).
4. The PMC index is available via Remco Zwinkels' website at https://research.vu.nl/en/persons/remco-zwinkels.
5. Available at https://bulkdata.uspto.gov/.
6. Available at https://wrds-www.wharton.upenn.edu/pages/analytics/wrds-us-patents/.
7. See https://www.wipo.int/classifications/ipc/green-inventory/home.
8. Note that Ardia et al. (2023) do not find evidence for such a shift from brown to green, but rather only observe a divestment away from brown firms. Regardless of the nature of this response, both types of shifts would be reflected in the returns on our PMC index.
9. See Pástor and Veronesi (2013) for political risk in general.
10. Besides considering several alternative carbon risk factor definitions (as shown in Figure B1 and Table B2), we have further included the Fama and French (2015) profitability and investments factors, performed the regression on monthly instead of daily return observations, utilized an industry-neutral carbon risk factor, and considered a carbon risk factor based on carbon intensities. Our validation results remain qualitatively similar.
11. Our results are virtually unaffected by omitting to winsorize and by increasing the extent of winsorization to 2% and 98% cutoff points.
12. When including both carbon beta and emissions intensities, the carbon beta effect remains significant, whereas the significance on emissions disappears. Results are available on request.
13. 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.
14. Available at https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
15. More information can be obtained from https://ghgprotocol.org.
16. Our Trucost data only include 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.
17. Available at https://en.wikipedia.org/wiki/Category:Climate_change.
18. These involve, in the following order: removing punctuation, tokenizing (splitting sentences into words), removing stop words, lemmatizing (reducing words to their word roots, e.g., the words "climate" and "climatology" both become "climat"), and converting terms into bigrams (two-word collections of consecutive words).
19. The TF-IDF algorithm converts words, in our case bigrams, into scores determined by the word's frequency within a document, penalized 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.
20. 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 normalized to have unitary length. The cosine similarity reaches its maximum of 1 when the angle between v_{CC} and $v_{WSJ,t}$ equals 0°.
21. The construction of our CPU index closely follows that of the Engle et al. (2020) Climate Change News Index (CCNI). The difference mainly lies in the composition of our climate change corpus. First, our climate change corpus only includes the five Assessment Reports by the IPCC, while Engle et al.'s (2020) 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%.

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22. The data are available at https://osf.io/fd6jq/.

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

24. Obtained from https://www.ncei.noaa.gov/access/monitoring/historical-palmers/.

25. More information available at https://www.msci.com/documents/1296102/16985724/MSCI-ClimateVaR-Introduction-Feb2020.pdf/f0ff1d77-3278-e409-7a2a-bf1da9d53f30.

26. Downloaded from https://sentometrics-research.com/download/mccc/.

27. Available at Renato Faccini's webpage at https://sites.google.com/site/econrenatofaccini/home/research.

28. Available at https://bulkdata.uspto.gov/.

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

30. We obtain more than 99% of the patents in the WRDS database for the 2011–2019 period for which WRDS has patent data available.

31. See https://www.wipo.int/classifications/ipc/green-inventory/home.

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Appendix A. Details on Data and Sample Construction

In this Appendix, we provide further details on the data used in our analysis and the dataset construction procedure.

Stock Market and Corporate Data

For the main analysis of this paper, we combine US stock market data from the Center for Research in Security Prices (CRSP) with financial statements data from S&P Capital IQ Compustat. We use 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.[13] 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 capitalization 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 winsorized at the 1% and 99% cutoffs 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 utilize daily returns obtained from CRSP's daily security file to estimate capital asset pricing model (CAPM)–implied market betas and idiosyncratic return volatilities. Estimations are based on rolling windows containing three years of daily return observations. We obtain data on US factor returns from Kenneth French's data library, which we use in the estimation of CAPM betas, idiosyncratic volatilities, and carbon betas.[14]

Panel A of Table 1 reports descriptive statistics for our stock market dataset. After merging CRSP with Compustat data and applying our filters, the sample contains more than 780,000 monthly return observations for more than 7,100 unique firms. The average monthly return in excess of the risk-free rate equals 0.68%. Moreover, the average (median) firm in our sample has a market capitalization of about \$5.4 billion (\$592 million). Average book-to-market, book leverage, and investment-to-assets equal 0.66, 0.19, and 0.04, respectively. The average firm has a market beta of 0.98 and annualized idiosyncratic volatility of 41%. 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.

