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Carbon risk and equity prices

Arthur Enders[1] | **Thomas Lontzek**[1] | **Karl Schmedders**[2] | **Marco Thalhammer**[1]

[1]RWTH Aachen University, Aachen, Germany

[2]International Institute for Management Development Lausanne, Lausanne, Switzerland

Correspondence
Arthur Enders, RWTH Aachen University, Templergraben 64, D-52062 Aachen, Germany.
Email: enders@econ.rwth-aachen.de

Abstract

We study the effects of carbon transition risk on equity prices in the United States and Europe using disclosed carbon intensity data and find a negative effect on the cross section of returns and a negative carbon premium for the period 2009–2019. Examining fund flows, we find that institutional investors had an aversion to carbon-intensive stocks, which could help explain the outperformance of green stocks. We find that after the Paris Agreement this negative carbon premium disappears, and expect a positive premium in the future. We apply an asset-pricing approach to quantify the carbon risk exposure of any given asset.

KEYWORDS
carbon emissions, carbon risk, climate change, equity returns, factor model, institutional investors

JEL CLASSIFICATION
G11, G12, Q51, Q54

1 | INTRODUCTION

We examine the effects of the disclosed carbon emissions[1] of publicly traded companies in the United States and Europe on their stock returns from 2009 to 2019. We characterize companies by their "carbon intensity," the ratio of their disclosed (scopes 1 and 2) carbon emissions to their annual revenues. Using this metric, we document several noteworthy results. Low-carbon portfolios outperform high-carbon portfolios, which is statistically significant even after controlling for common risk factor exposures. Carbon intensity has statistically significant explanatory power

[1] In the present paper, the term "carbon emissions" always refers to total CO_2 equivalent emissions of all relevant greenhouse gases.

and, on average, a negative effect on the cross section of returns. In our time frame and sample, the carbon premium is negative, and investors are not compensated for carbon risk[2] exposure. The effects become more nuanced when we examine US and European stocks separately or when we distinguish between the periods before and after the Paris Agreement of December 2015. While the negative effect of carbon intensity is statistically highly significant in Europe, it is not in the United States. Before the Paris Agreement, the effect is negative and highly significant, but vanishes afterward.

Considering the increasing relevance of climate change in public discourse and the emergence of carbon risk on financial markets, we would expect investors to be aware of the risks associated with investments in carbon-intensive companies. Policy responses to climate change significantly influence the current and future profitability of companies. For instance, policies such as the European Union Emissions Trading System (EU ETS) in Europe or the Clean Power Plan in the United States have significantly influenced corporate behavior, especially in the energy sector.[3]

Our analysis of the link between carbon emissions and fund flows reveals a fourth noteworthy result: carbon intensity has a significant negative effect on institutional ownership. Professional investors actively reduced their holdings in carbon-intensive companies to avoid carbon risk exposure. We consequently develop a measure of carbon risk by constructing a carbon premium portfolio that is long in high CO_2 intensity portfolios ("brown" stocks) and short in low CO_2 intensity portfolios ("green" stocks). We include this portfolio as an additional factor, "Brown-minus-Green," in standard multifactor models. We call the loading on this new factor the "carbon beta." Notably, we can estimate the factor loading for every stock using only publicly available returns data—that is, even for stocks that do not publicly disclose their greenhouse gas (GHG) emissions.

We complete our analysis by reporting average carbon betas for different sectors and countries. We detect large variations between as well as within both. Carbon betas are high for Energy and Utilities but low or negative for Technology and Consumer Cyclicals. Carbon risk exposure is high for Russia and Norway, and low (negative) for many EU countries, including Greece, Germany, and France.

Furthermore, there are remarkable discrepancies between the average levels of carbon intensity and the average carbon betas. We calculate carbon intensities based on scopes 1 and 2 emissions, as scope 3 data are limited. Investors, however, likely understand the impact of indirect (scope 3) emissions on carbon risk, and so we should observe the effect of these emissions on carbon betas. For example, the Energy sector has a carbon beta more than three times higher than that of the Utilities sector, despite having a lower average carbon intensity. This disparity arises from significantly higher average scope 3 carbon emissions in the Energy sector. This anecdotal evidence suggests that our Brown-minus-Green (BMG) factor extracts valuable additional information on carbon risk from financial market data, despite the absence of scope 3 emissions data. A thorough analysis is challenging, however, due to the lack of reliable scope 3 data.

The literature provides much evidence that investors care about carbon risk. According to an extensive survey by Krueger et al. (2020), institutional investors are also aware of climate-related risks and believe they have an impact on their portfolios' financial performance that has already started to materialize. Bolton and Kacperczyk (2021) suggest that investors care about carbon risk, by showing a negative relationship between company emissions and institutional ownership. In their sample, this effect is only significant with regard to the level and growth rate of total emissions. However, Aswani et al. (2024) show that using unscaled emissions data can disturb and bias the effect. We agree with this criticism and therefore use scaled emissions. As Bauer et al. (2022) emphasize, emission intensity has for some time been the industry standard for determining the carbon exposure of stock indices (e.g., MSCI, 2022; S&P Global, 2020). Contrary to Bolton and Kacperczyk (2021), by using emission intensities instead of simple emissions, we find a

[2] In this paper, "carbon risk" refers to carbon transition risk. We acknowledge that global warming also increases the likelihood of extreme weather events, so-called physical risks. We restrict our focus to transition risk as, idiosyncratically, carbon-intensive business models are more likely to be affected by transitional than by physical climate risks.

[3] Table A5 in the online appendix provides a more comprehensive overview of key climate regulations and initiatives between 2009 and 2019. The online appendix is available in the supporting materials section online.

statistically significant negative effect of carbon intensity on institutional ownership. Investors care about carbon risk and have developed a general aversion to carbon-intensive stocks.

Unlike Pástor et al. (2022) or many other studies in this field, we deliberately decide against using environmental scores since they are very noisy and highly dependent on the rating agency that provides them. Berg et al. (2022) show low correlations for the environmental, social, and governance (ESG) ratings of different ESG rating agencies. This high divergence has its roots mainly in differences in measurement and scope, and there are fundamental disagreements about the underlying data. Furthermore, Alves et al. (2023) find little evidence that ESG ratings significantly impacted global stock returns in 2001–2020. We, therefore, only use the raw data from companies' disclosed carbon intensities.

While there is a broad consensus that carbon risk affects asset valuations, recent studies have yielded different results as to the way in which returns are affected. From a theoretical standpoint, green assets offer lower expected returns in equilibrium, hinting at a so-called negative "greenium" (e.g., Pástor et al., 2021). This greenium may arise from the nonmonetary utility derived by green investors holding green stocks or the potential for these stocks to serve as a more effective hedge against specific types of climate risks. Bolton and Kacperczyk (2021) study the effects of carbon emissions on the cross section of returns in the US stock market, finding that stocks with a higher total level of (and change in) carbon emissions earn higher returns. They extend this analysis to global markets and find similar results (Bolton & Kacperczyk, 2023). Oestreich and Tsiakas (2015) report a positive carbon risk premium in the German market by investigating the effects of carbon emissions allowances in the EU ETS. Mo et al. (2012) analyze the different phases of the EU ETS, revealing a positive relationship between the EU emissions allowance price and company value in phase I but a negative relationship in phase II. Other studies could not find such a carbon premium. In et al. (2017) show that a carbon-efficient (low-carbon intensity) portfolio generates a positive alpha. Garvey et al. (2018) link lower carbon intensities with higher future profitability. All this research though remains inconclusive. In our time frame and sample, using carbon intensity, we find a negative carbon premium.

