Characteristics-Driven Carbon Beta: What Do Investors Really Price?

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December 15, 2025

Abstract

The existence of a carbon premium is intensely debated. This paper argues that conflicting evidence stems from a measurement problem: traditional proxies for carbon risk exposure, such as historical carbon emissions or statistical carbon betas, are either noisy, incomplete, or backward-looking. We address this by introducing a dynamic, characteristics-driven carbon beta that conditions transition risk exposure on observable firm characteristics and market sentiment. Decomposing this economically interpretable measure for U.S. and European equities, we show that transition risk is anchored by historical Scope 1 emissions but is also shaped by public controversies and corporate climate commitments, while responding systematically to climate news and ESG fund flows. We also find evidence of market foresight, as the beta today acts as a leading indicator of a firm's realized decarbonization over the next two years. Finally, this enhanced measure sheds new light on the debate: we detect a significant carbon premium emerging after the Paris Agreement that is invisible when using raw emissions data.

Keywords: Climate finance, transition risk, carbon emission, asset pricing

JEL Classifications: G11, G12, Q54

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1 Introduction

The transition to a low-carbon economy introduces new and complex financial risks. A central question for investors and policymakers is whether, how, and when this climate transition risk is priced in equity markets. Much of the growing literature seeks evidence of a "carbon premium", hypothesizing that high-emitting firms should offer higher expected returns to compensate investors for greater exposure to climate-related regulatory, technological, and reputational risks (Bolton and Kacperczyk, 2021; Pástor et al., 2021). Although this topic has attracted considerable attention, the evidence is mixed, and what specific information investors actually incorporate into prices remains unclear.

At the heart of this uncertainty lies a measurement problem. Most empirical studies proxy transition risk with firms' historical carbon emissions (e.g., Bolton and Kacperczyk, 2021, 2023). While intuitive, this measure provides an incomplete and noisy signal; studies show the carbon premium is highly sensitive to methodological choices, such as relying on estimated versus reported emissions (Aswani et al., 2024) or accounting for significant lags in corporate carbon reporting (Zhang, 2025). Moreover, this measure is backward-looking. Emissions reflect past activity, not necessarily a firm's future vulnerability or adaptability. An alternative strand of research measures exposure through a "carbon beta", the sensitivity of a firm's return to a systematic climate risk factor (Görgen et al., 2019; Huij et al., 2023). This approach is conceptually appealing, as it captures investors' perceptions of climate risk, but it is empirically fragile: firm-level betas estimated from short time series are noisy, and the economic drivers of this sensitivity remain opaque.

This paper bridges the gap between these two approaches by taming and decomposing the carbon beta, transforming it from a noisy estimate into a reliable economic signal. We develop a framework that explicitly decomposes what drives firms' exposure to climate transition risk, allowing us to identify what information investors actually price. Instead of treating the carbon beta as a statistical coefficient estimated from returns alone, we explicitly model it as a time-varying function of observable firm, sectoral, and macro characteristics—including emissions, corporate climate commitments, financial structure, and market sentiment proxies such as climate news and ESG flows. Our framework thus integrates the strengths of both approaches: it retains the forward-looking nature of returns but filters out the statistical noise by grounding the beta in firm fundamentals. The measure becomes both statistically robust and economically interpretable.

Our empirical analysis uses a comprehensive panel of listed U.S. and European firms from 2010 to 2025. We implement a three-step empirical framework. First, we construct regional Brown-minus-Green (BMG) climate risk factors that capture systematic transition shocks. Second, we isolate firm-specific returns by orthogonalizing them to the Fama–French six-factor model within a Dynamic Conditional Beta (DCB) framework (Bali et al., 2017; Engle, 2016). Third, we estimate the carbon beta as an interaction-term panel model (à la Bekaert et al., 2014), where the sensitivity to the climate factor depends on firm, sector, and macro characteristics. This specification allows us to disentangle the economic channels that shape transition exposure and to examine how these exposures evolve with market dynamics and climate-related sentiment.

This framework produces several novel insights. First, we identify which firm characteristics explain transition exposure: direct (Scope 1) emissions are the primary driver, while Scope 2 and 3 are not significant once country and sector effects are accounted for. Second, we show the beta incorporates a sophisticated information set: it amplifies significantly in response to public controversies, and we also find some evidence that it decreases following the adoption of forward-looking signals like emission targets or the use of renewable energy. Third, the carbon beta anticipates future decarbonization: firms with lower current exposure subsequently reduce emissions more, implying that markets partially foresee transition paths. Fourth, exposure is distinct from traditional financial risks like leverage and profitability, confirming that investors perceive climate transition as a unique risk dimension. Finally, we show that a positive carbon premium emerges only after the Paris Agreement, and only when using our characteristic-driven transition risk measure. The premium is invisible in raw emissions data, but clearly priced once transition risk reflects the comprehensive set of climate-related information available to investors.

Overall, our findings move the climate-finance debate beyond a simple focus on raw emissions. We show that markets do not price emissions in isolation; rather, they price a sophisticated information set that integrates firms' actual emissions, decarbonization trends, public reputation, and evolving climate sentiment. By decomposing this signal, our paper provides a unified empirical framework to understand the underlying mechanism of transition risk exposure and the carbon premium.

Related literature— Our paper contributes to a large and active literature on the measurement and pricing of climate risk (Giglio et al., 2021). Studies document a carbon risk premium, showing that high-emission firms earn higher expected returns (e.g., Bolton and Kacperczyk, 2021, 2023; Hsu et al., 2023). This is consistent with evidence from other asset classes, such as option markets, which price significant downside tail risk in brown stocks (Ilhan et al., 2021). Survey-based evidence confirms this, finding that institutional investors view climate risks as financially material (Krueger et al., 2020) but as currently underpriced by markets (Stroebel and Wurgler, 2021). However, this premium is intensely debated. Recent studies show it is highly sensitive to methodological choices, such as using estimated versus reported data (Aswani et al., 2024), or accounting for substantial data lags (Zhang, 2025). Furthermore, the premium often disappears when using carbon intensities rather than absolute emission levels (Bolton and Kacperczyk, 2021; Aswani et al., 2024). This measurement uncertainty complicates the search for effective hedging strategies, another central theme in the literature (Alekseev et al., 2022; Andersson et al., 2016; Engle et al., 2020).

This measurement debate has spurred innovations in how climate exposure is quantified. Recognizing that historical emissions are a backward-looking proxy, researchers aims to develop forward-looking measures. As Giglio et al. (2021) mention in their survey, there is "substantial scope for improvements of the measures of climate risk exposure". Reflecting this need, Ilhan et al. (2023) show that institutional investors are a key force in demanding better climate disclosure, viewing it as critical for their investment and engagement decisions. This demand for better data has been met by new methods, such as textual analysis of corporate disclosures (e.g., earnings calls) to build topic-based measures of risk and opportunity (Hu et al., 2022; Leippold and Yu, 2025; Li et al., 2024; Sautner et al., 2023). However, this textual approach requires distinguishing credible signals from "greenwashing," as Bingler et al. (2024) find that cheap talk in annual reports is associated with higher future emissions growth and greater reputation risk. By contrast, Flammer (2021) shows that green bond issuance acts as a credible corporate signal that is rewarded by investors. Other approaches track aggregate news-based indices to capture climate-related attention (Ardia et al., 2023; Engle et al., 2020). Choi et al. (2020) show carbon-intensive firms underperform during these high attention periods. A separate approach infers risk exposure not from what firms say, but from what markets and investors do. Görgen et al. (2019) and Huij et al. (2023) estimate the sensitivity of a firm's return to a systematic climate factor, which better captures investors' perceptions of climate risk. Alekseev et al. (2022) introduce a quantity-based method that observes how fund managers trade in response to idiosyncratic belief shocks (like local heat waves) to build hedge portfolios. Our paper bridges these approaches: we construct a new carbon beta that is grounded in fundamentals (like emissions) but is also driven by corporate commitments, as well as the attention channel and investor behavior highlighted by the literature.

Finally, our work speaks to a fundamental question: do climate-related return differentials reflect risk, mispricing, or shifts in investor preferences? This question is highlighted by the recent outperformance of green stocks (In et al., 2019; Pástor et al., 2022), a pattern frequently attributed to a series of unexpected climate concern shocks (Ardia et al., 2023; Pástor et al., 2021). Event studies similarly show that increases in the likelihood of future climate policy action decrease equity prices for high-exposure firms (Barnett, 2023), while realized policy shocks, such as the 2020 U.S. election, led to the outperformance of climate-responsible firms (Ramelli et al., 2021). Conversely, Atilgan et al. (2024) argue for mispricing, as they find the premium for high-emission firms is strongly associated with positive earnings surprises and announcement returns, suggesting it is an unexpected return investors are failing to anticipate, not a risk premium. Together, these findings point to the powerful role of investor demand, where shifts in green preferences or large-scale ESG flows (Van der Beck, 2025) can shape asset prices independently of fundamentals, as modeled by Pástor et al. (2021); Pedersen et al. (2021). This is consistent with evidence that ESG firms outperform during crises, suggesting social capital acts as a risk-reducing feature (Hoepner et al., 2024; Lins et al., 2017). Our framework directly addresses this by modeling news (sentiment shocks) and ESG flows (demand shocks) as explicit drivers of the carbon beta, allowing us to disentangle these channels.

The remainder of the paper is organized as follows. Section 2 describes the data and empirical framework. Section 3 presents the results, and Section 4 concludes.

2 Methodology and Data

Our empirical approach consists of three steps. First, we construct a systematic climate risk factor that captures differences in returns between high- and low-emission firms. Second, we orthogonalize individual stock returns to standard sources of financial risk using a Dynamic Conditional Beta (DCB) model, ensuring that our analysis focuses on return components not explained by traditional factors. Third, we estimate a characteristics-driven panel regression that disciplines and decomposes the carbon beta, allowing us to identify the drivers of firms' exposure to climate transition risk.