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 utilizes 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.[15] The Greenhouse Gas Protocol decomposes emissions into three "scopes." Scope 1 emissions include the direct emissions occurring in a company's production process. Scope 2 emissions are the indirect emissions associated with the purchase of electricity, heat, or steam. All other emissions taking place in a company's value chain are accounted for as scope 3. As our database does not contain the complete data for scope 3 emissions, we only include scope 1 and scope 2 emissions in our analyses.[16] We sum scope 1 and scope 2 to a combined scope 1&2 and calculate emission intensities for the combined and separate scope 1 and 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.

CPU 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 theorize that periods of high levels of climate change news are indicative of increased uncertainty around climate change regulation. Following similarly constructed indices for Economic Policy Uncertainty (see Baker, Bloom, and Davis 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 Li et al. 2024; Sautner et al. 2023), we extend the climate change corpus with articles in the "climate change" category on Wikipedia.[17] 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.[18] We then perform a term frequency–inverse document frequency (TF-IDF) transformation to convert our collection of

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text articles into numerical vector form.[19] 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 v_{CC} and $v_{WSJ,t}$. Finally, for each day we compare $v_{WSJ,t}$ with v_{CC} by cosine similarity.[20] The intuition behind this approach is that when news articles use climate change terms in similar proportions as the texts related to climate change, the index indicates a high level of climate change news risk (Engle et al. 2020).[21] 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 3 plots the CPU 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.

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.

Firm-Level Climate Change Exposure.

We compare our estimates of carbon beta with the Sautner et al. (2023) Climate Change Exposures (hereafter also referred to as SLVZ20 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 CCE, Sautner et al. (2023) determine separate vocabularies for risks, opportunities, and regulations related to climate change.[22] We use the three components as well as general climate change exposure in our analysis. We cross-sectionally standardize all CCE exposure values to make their scales comparable.

Temperature and Drought Statistics.

We collect monthly temperature anomalies for the United States from the US Climate Reference Network.[23] 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.[24] 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. Values of −4 indicate extreme drought, values between −1 and 1 indicate regular conditions, and values of +4 indicate unusually wet periods.

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.[25] 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 standardize 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.

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 US 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 the Online Appendix.

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Other Climate Change Attention Series. We download several other proxies for climate change attention that are similar in spirit to the CPU index that we constructed. We use these different proxies in robustness tests to ensure that none of our results are driven by the choice of a CPU measure. In determining which proxies to include, we consider three factors: a potential proxy variable must (1) have a global or US geographic focus; (2) be available for the majority of the sample period we study, and (3) be intended to capture risks related to climate policy and the climate transition. We include three of such proxies: the Climate Change News Index (CCNI) by Engle et al. (2020), whose methodological approach we have adopted in the construction of our CPU index, the Media Climate Change Concerns index by Ardia et al. (2023),[26] and the Climate Policy textual factor by Faccini, Matin, and Skiadopoulos (2023).[27]

Green Patents. Following Cohen, Gurun, and Nguyen (2020), we download US patents through the USPTO Bulk Data Storage System.[28] The USPTO provides text files for all patents issued in the United States from 1976 onward. We download patents 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 the WRDS newly released US Patents (Beta) product.[29] 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.[30] 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. 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 the WRDS 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.[31] 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, Gurun, and Nguyen 2020). We download more than 750,000 unique patents, matched to more than 3,000 firms. A little less than 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.