Measuring carbon risk is important for investors but also for firms and policymakers. Using such a measurement, investors can evaluate and optimize their portfolios' exposure levels, and firms can review their own exposure and compare it to peers. Policymakers, meanwhile, could use it to assess a new regulation's impact on specific companies, sectors, and countries.

Various methods of measuring carbon risk, often called carbon beta, have been proposed. Görgen et al. (2020) construct a carbon premium portfolio by categorizing companies into brown and green portfolios according to their "Brown-Green-Score," which incorporates a range of measures relevant to the carbon transition process. They compute carbon betas for equities across 43 countries, providing a detailed analysis of carbon risk exposures for different companies, sectors, and countries through their carbon betas. Sautner et al. (2023a) measure companies' climate exposure through a textual analysis of earnings conference call transcripts. They show explanatory power to predict green job creation and green technology. They also estimate climate risk premiums, and find a positive expected risk premium for firms with higher exposures (Sautner et al., 2023b). Huij et al. (2023) build a carbon premium portfolio by sorting US companies by total emissions, using reported and estimated emissions data. We extend this research with our own approach, which uses only reported emissions intensity data for US and European stocks.

Another strand of the literature explores the implications of climate risk from an asset-pricing perspective. Hong et al. (2019) study the effect of droughts on food companies' cash flows and find a significant negative impact on profitability ratios. Pástor et al. (2021) develop an equilibrium model that considers ESG criteria to explore the effects of climate risk on returns. They assume that green assets have lower expected returns because investors enjoy holding them and because green assets hedge climate risk. Green assets can, however, still outperform brown assets because of a shift in customer and investor tastes. Pástor et al. (2022) also provide empirical evidence that a greenium exists, with data from German green bonds as well as US stocks.

In summary, our study suggests that carbon intensity has a significant effect on returns and that carbon risk is prevalent. We show that from 2009 until 2019, this effect was significantly negative and that green stocks notably outperformed brown stocks in our sample. We demonstrate that institutional investors actively decarbonized their portfolio holdings and sought to lower their carbon risk exposure. Once such rebalancing is complete, we expect that carbon risk will be priced and that brown assets will have higher returns in the future. Our capital market approach effectively quantifies carbon risk through a carbon beta measure. All countries and industries are exposed to carbon risk to various degrees, and we demonstrate large variations.

2 | DATA

All firm-level data are collected from Refinitiv. Monthly risk factors and risk-free rates are retrieved from the website of Kenneth R. French. We restrict the data collection to common stocks with a country of issuance either as the United States or in Europe. Our time frame ranges from the beginning of 2009 to the end of 2019 for a total of 11 years of data. We believe that awareness of carbon risk has only recently gained attention from investors and that the carbon transition is particularly being demanded by the public in the United States and Europe. The time frame also excludes large nonlinear effects from the financial crisis of 2007–2008 as well as from the COVID-19 pandemic of 2020–2021 and the Russian invasion of Ukraine in 2022. Our final sample only includes companies that disclosed their GHG emissions at some point during our time frame. Similar to Fama and French (1993), we exclude firms with a negative book value and require at least 6 months of return data if a firm is to be included in a portfolio. We also follow prior literature by excluding companies that are marked as "Financials" under the Refinitiv Business Classification because financial firms are not directly exposed to carbon risks.[4] The final data sample consists of 1883 unique firms from across 25 countries, with 668 from the United States and 1215 from Europe.

2.1 | Emissions data

To separate green from brown stocks, we use solely companies' disclosed carbon emissions data. We exclude companies without disclosed emissions even if estimated emissions are available. Aswani et al. (2024) show that these estimates can be biased and disturb analysis. Bolton and Kacperczyk (2023) argue that the level of carbon emissions is the most appropriate proxy for a company's carbon risk exposure because it relates to a firm's distance from carbon neutrality. Aswani et al. (2024) counter, however, that unscaled emissions are primarily influenced by the volume of goods produced. They elaborate that any correlation observed between unscaled emissions and stock returns should be interpreted as indicative of a connection between a company's productivity and its stock's performance. To avoid this disturbance in the effect, we scale the emissions by revenue, the result of which is commonly known as the carbon intensity.

The carbon (CO_2) intensity of a company measures the total CO_2 equivalent (CO_2e) emissions in a year (in tonnes) divided by the total revenue in that year (in millions of US dollars (USD)). Total CO_2 equivalent emissions is the aggregated total CO_2 equivalent output in scope 1 and scope 2 emissions. Figure 1 shows the number of firms that reported the necessary emissions data (left) as well as the average CO_2 intensity of the firms in our sample (right). The sample is unbalanced and rather small at the beginning of our time frame with only 505 firms at the beginning of 2009. We see that over time more firms started to report their emissions. At the end of our time frame, in 2019, 1557 unique firms reported emissions data.[5]

In the panel on the right of Figure 1, we see that the average CO_2 intensity drops over time. Carbon-intensive firms are often obliged to disclose their emissions and were among the first to have such an obligation imposed. This led to a high carbon intensity to begin with, with an average CO_2 intensity of 546 tonnes of CO_2e/million USD. Many

[4] Financial firms remain indirectly exposed to carbon risks via their loan and investment portfolios, but our carbon intensity measure does not capture these indirect risks.

[5] This number differs from the total of 1883 unique companies during the total time frame since some companies stopped reporting their emissions or their stocks were delisted.

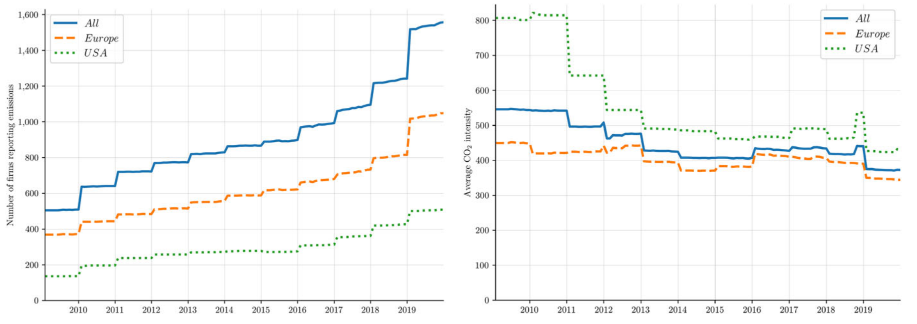

FIGURE 1 Carbon emissions sample over time. The graph on the left shows the number of unique firms with valid emissions data included in our data sample over the time frame of 2009 to the end of 2019. The graph on the right shows the resulting average CO_2 intensity of all the firms in the sample in the same time frame.

other companies, particularly more sustainable ones, then started to disclose their emissions, which decreased the average CO_2 intensity to 373 tonnes of CO_2e/million USD in 2019. We also observe this trend being more pronounced among the US firms in our sample. This suggests a potential selection bias over time, as brown firms were required to report before green firms were. This selection issue, however, is less evident among European firms. Where applicable, we additionally conduct separate analyses for US and European firms to account for and mitigate the impact of this potential selection bias.

Table 1 provides summary statistics for carbon intensity for all firms over the whole time frame. An average firm in our sample has a carbon intensity of 438 tonnes of CO_2e/million USD. The deviation between the firms is very high, with a standard deviation of 1805, and the median in our sample—with only 45 tonnes of CO_2e/million USD—is much lower than the mean.

2.2 | Firm-level data

Our return and market capitalization data are always measured monthly. All other company financial data are collected yearly. Table 1 presents all the firm-level data that are used in the following analyses.