2.1 Climate Transition Risk Factor

To obtain a proxy for transition climate shocks, we develop a Brown-minus-Green factor (F_t^{Climate}) along the lines of the standard portfolio-sorting methodology of Fama and French (1993). The approach of mimicking portfolios to capture carbon risk is widely used in recent climate asset pricing research, including Görgen et al. (2019), Huij et al. (2023), and Pástor et al. (2022). Our baseline measure to build high- and low-emission portfolios is the firm-level carbon intensity, defined as Scope 1 and Scope 2 greenhouse gas emissions scaled by total sales:

$$CI_{i,t} = \frac{\text{Emissions}_{i,t}^{(\text{Scope 1 + Scope 2})}}{\text{Total Sales}_{i,t}}$$

Scaling emissions by firm sales provides comparability across firms and mitigates mechanical correlations between emission levels and size. Recent work emphasizes that intensity-based measures better capture the economic relevance of transition costs and regulatory exposure (Aswani et al., 2024; Giglio et al., 2021; Zhang, 2025). For example, for a given level of carbon emissions, carbon taxes would affect the profitability of smaller firms more than that of larger firms.

At the end of each calendar month, we retrieve 1-month lagged market capitalization (Size) and 24-month lagged carbon intensity (CI).[1] Firms are then independently sorted into two groups based on the median of their size and their lagged CI. This yields four value-weighted portfolios: Small-Green (SG), Big-Green (BG), Small-Brown (SB), and Big-Brown (BB). The climate factor is then constructed monthly as:

$$F_t^{\text{Climate}} = \frac{1}{2}(SB_t + BB_t) - \frac{1}{2}(SG_t + BG_t) \tag{1}$$

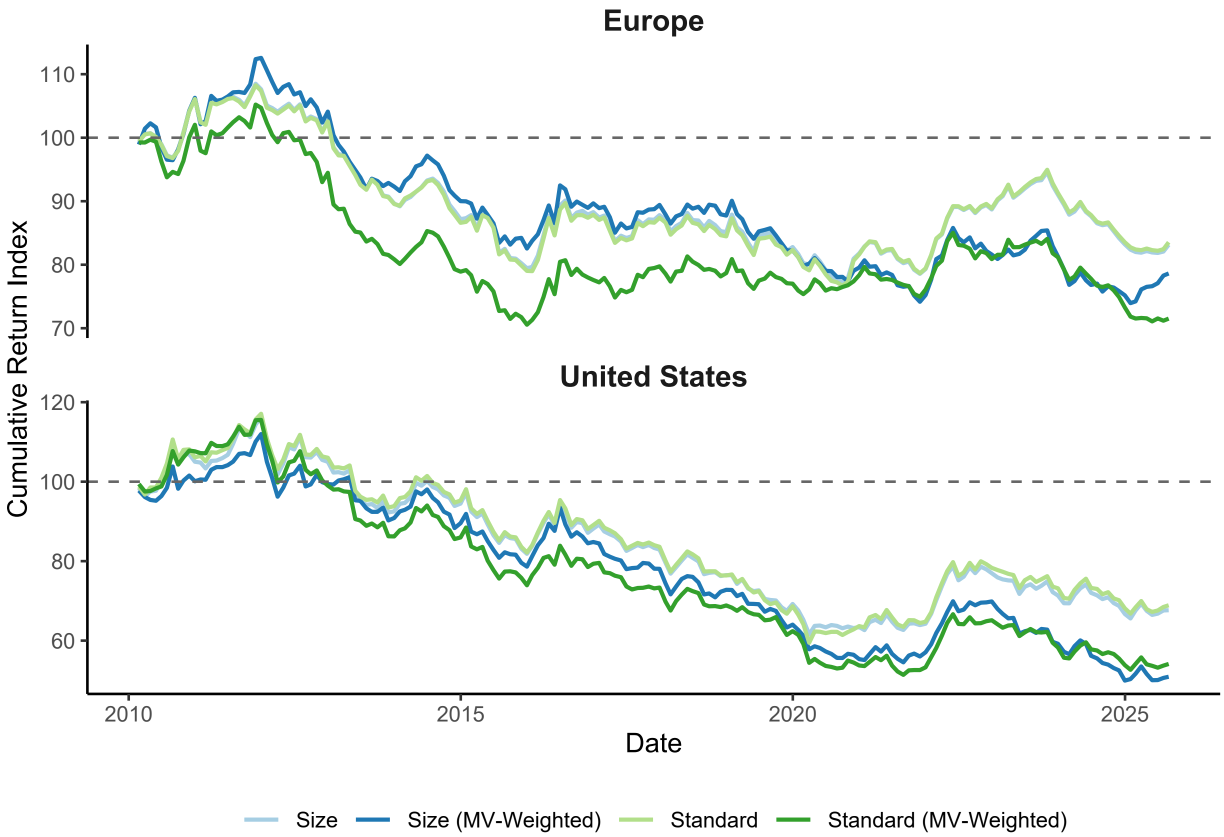
which represents the return spread between high-intensity and low-intensity firms. A long-term positive value of F_t^{Climate} indicates that carbon-intensive firms earn higher returns in

[1] We lag carbon intensities by 24 months to account for the significant delay in reporting the data. We also winsorize market capitalization at the 5% and 95% levels to mitigate the influence of large firms on the climate factor.

month t, consistent with a transition risk premium.

We construct the factor separately for U.S. and European firms to account for cross-regional differences in climate policy and investor climate preferences, as documented in Bolton and Kacperczyk (2023). Figure 1 plots the cumulative returns of the BMG factor for the U.S. and Europe. Both series exhibit a persistent decline over the mid-2010s onward, indicating that low-emission (green) firms have outperformed high-emission (brown) firms in recent years. This pattern is consistent the climate attention shocks documented in Ardia et al. (2023) and Pástor et al. (2022). The initial downward trend is more pronounced in Europe, which is aligned with earlier and more credible climate policy implementation in EU markets. In contrast, the U.S. factor declines later, reflecting greater policy uncertainty and slower increase in regulatory pressure (Bolton and Kacperczyk, 2023; Ramelli et al., 2021). These differences suggest that the transition risk exposure and premium may be state-dependent and may vary with the institutional environment. Within each region, the cumulative return patterns are similar across portfolio weighting schemes (value-weighted vs. equal-weighted), indicating that the observed return spread is not driven by size composition differences within the brown and green portfolios. This suggests that the signal embedded in the Brown-minus-Green factor is broad-based rather than concentrated in a particular segment of the market.

Figure 1: Cumulative returns of the climate transition risk factor across regions



Note: This chart shows the cumulative returns of climate risk factors in the United States and Europe. We compare these dynamics between the two regions and according to different weighting schemes and portfolio construction methods.

2.2 Returns Orthogonalization

A challenge in identifying the effect of climate transition risk on stock returns is that a firm's exposure to climate-related factors may be correlated with exposures to standard sources of systematic risk such as market, size, value, profitability, investment, or momentum. Before estimating the effect of climate transition risk on returns, we remove the variation in stock returns attributable to these risk factors. Specifically, we orthogonalize firm-level excess returns with respect to the Fama-French six-factor model (including momentum)[2]. The goal is to obtain a return component where any remaining systematic co-movement is potentially attributable to climate-related exposure.

A critical modeling choice is whether to treat factor loadings as constant or time-varying. Since both factor volatilities and cross-asset correlations exhibit persistent time-variation, assuming constant exposure ignores important market dynamics. We therefore adopt the conditional asset pricing framework of Engle (2002, 2016) and Bali et al. (2017). Instead of relying on arbitrary rolling windows, we estimate dynamic conditional betas directly from the evolution of the conditional covariance matrix of returns.

Let $r_{i,t}$ denote the excess return of firm i at time t, and let f_t denote the vector of the Fama-French six factor returns, including momentum. The time-varying beta of firm i with respect to the factor vector is then obtained from:

$$\beta_{i,t}^{FF6} = H_{ff,t}^{-1} H_{rf,t}, \tag{2}$$

where $H_{ff,t}$ is the (6×6) conditional covariance matrix of the factors, and $H_{rf,t}$ is the (6×1) conditional covariance vector between $r_{i,t}$ and f_t.

To estimate these components in a computationally robust manner (see Engle, 2016), we follow a two-stage procedure. First, we estimate the factor-only covariance matrix $H_{ff,t}$ using a 6-variate DCC-GARCH(1,1) model. This is done separately for the U.S. and Euro-

[2] Fama-French factors are downloaded from Kenneth French's website. We use different versions of the Fama-French factors depending on the regional location of the company (U.S. vs. Europe).

pean factor sets. Second, for each firm i, we estimate the required $H_{rf,t}$ vector by fitting a series of bivariate DCC-GARCH(1,1) models. Finally, we obtain the multivariate dynamic betas by multiplying this covariance vector by the inverse of the factor covariance matrix ($H_{ff,t}^{-1}$). This step ensures that the resulting betas are properly adjusted for the time-varying correlations among the factors themselves.

This specification allows variances and correlations to evolve separately, capturing volatility clustering and correlation persistence without imposing an arbitrary window length, in contrast to rolling regressions. The orthogonalized or idiosyncratic return used in our main analysis is then computed as the residual from this projection:

$$\varepsilon_{i,t} = r_{i,t} - (\beta_{i,t}^{FF6})' f_t, \tag{3}$$

The residual $\varepsilon_{i,t}$ isolates the component of returns that is not explained by standard risk factors and thus provides a clean outcome variable for analyzing exposure to climate transition shocks.

2.3 Characteristics-Driven Carbon Beta Model

The core of our empirical framework is a panel model designed to identify the determinants of firms' exposure to transition climate risk. We model a firm's idiosyncratic return, $\varepsilon_{i,t}$ (the residual from Equation 3), as a function of its exposure to the climate transition risk factor, F_t^{Climate} (Equation 1). Departing from standard models with constant factor loadings, we allow this exposure, the carbon beta ($\beta_{i,t}^{\text{Climate}}$), to vary over time and across firms, conditioned on observable firm, country, and time-specific characteristics.