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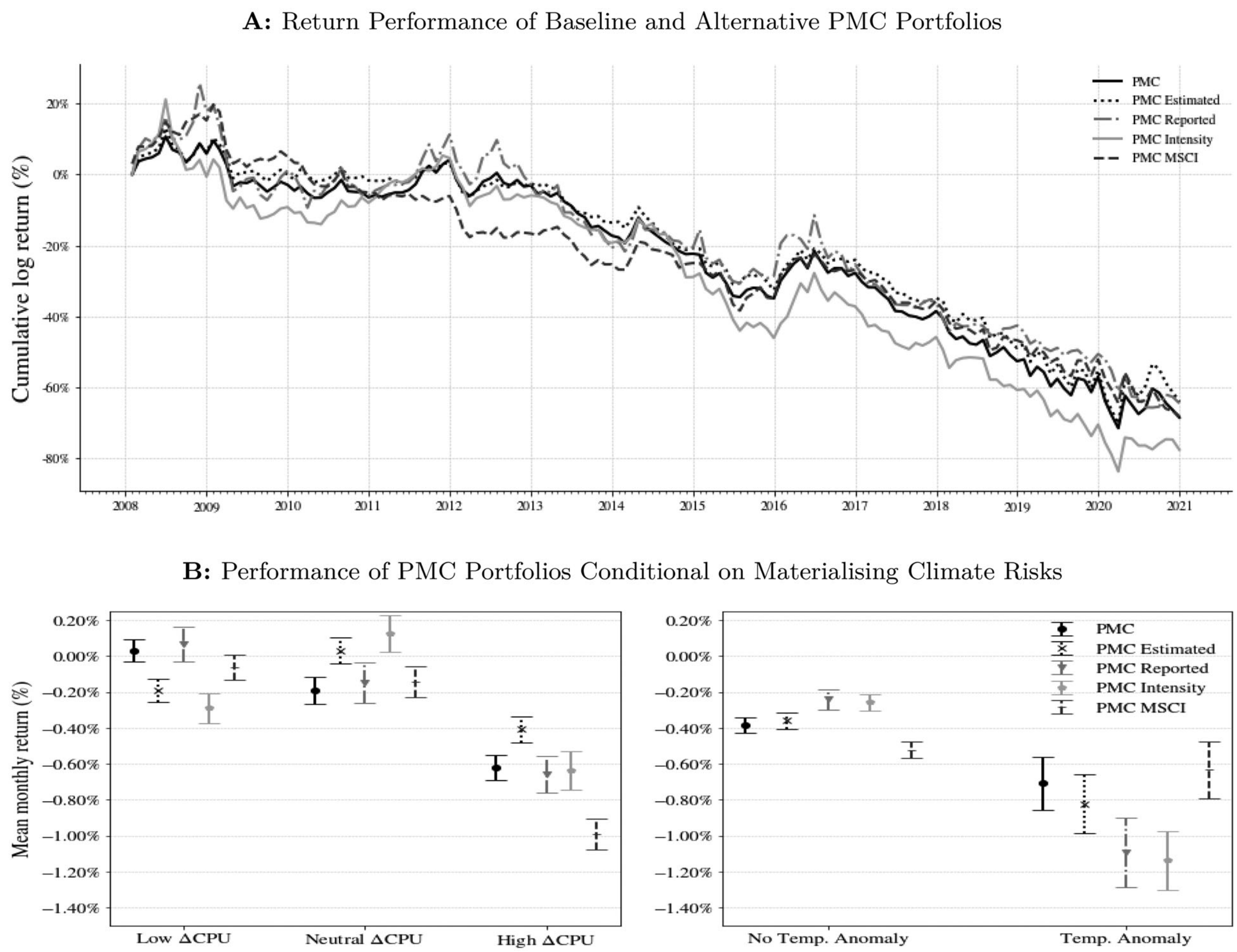
Appendix B: Additional Figures and Tables

Figure B1. PMC Portfolio: Robustness to Alternative Definitions



Notes: 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. The figure displays PMC portfolios that were constructed in different ways. The baseline PMC as used in the paper is based on emissions data provided by Trucost. We compare this to alternative constructions based on estimated emissions (PMC Estimated), reported emissions (PMC Reported), emission intensities (PMC Intensity), and emissions provided by MSCI (PMC MSCI). Panel A reports cumulative returns over the sample period. Panel B plots the performance of the PMC portfolios conditional on two proxies for materializing climate risks: Terciles of monthly innovations in the CPU index and the 10% of months with the highest temperature deviations from long-term averages.