An average company in our sample has a monthly return of 1.2% with a market capitalization of USD 20.9 billion. It has a book-to-market ratio of 0.64 and USD 6.9 billion worth of property, plant, and equipment. It has a yearly revenue growth of 7.2% and a return on equity of 19.71%. The average estimated market beta is below the general market beta at 0.85, and 55.64% of the company's shares are held by major institutions.

2.3 | Risk factor data

Risk factor data and risk-free rates are retrieved from the data library of the website of Kenneth R. French (French, 2021). Griffin (2002) suggests that domestic Fama and French factors work better than global factors. We, therefore, use monthly factor data from the United States and Europe separately wherever possible to better explain the time series variations in our returns.

In our time frame of 2009–2019, the average monthly market return is 1.2%. The SMB and RMW factors also return positive average monthly returns premiums while the HML, WML, and CMA factors each have an average negative returns premium. The medians are still positive for all factors except for the HML factor. Pástor et al. (2022) explain the poor performance of value stocks in the 2010s by the recent outperformance of green stocks, as value stocks are, on average, more brown than green.

TABLE 1 Data statistics.

Variable	Mean	Median	SD
Firm-level variables			
Monthly Stock Returns (%)	1.20	1.04	8.89
Log CO_2 Intensity (tonnes CO_2e/USD M)	4.05	3.82	1.96
Log Market Capitalization (USD M)	8.67	8.76	1.72
Log Book-to-Market Ratio	–0.85	–0.81	0.86
Log Property, Plant, and Equipment (USD M)	6.96	7.12	2.33
Yearly Revenue Growth (%)	7.20	3.11	196.80
Return on Equity (%)	19.71	13.20	121.64
Institutional Ownership (%)	55.64	57.53	32.02
Market Beta	0.85	0.77	0.57
Monthly Risk Factors			
Mkt-RF (%)	1.20	1.48	4.02
SMB (%)	0.04	0.26	2.44
HML (%)	–0.20	–0.32	2.67
WML (%)	–0.24	0.17	4.66
RMW (%)	0.12	0.18	1.52
CMA (%)	–0.01	0.00	1.47

Note: This table reports general statistics (mean, median, and standard deviation) for all variables used in the analyses in this paper. The sample period is 2009–2019. All firm-level variables are retrieved from Refinitiv Datastream. The CO_2 Intensity is the yearly CO_2 equivalent (CO_2e) emissions output (scopes 1 and 2, in tonnes of CO_2e) divided by the yearly sales (in USD M). Market Beta is the CAPM beta computed over a 5-year rolling horizon using monthly returns. Institutional Ownership is the fraction of the shares held by major institutions. Major institutions are defined as firms or individuals that exercise investment discretion, over the assets of others, in excess of USD 100 million. Mkt-RF is the monthly excess returns of a value-weighted stock portfolio over the risk-free rate. SMB is the returns of a portfolio that is long in small stocks and short in large stocks. HML is the returns of a portfolio that is long in value stocks and short in growth stocks. WML is the returns of a portfolio that is long in winner stocks and short in loser stocks. RMW is the returns of a portfolio that is long in robust stocks, with high operating profitability, and short in weak stocks. CMA is the returns of a portfolio that is long in conservative investment stocks and short in aggressive investment stocks. Table A1 in the online appendix additionally reports quartiles for some key variables and also separate results for United States and European firms.

3 | RESULTS

We first examine general determinants of a company's carbon emissions. We then form univariate portfolios based on the carbon intensity and compare their performance over time. We continue to analyze the effect of carbon intensity on the cross section of returns with cross-sectional Fama–MacBeth regressions. We next study the behavior of institutional investors with regard to emissions output and carbon risk by looking at Institutional Ownership in relation to carbon intensity. Finally, we create a multifactor model to measure an asset's carbon risk by looking at its sensitivity to a carbon premium portfolio. We report carbon risk distributions for all sectors and countries in our sample.

3.1 | Analysis of the carbon intensity

We first investigate the relation of a company's carbon intensity to other firm-level variables to assess occurrences of possible pseudo causalities in our analyses. Table 2 provides the coefficients of the pooled regression. Model (2)

TABLE 2 Determinants of the carbon intensity.

Variable	(1) *log*(CO_2 *Intensity*)	(2) *log*(CO_2 *Intensity*)
Intercept	3.22***	3.21***
log(*Size*)	−0.43***	−0.34***
BM	0.53***	0.06
Sales Growth	−0.28	−0.25
log(*PPE*)	0.61***	0.46***
ROE	−0.02	0.01
Year F.E.	No	Yes
Industry F.E.	No	Yes
Adj. R^2	0.33	0.54

Note: The sample period is 2009–2019. The dependent variable is the natural logarithm of the carbon intensity (further explained in Table 1). This table reports the results of the pooled regression with standard errors clustered at the firm and year levels. All variables are winsorized at the 2.5 and 97.5% levels. *Size* is the market capitalization; *BM* is the book-to-market ratio; *Sales Growth* is the yearly revenue growth; *PPE* is the property, plant, and equipment value; and *ROE* is the return on equity. The regression in the right column also includes year and industry fixed effects.
***1% significance, **5% significance, *10% significance.

additionally includes year and industry fixed effects. In both models, we cluster standard errors at the firm and year levels as carbon intensity is likely to be very persistent.

We see in regression (2) that the size of a company has a negative coefficient that is significant at the 1% level. Larger companies have, on average, a lower carbon intensity. Larger companies might be more efficient in their production because of economies of scale. We also see a strong positive effect of property, plant, and equipment (*PPE*) on the carbon intensity. Unsurprisingly, companies with higher levels of equipment, such as machinery, produce, on average, more emissions. Finally, industry fixed effects notably increase the explanatory power of the model. This finding shows that the carbon intensity differs significantly across industries.

3.2 | Univariate portfolio returns

We construct quintile portfolios based on the carbon intensity. Each year at the end of June, all valid stocks are sorted by their carbon intensity. A stock is eligible for inclusion in a portfolio if the company has reported its carbon emissions for the last year, if at least 6 months of valid returns data are available, and if the company has a market capitalization larger than USD 100 million and a positive book value. The univariate sorting constructs five quintile portfolios from Q_1 to Q_5. Quintiles are rebalanced yearly at the end of June and include all stocks with valid data in the given year.

The lower quintile portfolios, Q_1 and Q_2, include the stocks with the lowest carbon intensities. Stocks in these portfolios, thus, result in fewer emissions per unit of revenue earned, so we consider them "green" firms. The higher quintile portfolios, Q_4 and Q_5, are comprised of stocks with the highest carbon intensities. The stocks in these portfolios are more carbon-intensive so we consider them "brown" stocks. All portfolios are value-weighted by the stocks' market capitalizations.