Formally, we specify:

$$\varepsilon_{i,t} = \alpha_i + \delta_t + \beta_{i,t}^{\text{Climate}} F_t^{\text{Climate}} + \epsilon_{i,t} \tag{4}$$

$$\beta_{i,t}^{\text{Climate}} = \gamma_0 + \sum_{k=1}^{K} \gamma_k Z_{i,t-1,k} \tag{5}$$

where α_i and δ_t denote firm and time fixed effects, respectively, and $Z_{i,t-1,k}$ represents a set of lagged firm-level, macroeconomic, and environmental variables. Substituting Equation (5) into Equation (4) yields the interaction specification:

$$\varepsilon_{i,t} = \alpha_i + \delta_t + \gamma_0 F_t^{\text{Climate}} + \sum_{k=1}^{K} \gamma_k (F_t^{\text{Climate}} \times Z_{i,t-1,k}) + \epsilon_{i,t}. \tag{6}$$

Equation (6) decomposes the sensitivity of firm-specific residual returns to the climate factor into contributions associated with distinct observable drivers. The coefficients γ_k measure how each characteristic Z_k amplifies or dampens the firm's conditional exposure to transition climate risk. We estimate Equation (6) using two-way fixed effects and standard errors clustered by both firm and time to account for serial and cross-sectional correlation.

This specification builds on the characteristics-driven market beta approach used by Bekaert et al. (2014). They model time variation in international equity market exposures as a linear function of lagged macro-financial variables to identify contagion channels. In their setting, $\beta_{i,t}$ captures the dynamic sensitivity of country-sector portfolios to global and U.S. market factors, allowing exposures to respond to financial integration and crisis indicators. Our framework adapts this methodology to the firm level and to the domain of climate finance, where exposures evolve dynamically with firms' emissions, climate commitments, policy regimes, and investor preferences.

The conditioning variables, $Z_{i,t-1,k}$, are chosen to span firm-specific, financial, and macroeconomic determinants of transition risk exposure. Firm-level climate characteristics reflect both backward- and forward-looking aspects, including historical carbon intensity, the composition of Scope 1 and Scope 2 emissions, stated decarbonization targets or environmental controversies. These variables aim to capture differences in transition vulnerability and credibility of corporate climate strategies. Firm-level financial characteristics such as size, value, profitability, leverage, and investment intensity are included to control for traditional cross-sectional predictors of returns that may correlate with both climate exposure and expected performance. Finally, our time-series drivers capture market-wide factors that may affect the integration of transition risk into asset prices. These include macroeconomic shocks (such as changes in interest rates and market volatility), key commodity price shocks (notably oil for energy demand and copper for transition-metal demand), carbon prices, and investor sentiment proxies (like climate news attention and ESG fund flows). Together, these categories provide a rich empirical basis for explaining variation in the carbon beta across firms, time, and regulatory regimes.

Our approach improves on standard beta estimation in two fundamental ways. First, by anchoring the beta to fundamentals, it filters out the statistical noise inherent in standard time-series regressions. Second, it opens the black box: the beta becomes an economically interpretable measure, directly linked to specific firm and market drivers.

2.4 Data

Our empirical analysis draws on firm-level and macro-financial datasets. The primary firm-level data are sourced from Refinitiv Datastream and the Refinitiv ESG database. We collect monthly total returns (i.e. including dividends), stock prices, and accounting variables such as market capitalization, book value, sales and total assets. The ESG database provides climate-related corporate characteristics, including Scope 1 and Scope 2 greenhouse-gas emissions (and estimated Scope 3), plus qualitative indicators such as emission-reduction targets and environmental controversies. A complete list and definition of all variables used in the study are given in Table A.8.

Our sample spans January 2010 through August 2025 and covers firms listed and domiciled in either the United States or Europe. We focus exclusively on common equities, excluding preferred shares, warrants, closed-end funds and depositary receipts; for firms with multiple listings, we retain the primary listing location. To ensure data quality and comparability we follow the screening process of Landis and Skouras (2021) and implement the following filters: we screen company names to remove non-equity entities misclassified in Datastream, then exclude any firm for which (i) more than 95% of its monthly returns share the same sign, (ii) more than 25% of monthly returns are zero (indicating illiquidity), or (iii) the standard deviation of monthly returns falls below 0.01% or exceeds 40%.

We further restrict the sample to firms that report carbon emissions (Scope 1 or 2) at least once during the period. The final panel comprises 3,029 unique firms, of which 1,186 from the U.S. and 1,843 from Europe[3], spanning a broad range of industries and including both continuing and delisted firms as of 2025. The sample is diversified across all major sectors.[4] Importantly, the coverage of carbon-emission disclosures expands significantly over time, from 621 reporting firms in 2008 (used in the 2010 climate factor construction) to 2,948 in 2025, reflecting regulatory and market disclosure trends.

In addition to the firm-level data, we use macroeconomic and financial time-series variables (see Table A.9). These include the Media Climate Change Concern (MCCC) index (Ardia et al., 2023), monthly ESG-fund flows from EPFR, government bond yields, commodity prices (Brent crude oil and copper from S&P GSCI), and market-volatility indices (VIX for the U.S., V2X for Europe) downloaded from Datastream. To ensure stationarity and avoid spurious relationships, all time-series variables are converted into either monthly returns or first differences before inclusion in the empirical analyses.

Table 1 reports descriptive statistics for the full panel of up to 530,048 firm–month observations from 2010 to 2025. Several patterns emerge that guide our empirical specification. The dependent variable, the orthogonalized stock residual, has a mean of zero but displays substantial dispersion (standard deviation of 8% per month), indicating meaningful firm-

[3]UK: 578 firms; Sweden: 189; Germany: 176; France: 166; Switzerland: 131; Italy: 110; Spain: 72; Finland: 63; Norway: 63; Netherlands: 60; Denmark: 54; Belgium: 51; Ireland: 39; Poland: 38; Austria: 32; Greece: 28; Luxembourg: 18; Portugal: 15; Hungary: 6; Czech republic: 4; Romania: 4; Malta: 3; Slovenia: 2; Cyprus: 1

[4]Industrials: 594 firms; Consumer Cyclicals: 482; Technology: 430; Financials: 345; Basic Materials: 249; Healthcare: 237; Real Estate: 214; Consumer Non-Cyclicals: 207; Energy: 150; Utilities: 118, Academic & Educational Services: 3.

level heterogeneity even after controlling for the six Fama–French factors. The underlying stock returns exhibit a similar spread (standard deviation of 9%), suggesting that the orthogonalization preserves economically relevant variation. Turning to firm fundamentals, the average firm in the sample is large and profitable, with a mean log market value of 7.8 and an average return on assets of 12%. Leverage ratios average 26%, while investment ratios are modest (4% of total assets). Analyst coverage is broad (mean of 10 analysts per firm), consistent with a liquid, investable universe.

Climate characteristics reveal strong right skewness in emission distributions. Mean carbon intensity is 2.1, corresponding roughly to a tenfold difference between median and mean intensity, reflecting a small subset of highly carbon-intensive firms. These heavy tails justify our use of logarithmic transformations throughout. The average firm has reduced its emissions modestly over time: current carbon-intensity trends are slightly negative (–0.01 on average), suggesting gradual decarbonization. At the same time, firm-level climate commitments are widespread: about half of firms (52%) report formal emission-reduction targets, 56% use renewable energy, and nearly three-quarters (74%) disclose an emission policy. More advanced transition practices remain uncommon, as only 3% of companies report an internal carbon price. Finally, 2% are involved in environmental controversies.

At the country level, the Carbon Pricing Index averages 13.3 but with wide dispersion (standard deviation 19.5), reflecting large cross-national differences in climate-policy regimes. The ND-GAIN Vulnerability Index displays limited variation across countries, with most developed economies clustered near 0.30. Finally, the time-series variables exhibit patterns consistent with episodic climate attention. The Climate Factor has near-zero mean but a standard deviation of 2%, indicating frequent shifts in relative performance between brown and green firms. The climate news shock series exhibit and increasing trend (mean 0.04) and is quite volatile (standard deviation 0.36), capturing spikes in media coverage following major policy announcements or extreme weather events. The average ESG flow differential is positive (0.5%), consistent with a structural reallocation of capital toward sustainable investment vehicles during the period.

Overall, the data reveal substantial heterogeneity across firms, sectors, and regions, particularly in carbon intensity and climate engagement—providing a rich setting to study the dynamic determinants of carbon betas and their interaction with firm-level and macroeconomic conditions. After all merging and cleaning procedures, our final panel is unbalanced and contains approximately 300,000 firm-month observations.