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Table B1. Variable Definitions

Variable	Description	Source
Excess Return$_{i,t}$	Return for stock *i* in month *t* in excess of the 1-month Treasury bill rate, winsorized at 0.5% and 99.5% cutoff points.	CRSP + KFDL
ln(Market Cap.)$_{i,t-1}$	Natural logarithm of market capitalization (in millions of US $), where market capitalization is defined as shares outstanding multiplied by share price at the end of month *t-1*.	CRSP
B/M$_{i,t-1}$	Book-to-market ratio is the book value of equity at the end of June of previous year divided by market capitalization at the end of month *t-1*, winsorized at 1% and 99% cutoff 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, winsorized at 1% and 99% cutoff 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, winsorized at 1% and 99% cutoff 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, winsorized at 1% and 99% cutoff points.	CS
PP&E/Assets$_{i,t-1}$	Property, Plant & Equipment divided by total assets at the end of June of previous year, winsorized at 1% and 99% cutoff points.	CS
R&D/Assets$_{i,t-1}$	Annual Research & Development expenses divided by total assets at the end of June of previous year, winsorized at 1% and 99% cutoff 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* winsorized at 1% and 99% cutoff points.	AC
Idio. Volatility$_{i,t-1}$	Idiosyncratic volatility is the annualized 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* winsorized at 1% and 99% cutoff 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* winsorized at 1% and 99% cutoff 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 tons of CO_2-equivalent), winsorized from above at 99% cutoff point.	TC
Emissions Intensity$_{i,t}$	Combined scope 1 and scope 2 emissions (in millions of tons of CO_2-equivalent) scaled by annual revenues of year *t-1*, winsorized from above at 99% cutoff 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 normalize the measure for easy of comparability.	SvLVZ
CVaR$_{i,t}$	Climate-Value-at-Risk measures firm-specific forward-looking valuation assessments regarding climate risks and opportunities. We normalize and invert the measure so that its interpretation is equivalent to conventional Value-at-Risk.	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

continued

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Table B1. Variable Definitions (continued)

Variable	Description	Source
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 is 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

Note: This table reports on the data sources and definitions of the variables used in our main analyses. KFDL = Kenneth French's Data Library, CRSP = Center for Research in Security Prices; 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; NOAA = National Oceanic and Atmospheric Administration; SvLVZ = Sautner et al. (2023).

Table B2. Correlations Between Alternative PMC Portfolios

	PMC	$PMC_{Estimated}$	$PMC_{Reported}$	$PMC_{Intensity}$	PMC_{MSCI}
PMC	1.00	–	–	–	
$PMC_{Estimated}$	0.95	1.00	–	–	–
$PMC_{Reported}$	0.73	0.59	1.00	–	–
$PMC_{Intensity}$	0.79	0.79	0.68	1.00	–
PMC_{MSCI}	0.85	0.83	0.63	0.72	1.00

Notes: This table reports pairwise correlation coefficients between alternatively constructed PMC portfolios. 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. The table compares PMC portfolios that were constructed in different ways. The baseline PMC as used in the paper is based on emissions data provided by Trucost. We compare this to alternative constructions based on estimated emissions (PMC Estimated), reported emissions (PMC Reported), emission intensities (PMC Intensity), and emissions provided by MSCI (PMC MSCI).

Table B3. Carbon Beta, Other Climate Attention Proxies, and Stock Returns

	Monthly Excess Return (×100)			
Dependent Variable:	(1)	(2)	(3)	(4)
Carbon $Beta^{\dagger} \times \Delta$ $CPU^{\dagger}$	−0.143**	–	–	–
	(0.019)	–	–	–
Carbon $Beta^{\dagger} \times \Delta$ $CCNI^{\dagger}$	–	−0.093**	–	–
	–	(0.019)	–	–
Carbon $Beta^{\dagger} \times \Delta$ $MCCC^{\dagger}$	–	–	−0.079**	–
	–	–	(0.027)	–
Carbon $Beta^{\dagger} \times \Delta$ $CPTF^{\dagger}$	–	–	–	−0.479**
	–	–	–	(0.089)
Carbon $Beta^{\dagger}$	0.043	0.065*	0.057*	0.007
	(0.028)	(0.029)	(0.029)	(0.028)
ln(Market Cap.)	−0.014	−0.066**	−0.070**	−0.015
	(0.013)	(0.014)	(0.013)	(0.013)

continued

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Table B3. Carbon Beta, Other Climate Attention Proxies, and Stock Returns (continued)