We also build a difference portfolio called Brown-minus-Green (BMG), following the nomenclature of Görgen et al. (2020). The BMG portfolio is equally long in the brown portfolios, Q_5 and Q_4, and equally short in the green portfolios,

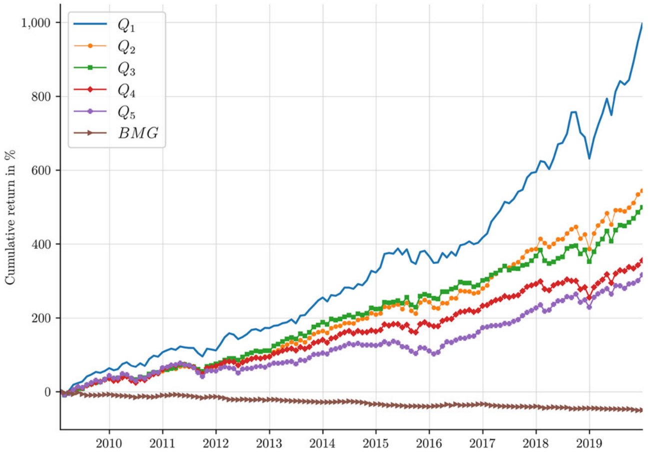

FIGURE 2 Performance of univariate portfolios sorted by carbon intensity. This figure shows the cumulative performance of the quintile portfolios sorted by carbon intensity, as well as that of the difference portfolio, *BMG*. The sample period is January 2009 to December 2019.

Q_1 and Q_2. The resulting returns are, thus,

$$BMG = \frac{1}{2}(Q_5 + Q_4) - \frac{1}{2}(Q_1 + Q_2). \tag{1}$$

The BMG portfolio gives the returns difference between brown and green firms. The returns represent the average carbon premium in a given month.

Figure 2 shows the cumulative performance of the portfolios during the time frame 2009–2019. We see a monotonic decrease in performance from Q_1 to Q_5. The green portfolios have significantly higher total returns during our time frame than those of their brown counterparts. From January 2009 to December 2019, the lowest quintile portfolio—Q_1, the greenest portfolio—has total cumulative returns of 997% over 11 years. The most carbon-intensive portfolio, Q_5, meanwhile, has cumulative returns of 317%. This represents a very notable returns difference between green and brown stocks.[6] The carbon premium portfolio, BMG, therefore has negative cumulative returns of –50% from 2009 to 2019.

Table 3 reports returns statistics for the sorted portfolios. We see the same pattern of monotonic decreasing mean and median returns from green to brown. Q_1 has a monthly mean return of 1.87% and an even higher monthly median return of 2.19%. Q_5 has a far lower monthly mean return of 1.12% and a monthly median return of 1.10%. The pattern persists on a risk-adjusted scale such as the Sharpe ratio. The green portfolio Q_1 has a fairly large Sharpe ratio of 0.46 whereas the brown portfolio Q_5 has a relatively low Sharpe ratio of 0.28. Because of these returns differences, the carbon premium portfolio, BMG, has a negative average monthly return of –0.51% and a negative Sharpe ratio of –0.29.

We also present alpha statistics, which control for risk exposures. We still see the same decreasing pattern in alpha performance from green to brown. The greenest portfolio, Q_1, produces a positive four-factor alpha of 0.64%, which is significant at the 1% level even after accounting for the portfolio's risk exposures. The brownest portfolio, Q_5, has a monthly alpha of 0.13%, which is not significantly different from 0. The six-factor alpha additionally includes two more risk factors: profitability and robustness. The effect does not change even after accounting for all six risk factor exposures. The alpha of Q_1 even increases to 0.66%. The alpha of Q_5 further decreases to 0.09%.

[6] The substantial gap in returns between the Q_1 and Q_5 portfolios may be influenced by factors beyond carbon risk alone. To mitigate sample selection biases, we conduct separate analyses for US and European markets, and simulations with fixed quintiles set in 2009 and 2019. These checks consistently reveal similar trends. Notably, the performance gap between Q_1 and Q_5 is least pronounced in the European sample. A significant portion of the superior performance of the greenest portfolio, Q_1, can be attributed to the strong performance of US technology firms during this period. Nonetheless, the trend of decreasing returns from the greenest to the brownest portfolios remains robust; see the additional results reported in Figure A1 in the online appendix.

TABLE 3 Return and risk statistics of univariate portfolio sorts based on the CO_2 intensity.

	Portfolio	Mean (%)	Median (%)	Std dev (%)	Sharpe ratio	4F Alpha (%)	6F Alpha (%)
Green	Q1	1.87	2.19	4.03	0.46	0.64***	0.66***
	Q2	1.45	1.83	3.27	0.43	0.40***	0.39***
	Q3	1.35	1.49	3.26	0.40	0.34**	0.26**
	Q4	1.18	1.45	3.47	0.33	0.16	0.08
Brown	Q5	1.12	1.10	3.89	0.28	0.13	0.09
Difference	BMG	−0.51	−0.38	1.91	−0.29	−0.41**	−0.48***

Note: This table presents monthly returns statistics for the quintile portfolios, sorted by the CO_2 intensity, and for the difference portfolio, *BMG*. The sample period is 2009–2019. The values are presented in percentages (except for the Sharpe ratio). The Sharpe ratio is the mean monthly returns in excess of the risk-free rate divided by the standard deviation of the excess returns. 4F Alpha is the four-factor alpha from the time series regression of monthly excess returns on the four risk factors Mkt-RF, SMB, HML, and WML. 6F Alpha is the six-factor alpha, which additionally includes the risk factors RMW and CMA. ***1% significance, **5% significance, *10% significance.

The significant differences in performance between the sorted portfolios show that the carbon intensity of a stock may have an impact on its returns. We observe that green stocks outperformed brown stocks during our time frame, which leads to an average negative carbon premium in our sample. Next, we investigate the effect of carbon intensity on the cross section of returns.

3.3 | The effect on the cross section

We analyze the effect of carbon intensity on the cross section of returns by running Fama–MacBeth regressions (Fama & MacBeth, 1973). For each month t, we regress a company's returns on the lagged logarithm of carbon intensity and other controls:

$$r_{nt} = \gamma_{0t} + \gamma_{1t} \log(CO_2)_{nt-1} + \gamma_{2t}\, Controls_{nt-1} + \epsilon_{nt}\,. \tag{2}$$

We control for a variety of firm-specific variables that could have an impact on the returns or are correlated with the carbon output, such as *Market Beta*, *BM*, *Size*, *Mom*, *PPE*, *ROE*, *Vola*, *Sales Growth*, and r_{t-1}. The time series averages of the regression coefficients γ_{1t} over the 132-month period give us the average effect of carbon intensity on the cross section of returns. Table 4 provides the average coefficients of the cross-sectional regressions, with t-statistics based on Newey–West adjusted standard errors in parentheses below.

Model (3) shows that the logarithm of carbon intensity has a negative effect on the cross section of returns that is significant at the 5% level even when controlling for all other firm-specific variables. The average of the regression coefficients is −0.07, with a Fama–MacBeth t-statistic of −2.42. Momentum ($log(1 + Mom)$) has a positive average coefficient of 0.94 that is significant at the 5% level, Return on Equity (*ROE*) also has a positive average coefficient of 0.76 that is significant at the 5% level, and Yearly Revenue Growth (*Sales Growth*) has a significantly negative average effect of −1.02. Finally, last month's return (r_{t-1}) to account for short-term return reversal has a significantly negative average effect of −4.42, significant at the 1% level. The effect of carbon intensity is consistent across the model specifications from Models (1) to (3), whereas the control variables differ. Only the magnitude of the effect changes slightly, which can be attributed to the weak multicollinearity of the independent variables. A significant coefficient of the CO_2 intensity provides empirical evidence that investors associate risk with companies' GHG emissions. This carbon risk stems from a company's possible exposure to the impact of climate transition actions. Investors should, thus, incorporate emissions data into their investing process and adjust their valuations according to this risk. If we

TABLE 4 Average coefficients of Fama–MacBeth regressions.