Table 1: Descriptive Statistics

Label	N	Mean	SD	Min	P25	Median	P75	Max
Key Variables								
Residual (Orthogonalized Return)	530,048	0.00	0.08	-0.35	-0.04	0.00	0.05	0.36
Stock Return	530,048	0.01	0.09	-0.60	-0.05	0.01	0.06	0.67
Financial Characteristics								
Log(Market Value) (t-1)	529,909	7.80	1.87	0.12	6.54	7.80	9.06	15.16
Book-to-Market (t-12)	529,156	0.62	0.55	-0.04	0.25	0.47	0.82	4.56
Return on Assets (t-12)	526,591	0.12	0.22	-0.89	0.04	0.11	0.19	1.04
Cash Ratio (t-12)	500,529	0.10	0.10	0.00	0.03	0.07	0.14	0.45
Leverage (t-12)	528,947	0.26	0.18	0.00	0.11	0.25	0.38	0.76
Idiosyncratic Volatility (t-1)	528,864	0.08	0.04	0.01	0.05	0.07	0.10	0.33
Investment Ratio (t-12)	528,640	0.04	0.04	0.00	0.01	0.03	0.05	0.19
Log(PPE) (t-12)	528,422	12.89	2.59	0.00	11.46	13.07	14.64	19.61
Log(Turnover) (t-1)	454,366	11.58	2.93	0.00	9.67	11.97	13.76	22.32
Analyst Coverage (t-1)	521,751	10.22	8.14	1.00	4.00	8.00	16.00	64.00
Firm-Level Climate Characteristics								
Log(Carbon Intensity, t-24)	295,280	3.54	1.92	0.00	2.18	3.34	4.65	12.31
Carbon Intensity (t-24) $/10^2$	295,280	2.13	5.46	0.00	0.08	0.27	1.03	40.20
Squared Carbon Intensity (t-24) $/10^4$	295,280	34.37	155.6	0.00	0.00	0.07	10.70	1,761
Log(Carbon S2 Intensity, t-24)	271,584	2.60	1.49	0.00	1.49	2.55	3.55	13.71
Log(Carbon S3 Intensity, t-24)	264,083	2.70	2.71	0.00	0.00	3.30	5.20	13.80
Past CI Trend (t-48 to t-24)	235,553	0.01	0.54	-0.76	-0.24	-0.08	0.06	6.21
Current CI Trend (t-24 to t)	228,234	-0.01	0.49	-0.76	-0.25	-0.09	0.05	3.99
Future CI Trend (t to t+24)	211,481	-0.01	0.48	-0.75	-0.25	-0.09	0.05	2.91
Indicator: Emission Target (t-24)	375,217	0.52	0.50	0.00	0.00	1.00	1.00	1.00
Indicator: Env. Controversies (t-24)	378,015	0.02	0.13	0.00	0.00	0.00	0.00	1.00
Indicator: Renewable Energy (t-24)	375,753	0.56	0.50	0.00	0.00	1.00	1.00	1.00
Indicator: Emission Policy (t-24)	377,691	0.74	0.44	0.00	0.00	1.00	1.00	1.00
Indicator: Internal C-Price (t-24)	377,451	0.03	0.18	0.00	0.00	0.00	0.00	1.00
Country-Level Characteristics								
Carbon Pricing Index (Country, t-12)	530,048	13.26	19.49	0.03	0.86	4.36	16.55	87.80
ND-GAIN Vulnerability (Country, t-24)	530,048	0.31	0.02	0.25	0.29	0.31	0.31	0.43
Time-Varying Factors								
Climate News Shock (AR1)	527,108	0.04	0.36	-0.99	-0.15	0.00	0.25	1.56
Climate Factor	530,048	0.00	0.02	-0.06	-0.01	0.00	0.01	0.07
ESG Flow Differential (%)	530,048	0.50	1.18	-2.83	-0.29	0.39	1.05	4.46
Oil Return	530,048	0.01	0.09	-0.22	-0.06	0.02	0.06	0.27
Copper Return	530,048	0.00	0.05	-0.13	-0.03	0.00	0.04	0.16
Yield Shock	530,048	0.00	0.23	-0.59	-0.14	0.00	0.14	0.66
Implied Market Volatility (%)	530,048	20.32	6.76	9.51	15.57	18.60	23.65	53.54
Time Trend (Years)	530,048	7.96	4.40	0.00	4.24	8.08	11.75	15.41
Indicator: Post-Paris	530,048	0.65	0.48	0.00	0.00	1.00	1.00	1.00

Notes: This table reports descriptive statistics for all variables used in the analysis. The sample consists of monthly firm-level observations from 2010 to 2025, covering up to 530,048 firm-months depending on variable availability. Residual returns are excess stock returns orthogonalized to the Fama–French factors and constitute the dependent variable in all carbon beta regressions. Financial characteristics are lagged by 12 months (except Market Value and Idiosyncratic Volatility, lagged by 1 month). Firm-level climate characteristics, including carbon intensities, emission scopes, and climate policies, are lagged by 24 months to reflect reporting cycles. Country-level variables (carbon pricing and physical risk) follow their respective data release lags. Time-varying global factors include climate news shocks, ESG fund flow differentials, commodity returns, yield shocks, and implied volatility. The definitions of these variables are presented in Table A.8.

3 Empirical Results

This section details the information incorporated into the characteristics-driven carbon beta and verifies its relevance to asset pricing. We proceed by testing the link with emission proxies and assess the model's ability to predict firm-level decarbonisation trajectories. We identify the microeconomic and time-series factors that drive the carbon beta variations and conclude by showing that the constructed measure identifies a carbon premium that would be undetectable using static risk proxies.

3.1 Links Between Emissions and the Carbon Beta

We begin by establishing the empirical link between firm-level emissions and exposure to transition shocks. Table A.1 explores different functional forms for the relationship between emission intensity and the carbon beta. In our most robust specifications with full fixed effects (even-numbered columns), the logarithmic form of carbon intensity provides the most consistent and statistically significant positive relationship with the carbon beta. The linear term also shows significance, while the squared term does not add explanatory power in the full model. This suggests a concave relationship: the carbon beta increases with carbon intensity, but at a decreasing rate. Overall, the persistence of the $\mathrm{CF} \times \log(\mathrm{CI})$ coefficient across all specifications reinforces the idea that high-emission firms load more strongly on transition shocks, either because their cash flows are more exposed to regulation and technological substitution or because investor sentiment toward them co-moves more with climate news.

Table 2 further decomposes this relationship across emission scopes. The interaction terms between the climate risk factor and the emission scopes $\mathrm{CF} \times \log(\mathrm{CI}^{S1})$ and $\mathrm{CF} \times \log(\mathrm{CI}^{S2})$ are positive and highly significant in the standalone scope specifications (Columns 1–4), with coefficients ranging from about 0.04 to 0.11. Once Scope 1, Scope 2, and Scope 3 are included jointly (Columns 7–8), both coefficients remain positive but only the Scope

1 interaction retains statistical significance, while the Scope 2 coefficient becomes small and statistically insignificant in the last column. These effects remain economically meaningful both with and without the "Sector/Country" controls, although their magnitude declines once these controls are introduced, suggesting that part of the raw relationship is driven by sectoral and geographic heterogeneity rather than purely firm-specific exposure (e.g., Bolton and Kacperczyk, 2021, 2023).

By contrast, Scope 3 intensity shows a negative and significant coefficient in the standalone specifications (Columns 5–6), but the effect becomes small and statistically insignificant once all scopes are included jointly (Columns 7–8). This instability is consistent with the substantial measurement error affecting value-chain emissions, which rely on modeled data rather than reported measures (Bolton and Kacperczyk, 2021; Aswani et al., 2024). A hypothesis would be that investors primarily price emissions under managerial control and measured with higher reliability. Following the standard approach in the literature, our subsequent analyses focus on Scope 1 & 2 emissions.

Table 2: Decomposing the Carbon Beta by Emission Scope

	Dependent variable: Stock Residuals							
	Scope 1		Scope 2		Scope 3		All Scopes	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Climate Factor	−0.285***	−0.382	−0.296***	−0.414	0.024	−0.180	−0.335**	−0.470
	(0.091)	(0.703)	(0.095)	(0.717)	(0.139)	(0.463)	(0.130)	(0.722)
Climate Factor x Log(CI Scope 1)	0.113***	0.048***					0.097***	0.040***
	(0.007)	(0.009)					(0.012)	(0.012)
Climate Factor x Log(CI Scope 2)			0.113***	0.044***			0.027**	0.019
			(0.010)	(0.010)			(0.013)	(0.012)
Climate Factor x Log(CI Scope 3)					−0.034***	−0.017**	−0.011	−0.003
					(0.008)	(0.007)	(0.009)	(0.008)
FE: Firm + Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls: CF x Sector/Country	No	Yes	No	Yes	No	Yes	No	Yes
Observations	275,852	275,852	271,584	271,584	264,083	264,083	203,692	203,692
R^2	0.038	0.041	0.037	0.041	0.033	0.037	0.041	0.043
Adjusted R^2	0.027	0.030	0.026	0.030	0.021	0.025	0.026	0.028

Notes: The table reports coefficient estimates from panel regressions of stock residuals on interactions between the climate factor and logarithmic carbon intensities across emission scopes. Columns (1)–(6) present standalone models for Scope 1 (direct operational emissions), Scope 2 (purchased energy), and Scope 3 (value-chain emissions). Columns (7)–(8) report the joint specification including all scopes simultaneously. Firm and Time fixed effects are included in all models, and even-numbered columns additionally absorb sector and country heterogeneity through CF × Sector/Country controls. The sample includes monthly observations for all firms in the dataset over 2010–2025. Standard errors are clustered at the firm and time levels. ***, **, and * denote significance at the 1%, 5% and 10% levels, respectively.

We next investigate whether investors price emissions uniformly across jurisdictions, or if they account for the specific regulatory environment. The financial materiality of transition risk should depend on the local climate policy: a ton of carbon emitted in a jurisdiction with stringent carbon taxes represents a more immediate liability than the same emission in a jurisdiction with lax regulation.

Table 3 tests this hypothesis by interacting the climate factor with country-level climate characteristics. Column (2) introduces the Carbon Pricing Index, a measure of the stringency of national carbon pricing schemes. The coefficient of interest is the triple interaction term CF $\times$ Carbon Pricing $\times$ log(CI). We find this coefficient to be positive and statistically significant. This indicates an amplification effect: for a given level of carbon intensity, a firm's exposure to transition risk (carbon beta) increases as the regulatory cost of carbon in its domicile country rises. This result suggests that investors are sophisticated enough to price not just the quantity of emissions, but the regulatory probability that these emissions will translate into financial costs. We find consistent evidence in Column (4) using the Climate Change Performance Index, a broader measure of a country's aggregate climate performance, accounting for GHG emissions, renewable energy, energy use, and climate policy. The positive and significant triple interaction confirms that firms operating in countries with better climate performances exhibit higher carbon betas for the same level of emissions.