	Monthly Excess Return (×100)			
Dependent Variable:	(1)	(2)	(3)	(4)
Book/Market	0.130**	0.250**	0.210**	0.129**
	(0.046)	(0.050)	(0.048)	(0.046)
Return on Equity	0.143**	0.136**	0.146**	0.142**
	(0.042)	(0.048)	(0.046)	(0.042)
Debt/Assets	0.148	0.062	0.032	0.148
	(0.111)	(0.123)	(0.119)	(0.111)
Investment/Assets	−1.660**	−1.852**	−2.098**	−1.634**
	(0.596)	(0.627)	(0.614)	(0.595)
PP&E/Assets	0.074	0.132	0.214**	0.071
	(0.073)	(0.078)	(0.076)	(0.073)
CAPM Beta	0.154**	0.263**	0.281**	0.155**
	(0.044)	(0.047)	(0.046)	(0.044)
Idio. Volatility	−1.522**	−2.429**	−2.364**	−1.526**
	(0.189)	(0.201)	(0.194)	(0.189)
Momentum	0.297**	0.294**	0.324**	0.299**
	(0.054)	(0.058)	(0.056)	(0.054)
Year-Month FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
No. Obs.	593,367	446,088	487,576	593,367
R^2 Adj.	0.175	0.158	0.151	0.175

Notes: This table reports the full set of coefficients obtained from estimating regression Equation (6). The sample period is from January 2007 to December 2020. Δ CPU is the monthly percentage change in the Climate Policy Uncertainty index. Δ CCNI is the innovation in the Engle et al. (2020) Climate Change News Index, Δ MCCC is the innovation in the Ardia et al. (2023) Media Climate Change Concerns index, and Δ CPTF is the innovation in the Faccini, Matin, and Skiadopoulos (2023) Climate Policy Textual Factor. 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 5% and 1% level, respectively. †Indicates a standardized variable. Firm-level variables are cross-sectionally standardized.

Table B4. Carbon Beta, Extreme Temperature, and Stock Returns

	Monthly Excess Return (×100)				
Dependent Variable:	(1)	(2)	(3)	(4)	(5)
Carbon Beta† × ExtrTemp	−0.321**	−0.307**	–	–	−0.342**
	(0.070)	(0.096)	–	–	(0.112)
Carbon Beta†	0.075**	0.099*	–	–	0.072
	(0.028)	(0.048)	–	–	(0.049)
Emissions Int.† × ExtrTemp	–	–	−0.052	–	0.060
	–	–	(0.067)	–	(0.073)
Emissions Int.†	–	–	−0.045	–	−0.118**
	–	–	(0.029)	–	(0.037)
ln(Emissions)† × ExtrTemp	–	–	–	−0.105	0.044
	–	–	–	(0.085)	(0.107)
ln(Emissions)†	–	–	–	0.192*	0.231*
	–	–	–	(0.081)	(0.093)
ln(Market Cap.)	−0.013	0.064**	0.065**	−0.001	−0.015
	(0.013)	(0.023)	(0.023)	(0.035)	(0.038)
Book/Market	0.131**	−0.173	−0.161	−0.238	−0.247
	(0.046)	(0.120)	(0.119)	(0.126)	(0.127)

continued

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Table B4. Carbon Beta, Extreme Temperature, and Stock Returns (continued)