	(1)	(2)	(3)
Intercept	1.64***	1.76***	1.71***
	(4.51)	(3.71)	(3.43)
log(CO_2)	−0.08**	−0.07**	−0.07**
	(−2.28)	(−2.47)	(−2.42)
Market Beta		0.23	0.47
		(0.61)	(0.91)
log(BM)		−0.07	0.06
		(−0.89)	(0.74)
log(Size)		−0.09**	−0.07
		(−2.22)	(−1.09)
log(1+Mom)		0.58	0.94**
		(1.32)	(2.51)
log(PPE)			−0.02
			(−0.66)
ROE			0.76**
			(2.36)
Vola			−0.24
			(−0.08)
Sales Growth			−1.02***
			(−3.04)
$r_t - 1$			−4.42***
			(−4.83)

Note: This table reports the average coefficients of cross-sectional Fama–MacBeth regressions. The dependent variables are monthly returns. In Table A2 in the online appendix, we present the results of the same regression using different returns as dependent variables for robustness checks. The effects remain similar and significant. The sample period is 2009–2019. The *t*-statistics, based on Newey–West adjusted standard errors with three lags, are given below in parentheses. All independent variables are winsorized monthly at the 2.5 and 97.5% levels. CO_2 is the carbon intensity; *Market Beta* is the 5-year rolling CAPM beta; *BM* is the book-to-market ratio; *Size* is the market capitalization; *Mom* is the cumulative returns for the trailing 12 months; *PPE* is the property, plant, and equipment value; *ROE* is the return on equity; *Vola* is the standard deviation of the trailing 12 months' returns; *Sales Growth* is the yearly revenue growth; and r_{t-1} is the last month's return.
***1% significance, **5% significance, *10% significance.

can assume this behavior in market participants, carbon risk should be priced. Contrary to our expectation and to a popular contribution to the literature by Bolton and Kacperczyk (2021), in our data and time frame, we find a negative relation between carbon emissions and stock returns. This result implies that carbon-intensive stocks do not offer higher returns. Instead, low-carbon companies realize higher returns on average.

This reversed risk–reward relationship means that investors are not sufficiently compensated for carbon risk exposure. Attention to climate change has only recently gained a lot of traction, and there are more and stricter carbon actions to come. Many large investors have possibly tried to reduce their exposure to these events and developed a general aversion to carbon-intensive stocks. A consequence of this aversion could be the selling of brown stocks, which would result in lower or even negative realized returns for brown firms and in higher returns for green firms. We investigate this hypothesis in the next subsection by examining companies' Institutional Ownership. In the long term, this reverse effect can lead to lower prices for brown firms that offer higher expected returns in the future. We

TABLE 5 Comparison of the average cross-sectional effects.

	All	US	Europe	Pre-Paris	Post-Paris
log(CO_2)	−0.07**	−0.06	−0.08***	−0.11***	0.00
	(−2.42)	(−1.36)	(−2.75)	(−3.05)	(−0.09)

Note: This table reports the average coefficients of cross-sectional Fama–MacBeth regressions with different samples. The dependent variables are monthly returns. The full regression model is specified as in Model (3) in Table 4. The *t*-statistics, based on Newey–West adjusted standard errors with three lags, are given below in parentheses. *All* includes the complete sample from the period 2009–2019. *US* includes only stocks with the country of issuance as the United States. *Europe* restricts the sample to European stocks. *Pre-Paris* concerns the time frame between January 2009 and November 2015. *Post-Paris* concerns the time frame after the Paris Agreement, from December 2015 to December 2019. CO_2 is the carbon intensity.
***1% significance, **5% significance, *10% significance.

further explore the relationship between carbon intensity and the cross section of returns across different regions and time horizons. Table 5 compares the effects between the United States and Europe as well as before and after the Paris Agreement.[7]

We observe that the effect is much stronger in Europe than in the United States. The average coefficient of the US sample is −0.06 and is not statistically significant. The average effect of carbon intensity on the cross section of returns in Europe is −0.08 and significant at the 1% level. Carbon risk could be more prevalent in Europe as the carbon transition is progressing faster there.[8] Climate policies are, thus, implemented more quickly and to a larger extent than in the United States, leaving European companies more exposed to carbon transition risks.

The cross-sectional effect of carbon intensity is also much stronger before the adoption of the Paris Agreement on December 12, 2015. In the part of our time frame before the Agreement, the effect is negative and highly significant, with an average coefficient of −0.11. After the Paris Agreement, this effect completely vanishes, with an average coefficient of 0.00. A possible reason for this could be a revaluation of green and brown stocks leading up to the Agreement. As the likelihood of climate policy implementation grew, brown stocks, which are exposed to the impacts of such policies, decreased in value, whereas the value of green stocks, which can benefit from the carbon transition, increased. In the long term, this effect may reverse, the cheaper brown stocks offering higher returns in the future to compensate for their carbon risk exposure.

Figure 3 shows the cumulative returns of the brown (average of Q_4 and Q_5) and the green (average of Q_1 and Q_2) portfolios 1 year before and after the Paris Agreement. The performance of the portfolios switches significantly around the month of the Agreement, December 2015. Before the Agreement, the green portfolio strongly outperforms the brown portfolio, with a cumulative return of 12.03%. The brown portfolio, in contrast, has a cumulative yearly return of only 2.21%. After the Agreement, in 2016, the brown portfolio considerably outperforms the green portfolio, delivering a total cumulative return of 24.06%, while the green portfolio only returns 10.75%.

The Paris Agreement may have been a turning point for the carbon premium in stock returns. Investors possibly needed time to evaluate and incorporate carbon risks into equity-price valuations because of the many uncertainties revolving around the carbon transition. The Agreement solidifies the existence of carbon risk and may have reduced some of the uncertainties surrounding the future implementation of climate policies. In the years leading up to the Agreement, investors' anticipation may have adjusted valuations accordingly. In line with the concept of the pollution premium discovered by Hsu et al. (2023), we expect to see a positive carbon premium in the future once carbon risk is fully priced into stock price valuations.

[7] Table A3 in the online appendix, additionally, reports the cross splits of the European and US samples before and after the Paris Agreement. There is no notable difference in these effects.

[8] For example, the world's first international emissions trading system, the EU ETS, was launched in 2005, and has become the largest multisector ETS in the world. To this day, the United States does not have a carbon tax at the national level. The first mandatory cap-and-trade program in the United States, the Regional Greenhouse Gas Initiative (RGGI), began to auction off emissions allowances in 2008. In 2021, 11 states participated in the RGGI. California started a cap-and-trade program in 2013. Since 2019, utilities in Massachusetts have been regulated under an additional cap-and-trade system.

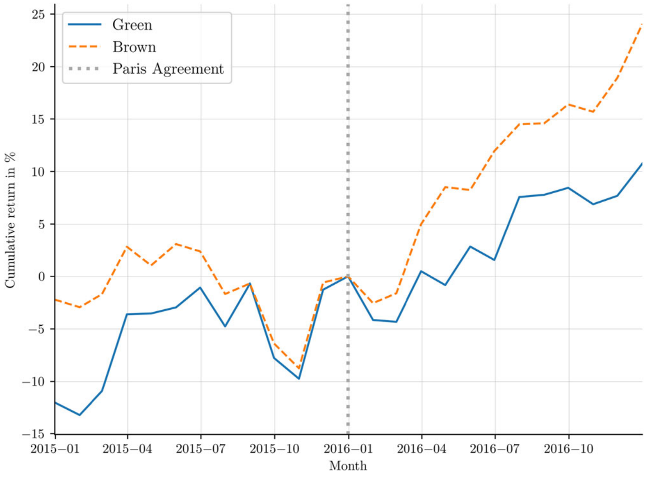

FIGURE 3 Comparison of returns around the Paris Agreement. This figure shows the raw cumulative returns of the green portfolio (average of Q_1 and Q_2) and the brown portfolio (average of Q_4 and Q_5), respectively, 1 year before and 1 year after the Paris Agreement. The cumulative returns series are releveled to 0 at the point of the Paris Agreement, which was reached in December 2015.