In contrast, Columns (5) and (6) examine country-level physical risk vulnerability. The interactions here are not statistically different from zero. This null result provides a validity check: since our climate risk factor is constructed to capture transition risk (by sorting on emissions), we should not expect it to respond systematically to physical risk variables, which represent a distinct dimension of climate exposure. A potential exception would be if exposure to local physical risks heightened general investor attention toward carbon risk. However, given that the shareholder base of these firms is geographically diversified, such local shocks are unlikely to systematically alter the market pricing of transition risk.

Table 3: Impact of Country-Level Climate Factors on Stock Residuals

	Dependent variable: Stock Residuals					
	Carbon Pricing		Climate Change Perf.		Physical Risk	
	(1)	(2)	(3)	(4)	(5)	(6)
Climate Factor (CF)	−0.615	−0.594	−0.535	−0.369	−0.319	−0.748
	(0.486)	(0.487)	(0.516)	(0.506)	(0.640)	(0.687)
CF x Log(CI)	0.063***	0.056***	0.061***	0.011	0.064***	0.193*
	(0.011)	(0.012)	(0.011)	(0.023)	(0.011)	(0.105)
CF x Carbon Pricing	−0.0004	−0.003				
	(0.002)	(0.002)				
CF x Carbon Pricing x Log(CI)		0.001**				
		(0.0004)				
CF x Climate Perf.			−0.002	−0.006**		
			(0.002)	(0.002)		
CF x Climate Perf. x Log(CI)				0.001**		
				(0.0004)		
CF x Physical Risk					−0.963	0.441
					(1.230)	(1.658)
CF x Physical Risk x Log(CI)						−0.420
						(0.341)
FE: Firm + Time	Yes	Yes	Yes	Yes	Yes	Yes
Controls: CF x Sector	Yes	Yes	Yes	Yes	Yes	Yes
Observations	295,280	295,280	295,280	295,280	295,280	295,280
R^2	0.040	0.040	0.040	0.040	0.040	0.040
Adjusted R^2	0.029	0.029	0.029	0.029	0.029	0.029

Notes: The table reports panel regressions examining how country-level climate characteristics affect the carbon beta. Carbon Pricing and Climate Change Performance indices are lagged by 12 months, while the ND-GAIN exposure index is lagged by 24 months. Each observation corresponds to a firm-month in the sample, over the period 2010–2025. Robust standard errors are clustered at both the firm and time levels. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

3.2 Forward-looking Climate Information and the Carbon Beta

We next investigate whether the carbon beta embeds forward-looking information about firms' climate commitments, internal processes, and public reputation (see Table 4).

The results reveal a nuanced picture. Variables related to commitments, such as emission targets, emission policies, and renewable energy use, are not statistically significant overall, though their coefficients remain consistently negative. To interpret this, we run an auxiliary analysis in Table A.2. We find that these commitments are indeed associated with realized future decarbonization (Column 4), particularly for renewable energy use, which should theoretically lower transition risk exposure. However, they are also strongly positively correlated with current high emission levels (Column 1), likely because heavy emitters face the greatest pressure to adopt formal targets. These opposing forces, i.e., the risk-reducing effect of future abatement versus the risk-amplifying signal of high current emissions, are likely to cancel each other out, explaining why the net impact on the carbon beta is statistically insignificant in the full model.

By contrast, internal process variables, specifically the presence of an environmental team and climate awareness, are associated with positive and marginally significant coefficients (0.040^{*} and 0.059^{*}, respectively). The auxiliary analysis (Table A.2) clarifies this puzzle as well. We find that these soft signals are strongly positively correlated with current high emission levels (Column 1) but, unlike commitments, show no significant association with realized future decarbonization (Column 4). This suggests that investors interpret these signals not as evidence of effective transition strategies, but rather as proxies for heavy emitters who have established governance structures because of their elevated risk exposure.

Public-reputation variables exhibit the most robust and economically meaningful effects. In both standalone and controlled specifications (Columns 5 and 6), environmental controversies enter with large positive coefficients (0.27 and 0.15, respectively), and these magnitudes persist in the full specification (0.25 and 0.14). Among all qualitative characteristics, controversies are the only variable that remains strongly statistically significant across all modeling choices. This confirms that reputational shocks amplify sensitivity to climate-related news.

Taken together, these results show that the carbon beta is more than a static measure of past emissions. It actively incorporates forward-looking signals regarding a firm's credibility and reputation. Investors appear to distinguish between genuine transition efforts and empty commitments, penalizing firms subject to controversies while discounting credible pledges, consistent with recent findings on climate signal quality (Bingler et al., 2024).

Table 4: Decomposing the Carbon Beta by Climate Characteristic Themes

	Dependent variable: Stock Residuals							
	Commitments		Internal Processes		Public Reputation		Full Model	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Climate Factor (CF)	−0.429***	−0.430	−0.500***	−0.454	−0.450***	−0.444	−0.453***	−0.401
	(0.100)	(0.528)	(0.103)	(0.526)	(0.094)	(0.523)	(0.105)	(0.535)
CF x Log(CI)	0.132***	0.059***	0.128***	0.058***	0.128***	0.059***	0.127***	0.057***
	(0.008)	(0.011)	(0.008)	(0.011)	(0.008)	(0.011)	(0.008)	(0.011)
CF x Has Emission Target	−0.016	−0.002					−0.044**	−0.025
	(0.021)	(0.023)					(0.021)	(0.022)
CF x Has Emission Policy	−0.009	−0.018					−0.034	−0.038
	(0.031)	(0.030)					(0.032)	(0.030)
CF x Use Renewable Energy	−0.020	0.005					−0.036	−0.009
	(0.024)	(0.019)					(0.024)	(0.019)
CF x Has Internal C-Price			0.043	0.018			0.036	0.013
			(0.058)	(0.056)			(0.056)	(0.054)
CF x Has Env. Team			0.032	0.029			0.049**	0.040*
			(0.023)	(0.020)			(0.024)	(0.021)
CF x Has Climate Awareness			0.045	0.044			0.069*	0.059*
			(0.037)	(0.035)			(0.037)	(0.035)
CF x Has Env. Controversies					0.266***	0.148**	0.253***	0.140**
					(0.070)	(0.064)	(0.067)	(0.062)
FE: Firm + Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls: CF x Sector/Country	No	Yes	No	Yes	No	Yes	No	Yes
Observations	293,389	293,389	294,040	294,040	295,280	295,280	293,316	293,316
R^2	0.038	0.040	0.038	0.040	0.038	0.040	0.038	0.040
Adjusted R^2	0.027	0.029	0.027	0.029	0.027	0.029	0.027	0.029

Notes: The table reports coefficient estimates for forward-looking corporate characteristics, grouped into three thematic categories: (i) Commitments (targets, policies, renewable energy use), (ii) Internal Processes (carbon pricing, environmental teams, climate awareness), and (iii) Public Reputation (environmental controversies). The sample includes monthly observations for all firms in the dataset over 2010–2025. Standard errors are clustered at both the firm and time levels. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Finally, Table 5 provides a test of the information horizon embedded in the carbon beta. While the level of historical emissions is the dominant driver, we find that investors also price the rate of change in a firm's carbon intensity. In the full specification (Column 8), which jointly estimates the impact of past ($t-48$ to $t-24$), current ($t-24$ to t), and future (t to $t+24$) trends, all three components enter with positive coefficients. The positive sign indicates that firms which are increasing their emissions intensity (a positive trend) face higher betas, while those successfully decarbonizing (a negative trend) enjoy lower risk exposure. Importantly, the coefficient on the future trend is not only highly statistically significant (0.15) but is also economically larger than both the past (0.04) and current (0.09) trend coefficients. This provides evidence of market foresight. It implies that the carbon beta today already reflects a firm's realized decarbonization over the subsequent two years, even after controlling for its historical trajectory. This result underscores that the carbon beta is not merely a backward-looking metric. It acts as a leading indicator, capturing investors' evolving expectations about a firm's ability to adapt to a low-carbon economy.

Table 5: Carbon Beta and the Information Horizon of Emissions Trends

	Dependent variable: Stock Residuals							
	Past Trend		Current Trend		Future Trend		Full Model	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Climate Factor (CF)	−0.477***	−0.609	−0.487***	−0.493	−0.653***	−1.172	−0.693***	−0.064
	(0.097)	(0.574)	(0.106)	(0.586)	(0.122)	(0.751)	(0.128)	(0.292)
CF x Log(CI at t-24)	0.135***	0.061***	0.136***	0.067***	0.145***	0.077***	0.154***	0.087***
	(0.008)	(0.012)	(0.009)	(0.011)	(0.010)	(0.020)	(0.010)	(0.016)
CF x Past Trend (t-48 to t-24)	0.024	0.039**					0.032	0.040*
	(0.020)	(0.019)					(0.022)	(0.022)
CF x Current Trend (t-24 to t)			0.084**	0.039			0.144***	0.090**
			(0.035)	(0.031)			(0.042)	(0.040)
CF x Future Trend (t to t+24)					0.166***	0.121**	0.198***	0.148***
					(0.037)	(0.048)	(0.039)	(0.039)
FE: Firm + Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls: CF x Sector/Country	No	Yes	No	Yes	No	Yes	No	Yes
Observations	235,553	235,553	228,234	228,234	166,725	166,725	132,377	132,377
R^2	0.041	0.043	0.041	0.043	0.044	0.046	0.042	0.045
Adjusted R^2	0.028	0.030	0.028	0.030	0.030	0.032	0.030	0.033

Notes: The table reports regression estimates for the carbon beta trends, which incorporates information from past, current, and future emissions trends. Each column isolates different horizons. All models include firm and time fixed effects, with even specifications adding sector and country interactions. The sample includes monthly observations for all firms in the dataset over 2010–2025. Robust standard errors are clustered at both the firm and time levels. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Overall, the results show that the carbon beta is not merely an emissions proxy but a forward-looking, credibility-sensitive measure that aggregates operational exposure, commitments, reputation risk, and investors' expectations about firms' future transition pathways.