	Monthly Excess Return (×100)				
Dependent Variable:	(1)	(2)	(3)	(4)	(5)
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	0.152	0.290	0.314	0.222	0.194
	(0.111)	(0.202)	(0.203)	(0.201)	(0.202)
Investment/Assets	−1.688**	−1.169	−1.140	−0.877	−0.991
	(0.596)	(1.216)	(1.208)	(1.213)	(1.201)
PP&E/Assets	0.080	−0.144	−0.109	−0.242	−0.231
	(0.073)	(0.134)	(0.135)	(0.138)	(0.138)
CAPM Beta	0.154**	−0.480**	−0.492**	−0.493**	−0.496**
	(0.044)	(0.111)	(0.109)	(0.109)	(0.112)
Idio. Volatility	−1.516**	3.939**	3.933**	3.912**	3.974**
	(0.189)	(0.539)	(0.538)	(0.539)	(0.536)
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
No. Obs.	593,367	200,309	200,309	200,309	200,309
R^2 Adj.	0.175	0.253	0.253	0.253	0.253

Notes: This table reports the full set of coefficients obtained from estimating regression Equation (7). The sample period is from January 2007 to December 2020. ExtrTemp is a dummy variable equal to 1 if the associated month's temperature anomaly is above the 90th percentile and 0 otherwise. All regressions include sector and year-month fixed effects. Standard errors are clustered at the firm level. * and ** denote statistical significance at the 5% and 1% level, respectively. †Indicates a standardized variable. Firm-level variables are cross-sectionally standardized.

Table B5. Carbon Beta, Extreme Drought, and Stock Returns

	Monthly Excess Return (×100)				
Dependent Variable:	(1)	(2)	(3)	(4)	(5)
Carbon Beta† × Drought	−0.384**	−0.304**	–	–	−0.439**
	(0.069)	(0.111)	–	–	(0.132)
Carbon Beta†	0.072**	0.080	–	–	0.059
	(0.028)	(0.047)	–	–	(0.047)
Emissions Intensity† × Drought	–	–	−0.077	–	−0.069
	–	–	(0.093)	–	(0.102)
Emissions Intensity†	–	–	−0.047	–	−0.107**
	–	–	(0.031)	–	(0.038)
ln(Emissions)† × Drought	–	–	–	0.063	0.336*
	–	–	–	(0.107)	(0.143)
ln(Emissions)†	–	–	–	0.177*	0.215*
	–	–	–	(0.083)	(0.094)
ln(Market Cap.)	−0.014	0.062**	0.064**	−0.003	−0.017
	(0.013)	(0.023)	(0.023)	(0.035)	(0.038)
Book/Market	0.127**	−0.184	−0.161	−0.240	−0.260*
	(0.046)	(0.121)	(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	0.148	0.284	0.314	0.218	0.189
	(0.111)	(0.202)	(0.203)	(0.201)	(0.201)

continued

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Table B5. Carbon Beta, Extreme Drought, and Stock Returns (continued)

	Monthly Excess Return (×100)				
Dependent Variable:	(1)	(2)	(3)	(4)	(5)
Investment/Assets	−1.684**	−1.184	−1.147	−0.885	−1.007
	(0.595)	(1.215)	(1.206)	(1.211)	(1.199)
PP&E/Assets	0.076	−0.146	−0.108	−0.243	−0.234
	(0.073)	(0.134)	(0.135)	(0.138)	(0.138)
CAPM Beta	0.153**	−0.479**	−0.493**	−0.493**	−0.486**
	(0.044)	(0.111)	(0.109)	(0.109)	(0.112)
Idio. Volatility	−1.525**	3.908**	3.931**	3.906**	3.931**
	(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)
Year-Month FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
No. Obs.	593,367	200,309	200,309	200,309	200,309
R^2 Adj.	0.175	0.253	0.253	0.253	0.254

Notes: This table reports the full set of coefficients obtained from estimating regression Equation (7). 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 10th percentile and 0 otherwise. All regressions include sector and year-month fixed effects. Standard errors are clustered at the firm level. * and ** denote statistical significance at the 5% and 1% level, respectively. †Indicates a standardized variable. Firm-level variables are cross-sectionally standardized.

Table B6. Carbon Beta and MSCI Green Patent Share

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)
PP&E/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. Obs.	150,576	6,539	4,423	4,423
R^2 Adj.	0.487	0.340	0.227	0.665

Notes: This table reports the coefficients obtained from estimating regression Equation (4). Here, MSCI Green Patent 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 5% and 1% level, respectively. †Indicates a cross-sectionally standardized variable.

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