3.4 | The behavior of institutional investors

Once aware of carbon transition risks, market participants might choose to actively divest carbon-intensive stocks and industries to lower their exposure. Rohleder et al. (2022) show that the decarbonization of mutual funds puts pressure on the prices of the stocks they divest. This rebalancing by investors could lead to price declines in carbon-intensive stocks. We investigate this by examining institutional investors' behavior using their portfolio holdings.

Institutional Ownership (*IO*) is the share of a stock held by major institutions. We first regress Institutional Ownership on the carbon intensity and other firm-specific control variables:

$$IO_{it} = \delta_0 + \delta_1 \log(CO_2)_{it} + \delta_2\, Controls_{it} + \epsilon_{it}. \tag{3}$$

Table 6 reports the results, with standard errors clustered at the industry level. The variable of interest is the estimated coefficient (δ_1) of the logarithm of the carbon intensity.

We observe a significant relationship between carbon intensity and the Institutional Ownership of a stock. A stock with a higher carbon intensity is generally held by fewer institutional investors and—in an aggregate sense—in smaller amounts. On average, Model (2) states that an increase in carbon intensity of 1% decreases the Institutional Ownership of a stock by 0.91 percentage points, which is significant at the 1% level.

We subsequently analyze the change in Institutional Ownership of green (bottom quintiles Q_1 and Q_2) and of brown (top quintiles Q_4 and Q_5) stocks over time to explore the asset managers' fund flows.[9] For each month, we calculate the weighted change in Institutional Ownership for the green and the brown stocks. The change in Institutional Ownership ($\Delta\, IO_{it}$) of a stock *i* in month *t* is defined as

$$\Delta\, IO_{i\,t} = IO_{i\,t} - IO_{i\,t-1}\ . \tag{4}$$

The total weighted (by market capitalization) change in Institutional Ownership ($\Delta^w IO_{Pt}$) for a portfolio *P* in month *t* is then given by

$$\Delta^w IO_{Pt} = \frac{\sum_{i\in P}(\Delta\, IO_{it} \cdot Market\ Cap_{it})}{\sum_{i\in P} Market\ Cap_{it}}\ , \tag{5}$$

[9] Fund flows refer to changes in all types of institutional fund holdings, including but not limited to hedge funds, pension funds, mutual funds, and ETFs.

TABLE 6 The effect of carbon risk on institutional ownership.

Variable	(1) *IO* (%)	(2) *IO* (%)
Intercept	80.86***	75.98***
$log(CO_2)$	−0.97***	−0.91***
Market Beta	6.43***	6.50***
BM	−6.33***	−5.48***
log(Size)	−0.68*	−0.54
$log(1 + Mom)$	−1.31	0.18
ROE	−0.13***	−0.12***
Vola	−36.50**	−31.17*
Sales Growth	0.02	0.02
Country F.E.	Yes	Yes
Year F.E.	No	Yes
Adj. R^2	0.66	0.67

Note: The sample period is 2009–2019. The dependent variable *IO* is the share of the stock held by major institutions (in percentage). This table reports the results of the pooled regression with standard errors clustered at the industry level. All independent variables are winsorized at the 2.5 and 97.5% levels. CO_2 is the carbon intensity, *Market Beta* is the 5-year rolling CAPM beta, *BM* is the book-to-market ratio, *Size* is the market capitalization, *Mom* is the cumulative returns for the trailing 12 months, *ROE* is the return on equity, *Vola* is the standard deviation of the trailing 12 months' returns, and *Sales Growth* is the yearly revenue growth. The regression in the first column includes country fixed effects. The second column additionally includes year fixed effects.

*** 1% significance, ** 5% significance, * 10% significance.

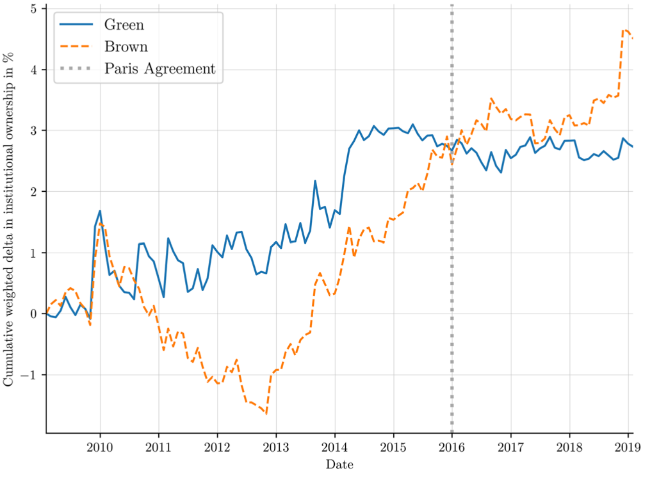

FIGURE 4 Cumulative weighted change in Institutional Ownership over time. This figure shows the cumulative weighted change in Institutional Ownership of the green portfolio (consisting of all stocks of the portfolios Q_1 and Q_2) and the brown portfolio (consisting of all stocks of Q_4 and Q_5) from 2009 to the end of 2019. The dotted gray line marks the Paris Agreement, reached in December 2015.

where *Market Cap*$_{it}$ is the market capitalization of stock *i* in month *t*. Figure 4 shows the cumulative weighted delta in Institutional Ownership over time.

We see that Institutional Ownership of brown stocks decreases from 2009 to the end of 2012 despite an overall increase in assets under management (Heredia et al., 2021). The cumulative delta for brown stocks remains lower than for green stocks until December 2015, coinciding with the Paris Agreement. Afterward, Institutional Ownership of brown stocks increases more than that of green stocks.[10]

Large fund flows out of brown stocks can put pressure on these stocks and result in lower prices. Similarly, higher inflows into green stocks raise the demand for them and can result in higher prices. This difference in fund flows could be one of the reasons for the difference in returns between green and brown stocks during our time frame. We see a strong outperformance of green stocks, with a higher fund inflow until 2016. Afterward, the negative carbon premium disappears and brown stocks start to outperform green stocks and also experience higher inflows. This aligns with the work of Nofsinger and Sias (1999), who find a strong correlation between changes in Institutional Ownership and returns measured over the same period. More closely related to the present paper, van der Beck (2021) analyzes the flows of sustainable funds and finds that their price pressure leads to higher returns for sustainable investing.

Our analysis indicates that institutional investors consider carbon emission information in their investment decisions—an indication supported by Krueger et al. (2020) and Bolton and Kacperczyk (2021). Major investment institutions generally avoided carbon-intensive companies, particularly from 2009 to the end of 2015. This divestment can be driven by social or moral pressure, as investment firms and fundholders push for greener portfolios. The high inflows to sustainable funds confirm this fundholder demand (BlackRock, 2021). Financial motives could also play a role, as managers divest to reduce carbon transition risks and improve performance. These motives are also the most common ones provided by the investors in the survey by Krueger et al. (2020). Institutional investors account for a large portion of market capital and can significantly impact asset prices. Their behavior could be one possible explanation for the negative carbon premium during our observed time frame.