3.3 Climate Risk Exposure and Financial Vulnerabilities

A central question in the climate–finance literature is whether climate risk represents a genuine source of systematic risk or merely a proxy for traditional financial vulnerabilities. Intuitively, one might expect that financially fragile firms, with high leverage, low profitability, or limited liquidity, would be the most sensitive to the costs of the transition, such as carbon taxes. Our characteristics-driven carbon beta allows us to test this hypothesis directly.

Table A.3 reveals that this intuition does not hold. Once we control for firm-level carbon intensity, standard measures of financial vulnerability, including leverage, profitability, cash holdings, and idiosyncratic volatility, do not significantly interact with the climate factor. This null result suggests that investors view transition risk as a specific exposure linked to the nature of a firm's operations rather than its balance sheet strength.

However, two robust financial characteristics do emerge as drivers. First, the firm's size exhibits a consistently positive and significant coefficient (Column 8). Larger firms show higher sensitivity to climate shocks, likely because they are more visible to regulators, the media, and ESG-oriented investors (Pedersen et al., 2021). Second, as shown in Table A.4, the investment ratio is positively associated with the carbon beta. This implies that firms undertaking heavy capital expenditures are perceived as riskier in the face of transition shocks, likely reflecting concerns about asset stranding.

We interpret these findings with a degree of caution. While our carbon beta appears orthogonal to financial distress variables, it is not fully decoupled from a firm's financial profile. Because our measure is anchored by carbon emissions—which are higher for large, capital-intensive industrial firms—it inevitably captures some of the economic characteristics associated with their business models. Nevertheless, by estimating these sensitivities on residual returns that have been pre-orthogonalized to the Fama-French factors, we provide a measure that isolates the climate-specific component of this risk more cleanly than raw emission indicators alone.

3.4 Dynamics of Climate Risk Exposure

We next examine whether climate risk varies with shifts in market sentiment and investor attention. Table 6 reveals that spikes in climate-related media coverage significantly amplify the carbon beta, with a coefficient around 0.6 on CF $\times$ Climate News Shock. This finding supports the salience channel proposed by Pástor et al. (2021, 2022); Ardia et al. (2023), showing that attention shocks raise the transition risk market-based exposure even absent changes in fundamentals. The mechanism is intuitive: when climate issues dominate the news, investors update expectations about future regulation and carbon pricing, which increases the covariance between stock returns and the climate factor.

Table 6: The Impact of Climate News and ESG Flows on the Carbon Beta

	Dependent variable: Stock Residuals							
	Climate News				ESG Flows			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Climate Factor (CF)	−0.488***	−0.484	−0.489***	−0.483	−0.413***	−0.329	−0.407***	−0.326
	(0.092)	(0.518)	(0.092)	(0.519)	(0.078)	(0.501)	(0.078)	(0.501)
CF x Log(CI)	0.132***	0.061***	0.132***	0.061***	0.129***	0.060***	0.127***	0.059***
	(0.008)	(0.011)	(0.008)	(0.011)	(0.008)	(0.011)	(0.008)	(0.011)
CF x Climate News Shock	0.608**	0.598**	0.616**	0.596**				
	(0.237)	(0.236)	(0.258)	(0.261)				
CF x News Shock x Log(CI)			−0.002	0.001				
			(0.024)	(0.025)				
CF x ESG Flow					−0.167***	−0.165**	−0.187***	−0.182***
					(0.061)	(0.068)	(0.059)	(0.066)
CF x ESG Flow x Log(CI)							0.005	0.005
							(0.006)	(0.006)
FE: Firm + Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls: CF x Sector/Country	No	Yes	No	Yes	No	Yes	No	Yes
Observations	292,340	292,340	292,340	292,340	295,280	295,280	295,280	295,280
R^2	0.039	0.041	0.039	0.041	0.039	0.041	0.039	0.041
Adjusted R^2	0.028	0.030	0.028	0.030	0.028	0.030	0.028	0.030

Notes: The table reports regressions of stock residuals on interactions between the climate factor and climate news shocks or ESG fund flows. All regressions include Firm and Time fixed effects, with even columns adding CF $\times$ Sector/Country controls. The sample includes monthly observations for all firms in the dataset over 2010–2025. Standard errors are clustered at both the firm and time levels. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Conversely, periods of strong ESG fund inflows are associated with a statistically significant decline in the carbon beta (Table 6, CF $\times$ ESG Flow ≈ -0.18). This finding confirms a powerful demand-side channel. High ESG flows boost demand for low-carbon assets, thereby compressing the price differential between brown and green firms. This pattern aligns with models suggesting that shifts in investor preferences or large-scale ESG flows can shape asset prices independently of fundamentals (Pástor et al., 2021; Pedersen et al., 2021; Van der Beck, 2025).

Turning to longer-term dynamics, Table A.5 provides little evidence of a deterministic trend in climate risk exposure. The coefficient on the time trend and the post-Paris dummy are statistically insignificant, indicating that the exposure to transition risk has not followed a linear or structural pattern since 2015. Instead, the evolution of carbon beta appears to be episodic, with bursts of attention and demand for green stocks rather than a steady increase in climate awareness.

Finally, macroeconomic and commodity shocks provide little explanatory power. Tables A.6–A.7 show that yield, volatility, and energy-price shocks have insignificant effects on the carbon beta. The lack of sensitivity to oil and copper price changes implies that the carbon beta captures transition risk distinct from conventional macro or commodity-market exposures. This is consistent with the argument that climate risk is not simply an indicator of the energy sector's volatility, but a distinct dimension of risk, determined by policies and expectations.

3.5 Carbon Beta Prediction

The final model, presented in Column (4) of Table 7, synthesizes all significant cross-sectional and time-series drivers into a single, predictive specification. Overall, the findings presented in earlier sections are robust: the carbon beta is anchored by Log(CI) (0.041^{***}), amplifies with controversies (0.180^{**}) and climate news shocks (0.603^{***}), and is compressed by ESG fund flows (-0.167^{***}).

Importantly, corporate commitments, specifically the interactions CF×Has Emission Target (-0.042^{*}) and CF × Use Renewable Energy (-0.048^{*}), gain statistical significance in this final dynamic framework. This reinforces the finding (non-significant in Table 4) that these proactive strategies are associated with reduced perceived risk, especially when integrated alongside real-time market sentiment and investor flows.

This decomposition serves as the core tool for our subsequent asset pricing tests. While earlier models included interactions between the climate factor and sector/country indicators to isolate heterogeneity, these structural controls are removed from the final model. By defining the time-varying beta ($\beta_{i,t}^{\text{Climate}}$) as a clean function of the remaining observable characteristics, we ensure that the measure used for the carbon premium estimation is an economically interpretable predictor of transition risk exposure. The increase in explanatory power (R^2 and Adjusted R^2) from Column (1) to Column (4) confirms the additive value of sophisticated models, validating the approach of moving beyond a simple emissions proxy.

Figure 2 compares the distributions of our key carbon beta measures. Relative to the simpler backward-looking (Column 2) and forward-looking (Column 3) specifications, the fully dynamic beta (Column 4) exhibits significantly fatter tails and greater dispersion. This heterogeneity is a key feature of our model: it shows that once time-varying characteristics, sentiment, and capital allocation effects are incorporated, the model achieves a more precise and varied identification of firm-level risk exposures. This contrasts with simple historical metrics, which flatten the distribution. The forward-looking beta further confirms this by showing wider dispersion than the backward-looking one, reflecting a more pronounced risk discrimination by investors than that inferred solely from basic emissions.

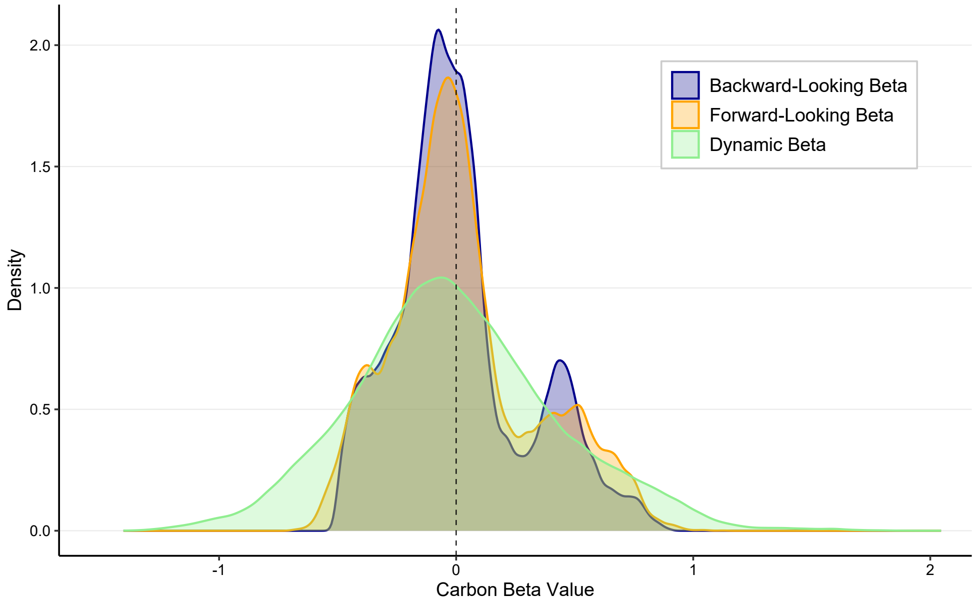
Figure 3 displays the evolution of the median and percentile bands of the dynamic carbon beta over time. While, the median exposure remains close to zero, the interquartile and 1st–99th percentile ranges demonstrate clear time variation, especially expanding after 2020. This widening dispersion coincides with the post-pandemic acceleration of ESG investment, intensified policy debates (EU Green Deal, U.S. IRA), and heightened climate news coverage. These dynamics thus align with the view that stock reaction to climate shocks is highly volatile and can quickly spike during periods of heightened market and regulatory uncertainty.