3.5 | A measure of carbon risk

Carbon intensity is a systemic risk factor if uniform climate policies are implemented that affect all companies that emit GHG emissions. Such policies might include an international carbon price. However, if interventions are introduced incrementally or selectively target-specific operations or sectors, carbon intensity might be an industry-specific risk instead. We argue that carbon risk is systemic, supported by its interconnectedness through general equilibrium effects (Pástor et al., 2021), potential for widespread regulation, and financial exposure. Its effects span sectors and regions, posing a significant threat to the stability of the economy and financial system. If carbon risk is substantiated, forward-looking market participants should price it as a systemic risk factor already today.

We show that carbon risk indeed exists and that investors are aware of it. We analyze the effect on equity prices and to what extent it had already materialized in our time frame, of 2009–2019. Based on these results using the carbon intensity, we build a model to quantitatively measure the carbon risk exposure of an asset. Along the lines of Görgen et al. (2020), we use the popular Fama–French multifactor model and extend it with an additional factor, carbon risk. The carbon premium portfolio, BMG, given by Equation (1), serves to mimic the carbon risk factor returns. This allows us to measure an asset's sensitivity to changes in the carbon premium portfolio while controlling for other common risk factor exposures of Fama and French (1993) and Carhart (1997).[11] We compute the coefficient of carbon risk with a time series regression of an asset's excess returns:

$$r_{nt} - rf_t = \alpha_n + \beta_{1n}\, Mkt_t + \beta_{2n}\, SMB_t + \beta_{3n}\, HML_t + \beta_{4n}\, WML_t + \beta_{5n}\, BMG_t + \epsilon_{nt}, \tag{6}$$

where $r_{nt} - rf_t$ is the return of an asset n minus the risk-free rate, Mkt_t is the market premium, SMB_t is the size premium, HML_t is the value premium, WML_t is the momentum premium, and BMG_t is the carbon premium in month t.

[10] To check for potential sample selection issues, we also run this analysis with fixed portfolios (using the original sample from the beginning of our time frame), and find similar results.

[11] Depending on a company's country of issuance, we use either US or European risk factors.

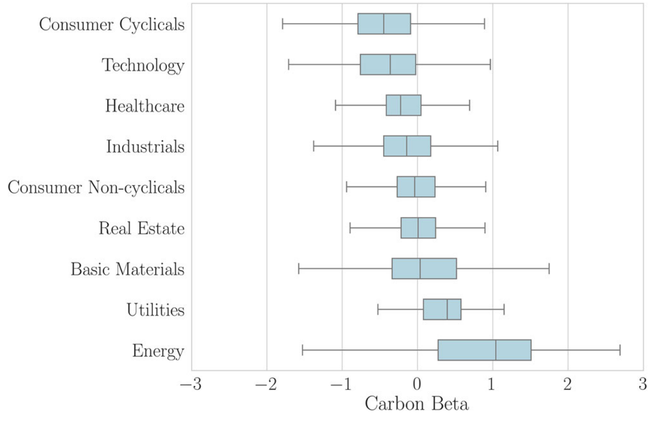

FIGURE 5 Carbon beta distributions for industries. This figure shows the carbon beta distributions within sectors as classified by the Refinitiv Business Classification. Carbon betas are computed by regressing monthly excess returns on the carbon premium factor and other risk factors; see Equation (6). Carbon betas are computed for all stocks valid in December 2019 using monthly returns from 2009 to 2019. The boxes show the quartiles while the whiskers extend the distribution past 1.5 times the interquartile ranges. The bars inside of the boxes mark the medians.

The regression coefficient of interest is β_5, which we call the carbon beta.[12] Carbon beta measures how the stock moves, on average, when the carbon premium portfolio (BMG) increases or decreases in value. A positive carbon beta implies that the stock price moves in accordance with the BMG portfolio, thus similar to that of brown stocks. A negative carbon beta implies that it moves in the opposite direction to that of the BMG portfolio and more in accordance with green firms, representing a hedge against carbon risks. A carbon beta close to 0 means no significant exposure to the BMG portfolio, which would imply no direct carbon risk. We investigate the relationship of the BMG returns to other factor returns in Table A4 in the online appendix and find that BMG is distinct from other common risk factors.

With our model in Equation (6), we can compute a quantitative carbon risk measure for every stock using only publicly available market returns data—that is, even for stocks that do not publicly disclose any emissions data. This measure gauges the relation of an equity to the carbon premium portfolio and thus its sensitivity to carbon transition risks. It is a single quantitative measure that is easily interpreted and directly comparable across firms. We compute carbon beta coefficients for all stocks in our sample and report statistics for all sectors (excluding Financials) covered in the Refinitiv Business Classification as well as all the countries that we have data for. We also run the same analyses using the total sample of stocks, which also includes all valid public companies that do not report their emissions data. The results between these samples are not notably different. This finding suggests that our restricted sample of stocks is fairly representative of the whole market.

Figure 5 shows box plots for the carbon beta distributions of different industries. The sector at the bottom, with the highest carbon beta average, is the Energy sector, with a median of 1.04. The Energy sector mainly consists of oil and gas companies, whose main products are very carbon-intensive and will have to be phased out during the carbon transition. It is followed by the Utilities sector, with a median of 0.40, and the Basic Materials sector, with a median of 0.04. These are the three sectors that bear the largest carbon risk exposure, and the model predicts that the carbon transition will have a substantial effect on their business models. At the opposite end of the spectrum, the Consumer Cyclicals sector has the largest negative carbon betas, with a median of −0.45. Consumer Cyclicals consists of businesses that depend heavily on prevailing economic conditions and includes furniture and luxury goods retailers. Bansal et al. (2018) find that socially responsible stocks (also called "good" stocks) tend to outperform during good economic times similar to luxury goods. Thus, stocks of the Consumer Cyclicals industry can perform similarly to our green stocks because of similarities in investors' preferences. The Technology sector also has a significant negative carbon beta median of −0.36. Many technology firms are known to be innovative, forward-thinking, and sustainable. On average, these firms present a hedge against carbon risks and can benefit from the transition to a low-carbon or even a carbon-neutral economy. The Consumer Noncyclicals sector is distributed closely around 0, with a median of

[12] Görgen et al. (2020) also define the coefficient of their BMG factor as the carbon beta. It is critical to underscore that their factor construction is contingent upon their Brown-Green-Score, which amalgamates three distinct company indicators: value chain, public perception, and adaptability. In contrast, our BMG factor is exclusively predicated on quantifiable carbon emission intensities reported by companies.

−0.04. This industry is composed of firms that produce essential goods, such as food and household products, which are always required, and demand for them will most likely be unaffected by climate policies.

We observe substantial differences in average carbon beta measures between the sectors. The effects of climate policies, positive or negative, vary considerably from sector to sector. It is important to note that there is also a wide distribution of carbon betas within each sector. This might be important for investors that want to diversify their portfolio concentration across various sectors while still divesting their carbon risk exposure. Investors can screen all sectors for firms with low carbon betas. Thus, sector diversity remains possible without the need to increase carbon risk exposure.

Table 7 provides average carbon intensity, carbon beta, and scope 3 carbon emissions intensity statistics for the sectors and countries. Again we observe stark differences in average carbon betas between the countries in our sample. Russia is the country with the highest weighted carbon beta, with a weighted mean of 0.69, most likely because of its very prominent energy sector. Norway, another major oil and gas exporter, has the second highest weighted carbon beta mean of 0.59. The country with the lowest carbon beta is Greece, with a weighted mean of −0.76, although this might not be representative as the sample is very small, with only 11 equities. Greece is followed by Germany, with a carbon beta of −0.43, and then by France, Denmark, and Finland, with weighted means of −0.38, −0.37, and −0.31, respectively. The United States also has a negative value-weighted carbon beta of −0.17, which reverses if we consider the slightly positive unweighted mean of 0.11. This difference probably occurs because of large US technology stocks with mostly negative carbon betas and very high market capitalizations.