Table 7: Drivers of the Dynamic Carbon Beta (Full Fixed Effects)

	Dependent variable:			
	Stock Residuals			
	Backward-Looking		Forward-Looking	Dynamic Beta
	(1)	(2)	(3)	(4)
Climate Factor (CF)	0.027	−0.453***	−0.902***	−0.902***
	(0.076)	(0.094)	(0.191)	(0.172)
CF x Log(CI)		0.130***	0.045***	0.041***
		(0.008)	(0.013)	(0.013)
CF x Sectoral CI			0.134***	0.142***
			(0.020)	(0.019)
CF x Has Emission Target			−0.025	−0.042*
			(0.024)	(0.023)
CF x Use Renewable Energy			−0.050*	−0.048*
			(0.027)	(0.027)
CF x Has Environmental Team			0.045*	0.045*
			(0.025)	(0.024)
CF x Env. Controversies			0.179***	0.180**
			(0.067)	(0.071)
CF x Past CI Trend			0.045**	0.046**
			(0.020)	(0.020)
CF x Carbon Pricing			−0.0001	0.0004
			(0.002)	(0.002)
CF x Investment Ratio			1.445***	1.334**
			(0.510)	(0.518)
CF x Log(MV)			0.025*	0.026**
			(0.013)	(0.013)
CF x ESG Flow				−0.167***
				(0.052)
CF x Climate News Shock				0.603***
				(0.204)
CF x Carbon Pricing x Log(CI)			0.001*	0.001*
			(0.0004)	(0.0004)
FE: Firm + Time	Yes	Yes	Yes	Yes
Controls: CF x Sector/Country	No	No	No	No
Observations	530,048	295,280	234,888	232,143
R^2	0.025	0.038	0.042	0.044
Adjusted R^2	0.019	0.027	0.030	0.032

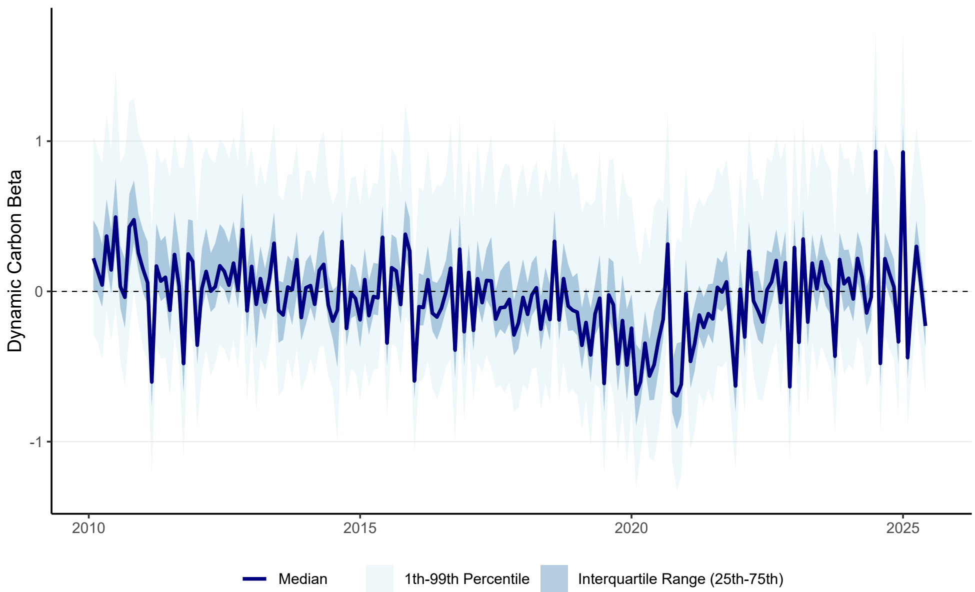
Notes: This table reports the progressive decomposition of the carbon beta ($\beta_{i,t}^{\text{Climate}}$) across four sequential models, with the final specification (Column 4) serving as the robust predictive measure. Stock residuals are regressed on a progression of models from the Backward-Looking model (Columns 1–2) to the Forward-Looking model (Column 3) and finally to the Dynamic Beta (Column 4) adding layers of economic information. The final model integrates the carbon intensity, key cross-sectional characteristics (Commitments, Controversies, Size, Investment), and real-time dynamic indicators (ESG Flows and Climate News Shock). All models include Firm and Time fixed effects. The sample includes monthly observations for all firms in the dataset over 2010–2025. Robust standard errors are clustered at both the firm and time levels. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Figure 2: Carbon Beta Density



Note: The figure compares the distributions of the backward-looking, forward-looking, and fully dynamic carbon betas. The dynamic specification exhibits markedly greater dispersion and fatter tails, indicating stronger cross-sectional differentiation in climate-risk exposure once time-varying characteristics, investor attention, and capital flows are incorporated. The forward-looking beta also displays wider dispersion than the backward-looking measure, suggesting that markets discriminate climate risk more finely than implied by emissions-based exposures alone.

Figure 3: Carbon Beta Dynamics



Note: This figure shows the time-series evolution of the average dynamic carbon beta estimated from the DCC-GARCH model. The beta captures the conditional exposure of firm-level residual returns to the climate factor and is averaged across firms at each point in time. Shaded areas indicate periods of heightened market stress, highlighting the time-varying nature of transition-risk exposure, highlighted by the interquartile range.

3.6 New Evidence on the Carbon Premium

Having established the determinants and dynamics of climate risk exposure, we now examine whether this exposure is priced in the cross-section of stock returns. The existence of a "carbon premium", where high-emitting firms offer higher returns, remains a central question in the literature, though its persistence and timing are debated.

Table 8 reports panel regressions of monthly stock returns on alternative measures of climate risk. We observe a consistent failure by static metrics to capture a significant premium. Based on carbon emissions (log(CI), Columns 1–2), the coefficients are statistically insignificant over the full sample and in the post-Paris period. This confirms that raw emission intensities alone are insufficient to explain variation in returns once sectoral and temporal effects are accounted for. Replacing static emissions with the backward-looking betas obtained from Table 4 (Column 2) yields a similarly insignificant premium in both the unconditional and post-Paris specifications. This evidence suggests that isolating the priced dimension of transition risk requires a measure that incorporates additional firm-specific characteristics and market dynamics.

In contrast to static and backward-looking measures, a significant premium emerges when using forward-looking betas based on firm and country climate characteristics. The interaction term $CB^{Forward}\times$Post-Paris is positive and marginally significant (0.007^{*}). This indicates that simply grounding the beta in observable firm features (like commitments and governance) captures some of the priced risk after the Paris Agreement. When we incorporate the full dynamic beta, including real-time sentiment and flow dynamics ($CB^{Dynamic}$), the result is strengthened. The interaction $CB^{Dynamic}\times$Post-Paris is positive and statistically significant (0.008^{**}). The dynamic measure provides a clearer identification of the premium than any simpler proxy.

Overall, the emergence of a post-Paris carbon premium validates the asset-pricing relevance of the dynamic, characteristic-driven carbon beta: transition risk is priced when measured through a forward-looking exposure that integrates firm-specific signals (e.g., com-

Table 8: Carbon Premium Analysis: Static vs. Dynamic Betas

	Dependent variable: Monthly Stock Return (log)							
	Log(CI)		Backward-Looking Beta		Forward-Looking Beta		Dynamic Beta	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(CI)	0.0002 (0.0003)	−0.0004 (0.0005)						
Log(CI) x Post-Paris (PP)		0.001 (0.001)						
Carbon Beta (Baseline)			0.006 (0.005)	0.001 (0.006)				
CB (Baseline) x PP				0.006 (0.004)				
CB (Forward)					0.001 (0.004)	−0.005 (0.005)		
CB (Forward) x PP						0.007* (0.004)		
CB (Dynamic)							0.006 (0.006)	−0.001 (0.006)
CB (Dynamic) x PP								0.008** (0.004)
Log(Market Value)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.0004 (0.001)	0.0004 (0.001)	0.0002 (0.001)	0.0002 (0.001)
Book-to-Market	0.003** (0.001)	0.003** (0.001)	0.003** (0.001)	0.003** (0.001)	0.003** (0.001)	0.003** (0.001)	0.003** (0.001)	0.003** (0.001)
Leverage	−0.004* (0.002)	−0.004* (0.002)	−0.004* (0.002)	−0.004* (0.002)	−0.004* (0.002)	−0.004** (0.002)	−0.005** (0.002)	−0.005** (0.002)
Momentum	0.005 (0.004)	0.005 (0.004)	0.005 (0.004)	0.005 (0.004)	0.005 (0.005)	0.005 (0.005)	0.005 (0.005)	0.005 (0.005)
Investment Ratio	−0.039*** (0.012)	−0.038*** (0.012)	−0.040*** (0.012)	−0.039*** (0.012)	−0.039*** (0.015)	−0.037** (0.015)	−0.050*** (0.016)	−0.049*** (0.016)
Log(PPE)	0.0003 (0.0002)	0.0003 (0.0002)	0.0002 (0.0002)	0.0002 (0.0002)	0.0002 (0.0002)	0.0002 (0.0002)	0.0001 (0.0002)	0.0001 (0.0002)
Return on Equity	0.0001*** (0.00002)	0.0001*** (0.00002)	0.0001*** (0.00002)	0.0001*** (0.00002)	0.0001*** (0.00002)	0.0001*** (0.00002)	0.0001*** (0.00002)	0.0001*** (0.00002)
Idiosyncratic Vol.	−0.029 (0.025)	−0.030 (0.025)	−0.029 (0.025)	−0.030 (0.025)	−0.031 (0.026)	−0.032 (0.026)	−0.036 (0.026)	−0.037 (0.026)
FE: Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: Sector	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	294,119	294,119	294,119	294,119	234,321	234,321	231,579	231,579
R^2	0.324	0.324	0.324	0.324	0.318	0.318	0.321	0.321
Adjusted R^2	0.323	0.323	0.323	0.323	0.317	0.317	0.320	0.320

Notes: This table reports panel regressions testing for the existence and timing of a carbon premium in monthly logarithmic stock returns. We compare the pricing ability of four primary climate risk measures: Log(Carbon Intensity) (Columns 1–2); a Backward-Looking Beta (Columns 3–4), estimated from Table 7 coefficients; a Forward-Looking Beta (Columns 5–6), derived from firm and country characteristics (Table 7); and our fully Dynamic Beta (Columns 7–8), based on all time-varying market and corporate signals (Table 7). All regressions control for a comprehensive set of conventional financial characteristics (e.g., Size, B/M, Momentum, Leverage), along with Time and Sector fixed effects. The key test is the conditional exposure, using the Post-Paris indicator (PP) to capture a potential regime shift in pricing. The sample includes monthly observations for all firms in the dataset over 2010–2025. Robust standard errors, clustered at the firm and time level, are in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

mitments) and market sentiment (e.g., news and flows). Static emissions fail to capture this priced dimension.