We generally observe a strong relation between the average carbon intensity and the carbon beta. The magnitude of carbon intensity, however, does not align monotonically with the associated carbon risk, as indicated by the carbon beta. This suggests that while the relationship is strong, the levels of carbon intensity and the corresponding carbon risk can vary significantly. One reason for this could be that we exclude scope 3 emissions for the measurement of the carbon intensity, but that investors are aware of them and we hence see them reflected in the carbon beta. For example, Energy is the sector with the highest average carbon beta but only has the third-highest average carbon intensity. The Utilities sector has an average carbon intensity almost four times that of the Energy sector but its average carbon beta is less than a third of that of the Energy sector. Scope 3 emissions account for a very high proportion of the total emissions of the Energy Sector—their average share is often estimated to range from 85% to 90%—but they are not included in our carbon intensity measure. For the Utilities sector, this share is much lower, and is estimated to range from 40% to 75% (Naqvi, 2020; CDP, 2022). The products of the Energy sector, such as oil and gas, are used as inputs in the Utilities sector. Scope 3 emissions from the Energy sector are, therefore, reflected in scope 1 emissions from the Utilities sector, which are included in our carbon intensity measure for that sector. We can conclude this from the average scope 3 intensities reported in Table 7. The Energy sector has a much higher average and weighted average scope 3 intensity than the Utilities sector.

The market, meanwhile, realizes this interrelation and thinks that the underlying carbon risk is much higher for those companies at the beginning of the production chain, in the Energy sector. This market sentiment is reflected in the higher average carbon beta, even though we do not use any scope 3 emissions data in the model. The carbon beta measure reflects more information than merely the emissions data. Our model should help capture this additional market information reflected in stock returns in order to efficiently measure carbon risk, even for companies that do not report their carbon emissions.

Our asset-pricing approach to measuring carbon risk relies on the ability of the BMG portfolio to efficiently represent the carbon premium returns. To construct the BMG portfolio, we use the carbon intensity. While we show its explanatory power in the cross section of returns, another variable might be more appropriate for separating brown from green stocks. This measure of carbon intensity only includes scopes 1 and 2 emissions, but scope 3 emissions could be of much greater importance for some companies. As such data are still very limited, for now, we have to rely on scopes 1 and 2 data alone. The emissions are scaled by total revenues in US dollars. For companies from Europe or the United States, exchange rate effects could have an impact on the emission intensity data and influence the analysis. The method for weighting the portfolios also influences the results. We, thus, tried other methods, including an

TABLE 7 Sector and country carbon statistics.

	Unique firms	Avg. carbon intensity	Weighted avg. carbon intensity	Avg. carbon beta	Weighted avg. carbon beta	Avg. scope 3 intensity	Weighted avg. scope 3 intensity	Firms in scope 3 sample
Sectors								
Industrials	396	235	144	−0.15	−0.13	584	1149	201
Consumer cyclicals	340	63	46	−0.45	−0.43	473	419	157
Technology	244	34	25	−0.37	−0.43	191	91	155
Basic materials	204	931	812	0.19	0.31	1031	2052	80
Consumer noncyclicals	175	104	62	−0.02	0.04	311	447	95
Real estate	155	81	94	−0.10	0.05	176	320	76
Healthcare	135	32	20	−0.21	−0.12	73	131	63
Energy	123	661	444	0.95	0.96	2554	2826	51
Utilities	109	2480	2055	0.30	0.37	1478	1945	58
Countries								
United States	668	401	203	0.11	−0.09	740	349	285
United Kingdom	317	158	210	−0.19	0.09	240	1394	154
France	114	187	114	−0.36	−0.38	643	629	80
Germany	111	232	218	−0.33	−0.43	589	647	58
Sweden	105	138	49	−0.19	−0.30	282	574	66

(Continues)

TABLE 7 (Continued)

	Unique firms	Avg. carbon intensity	Weighted avg. carbon intensity	Avg. carbon beta	Weighted avg. carbon beta	Avg. scope 3 intensity	Weighted avg. scope 3 intensity	Firms in scope 3 sample
Switzerland	74	660	152	−0.16	−0.26	790	213	41
Italy	66	331	403	−0.27	−0.05	489	1094	30
Spain	53	241	194	−0.17	−0.13	506	869	34
Finland	45	194	443	−0.19	−0.31	575	1093	33
Netherlands	44	165	114	−0.27	−0.19	715	2502	27
Norway	37	207	237	0.34	0.59	479	1999	21
Türkiye	33	1537	555	−0.06	−0.07	1187	566	15
Denmark	32	173	135	−0.22	−0.37	331	637	16
Belgium	30	426	180	−0.33	−0.16	298	511	16
Russia	28	3457	1038	0.51	0.69	2793	4308	7
Austria	28	295	349	−0.04	0.15	1168	2129	14
Ireland	27	158	139	−0.27	−0.28	2105	2063	12
Poland	21	1224	1369	−0.18	−0.09	523	494	4
Luxembourg	18	453	623	0.03	0.25	83	134	9
Portugal	12	347	415	−0.37	0.06	629	1329	9
Greece	11	773	477	−0.98	−0.76	78	162	4

Note: This table reports carbon statistics for different countries and sectors for all stocks in our sample valid in December 2019. Carbon betas are computed by regressing monthly excess returns on the carbon premium factor and other risk factors. The scope 3 intensity is the yearly CO_2 equivalent (CO_2e) scope 3 emissions output (in tonnes of CO_2e) divided by the yearly sales (in USD M). Weighting is done by market capitalization. Sectors are classified as per the Refinitiv Business Classification. The country of a stock is determined by the primary country of issuance.

additional distinction between big and small firms based on the median market value. These other approaches did not alter the qualitative results (which are available from the authors upon request).

4 | CONCLUSION

In this paper, we study the effect of carbon risk on equity prices from the United States and Europe, using disclosed carbon intensity data from 2009 to 2019. We find that carbon intensity has a significantly negative effect on the cross section of returns. In our time frame and sample, we document a negative carbon premium. In the investment activity of institutional investors, we observe a general aversion to carbon-intensive stocks. This behavior is a potential explanation for the negative carbon premium from 2009 until 2019. In the future, we expect to see this effect reverse and thus a significant positive carbon premium. We find supporting evidence for this theory in the time frame after the Paris Agreement, where brown stocks start to outperform green stocks. Carbon risk should be priced in the long term, and investors with high exposure should be compensated with higher returns.

Having secured evidence of the existence of carbon risk, we use a multifactor model to measure an asset's exposure as a carbon beta coefficient. We report carbon beta statistics for all industries and countries in our sample. The sectors with the highest exposure are the Energy and the Utilities sectors; those with the lowest carbon betas include the Consumer Cyclicals and the Technology sectors. The countries with the highest carbon risks are Russia and Norway.

Our model provides a new perspective on the quantification of carbon risk and the assessment of carbon risk implications for individual assets. Further, the model picks up additional carbon risk information from financial market data regarding undisclosed indirect emissions. The resulting evaluation provides the information necessary to allocate investments and to direct climate policies and facilitate a smooth carbon transition.

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ORCID

Arthur Enders https://orcid.org/0009-0002-6424-5683

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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