4 Conclusion

This paper addresses a central challenge in climate finance: how to accurately measure firms' exposure to transition risk. We argue that existing approaches, which rely on either static emissions (backward-looking and incomplete) or time-series carbon betas (statistically fragile and opaque), are flawed. We bridge this gap by developing a dynamic, characteristics-driven model to construct a robust and economically interpretable measure of the "carbon beta".

Our findings reveal three essential components of climate risk pricing. The carbon beta is a multidimensional metric, anchored by Scope 1 emissions (the dominant driver under managerial control) and amplified by public controversies. We show that investors are sophisticated, incorporating forward-looking factors and distinguishing credible corporate signals from generic commitments. Importantly, the beta is largely orthogonal to traditional financial vulnerabilities (e.g., leverage and liquidity), confirming that climate risk is a distinct dimension.

Moreover, the beta is inherently forward-looking, demonstrating market foresight by predicting and rewarding a firm's realized decarbonization over the subsequent two years. Furthermore, it is highly sensitive to real-time shocks: climate news temporarily raises exposure, while ESG fund inflows compress the risk exposure through demand effects.

Our sophisticated measure helps solving a central empirical puzzle. While static emissions data fail to reveal any premium, the characteristics-driven beta detects a positive and statistically significant carbon premium emerging only after the Paris Agreement. This materialization confirms that the reward for bearing transition risk is conditional on the regulatory environment and only visible once the exposure is measured via a comprehensive metric that integrates risk, governance, and expectation.

These results carry several direct implications. For investors, the characteristics-driven beta provides a superior, implementable measure for hedging and portfolio tilting. For policymakers, the evidence that markets react to forward-looking climate characteristics and controversies suggests that disclosure and information channels are central to how climate shocks are transmitted to asset prices. Future research could extend this framework to other asset classes or incorporate even richer, text-based measures of corporate climate strategy and sentiment.

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Appendix

4.1 Additional Tables

Table A.1: The Functional Form of the Carbon Beta

	Dependent variable: Stock Residuals							
	Linear CI		Log CI		Squared CI		Full Model	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Climate Factor (CF)	−0.036	−0.309	−0.453***	−0.452	0.008	−0.307	−0.441***	−0.450
	(0.088)	(0.503)	(0.094)	(0.523)	(0.088)	(0.503)	(0.100)	(0.523)
CF x CI/10^2	0.030***	0.011***					0.005	−0.003
	(0.003)	(0.003)					(0.010)	(0.010)
CF x Log(CI)			0.130***	0.060***			0.125***	0.060***
			(0.008)	(0.011)			(0.012)	(0.013)
CF x $CI^2/10^4$					0.001***	0.0003***	−0.0001	0.0001
					(0.0001)	(0.0001)	(0.0003)	(0.0002)
FE: Firm + Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls: CF x Sector/Country	No	Yes	No	Yes	No	Yes	No	Yes
Observations	295,280	295,280	295,280	295,280	295,280	295,280	295,280	295,280
R^2	0.036	0.040	0.038	0.040	0.035	0.040	0.038	0.040
Adjusted R^2	0.025	0.029	0.027	0.029	0.024	0.029	0.027	0.029

Notes: The table presents regressions exploring alternative functional forms of carbon intensity in determining the carbon beta. Carbon intensities are lagged by 24 months. All models include Firm and Time fixed effects, with even columns adding CF × Sector/Country controls. The sample covers monthly observations for 2010–2025. Standard errors are clustered at the firm and time levels.

Table A.2: Predicting Carbon Intensity Levels and Trends with Climate Characteristics

	Dependent variable:			
	Log(CI)	Past Trend	Current Trend	Future Trend
	(1)	(2)	(3)	(4)
Log(Carbon Intensity)		0.057***	−0.098***	−0.059***
		(0.005)	(0.006)	(0.005)
Emission Target	0.162***	−0.051***	−0.029***	−0.013
	(0.037)	(0.012)	(0.010)	(0.010)
Emission Policy	0.083*	−0.019	0.007	0.005
	(0.046)	(0.019)	(0.014)	(0.014)
Renewable Energy	0.275***	−0.045***	−0.004	−0.062**
	(0.067)	(0.015)	(0.020)	(0.031)
Internal C-Price	0.105***	−0.024**	−0.003	−0.007
	(0.038)	(0.010)	(0.009)	(0.009)
Env. Team	0.092**	0.024*	0.012	−0.014
	(0.038)	(0.013)	(0.010)	(0.011)
Climate Awareness	0.197**	0.004	0.012	0.008
	(0.076)	(0.019)	(0.020)	(0.025)
FE: Sector/Country/Time	Yes	Yes	Yes	Yes
Financial Controls	Yes	Yes	Yes	Yes
Observations	292,247	234,272	225,443	164,513
R^2	0.629	0.070	0.105	0.064
Adjusted R^2	0.629	0.069	0.104	0.063

Notes: This table tests the correlation between observable corporate climate signals and firm-level carbon intensity outcomes. The dependent variables are the log of carbon intensity (Column 1), which proxies for a firm's baseline emission profile, and the carbon intensity trend (Columns 2–4), which measures realized decarbonization rates over past, current, and future 24-month periods. The independent variables of interest are 24-months lagged binary indicators (e.g., emission target, renewable energy) for climate commitments and internal governance structures. All specifications include Sector, Country, and Time fixed effects, along with standard financial controls (see Table 8). The sample includes monthly observations for all firms in the dataset over 2010–2025. Robust standard errors, clustered at the firm and time level, are in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table A.3: Carbon Beta and Core Financial Vulnerabilities

	Dependent variable: Stock Residuals							
	Size & Value		Profit & Liquid.		Leverage & Risk		Full Model	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Climate Factor (CF)	-0.602^{***}	-0.518	-0.421^{***}	-0.485	-0.508^{***}	-0.528	-0.958^{***}	-0.798
	(0.171)	(0.531)	(0.094)	(0.533)	(0.110)	(0.540)	(0.207)	(0.579)
CF x Log(CI)	0.131^{***}	0.059^{***}	0.125^{***}	0.063^{***}	0.131^{***}	0.060^{***}	0.125^{***}	0.061^{***}
	(0.008)	(0.011)	(0.008)	(0.011)	(0.008)	(0.011)	(0.008)	(0.012)
CF x Log(Market Value)	0.017	0.012					0.048^{***}	0.032^{**}
	(0.013)	(0.012)					(0.014)	(0.014)
CF x Book-to-Market	-0.011	0.002					0.039	0.019
	(0.046)	(0.048)					(0.047)	(0.051)
CF x Return on Assets			-0.001	-0.001			-0.001	-0.001
			(0.001)	(0.001)			(0.001)	(0.001)
CF x Cash Ratio			0.224	0.260^{*}			0.237	0.289^{*}
			(0.172)	(0.142)			(0.169)	(0.151)
CF x Leverage					-0.044	-0.027	-0.046	0.001
					(0.103)	(0.089)	(0.109)	(0.103)
CF x Idio. Volatility					0.921	0.695	1.345	0.938
					(0.790)	(0.749)	(0.860)	(0.828)
FE: Firm + Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls: CF x Sector/Country	No	Yes	No	Yes	No	Yes	No	Yes
Observations	294,954	294,954	279,700	279,700	294,882	294,882	279,696	279,696
R^2	0.038	0.040	0.038	0.040	0.038	0.040	0.039	0.040
Adjusted R^2	0.027	0.029	0.027	0.029	0.027	0.029	0.028	0.030

Notes: The table reports panel regressions estimating whether the carbon beta varies with core financial characteristics. Financial variables (except market value) are lagged by 12 months, and market value is lagged by 1 month. The sample includes monthly observations for all firms in the dataset over 2010–2025. Robust standard errors are clustered at both the firm and time levels. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A.4: Carbon Beta: Investment, Attention, and Other Characteristics

	Dependent variable: Stock Residuals					
	Investment & Assets		Attention & Volume		Full Model	
	(1)	(2)	(3)	(4)	(5)	(6)
Climate Factor (CF)	-0.618^{***}	-0.537	-0.581^{***}	-0.493	-0.613^{***}	-0.480
	(0.148)	(0.541)	(0.182)	(0.562)	(0.204)	(0.563)
CF x Log(CI)	0.110^{***}	0.054^{***}	0.133^{***}	0.056^{***}	0.114^{***}	0.053^{***}
	(0.008)	(0.012)	(0.009)	(0.011)	(0.009)	(0.011)
CF x Investment Ratio	1.579^{***}	0.394			1.863^{***}	0.702
	(0.536)	(0.502)			(0.584)	(0.563)
CF x Log(PPE)	0.013	0.007			0.003	-0.003
	(0.008)	(0.007)			(0.008)	(0.008)
CF x Log(Turnover)			0.003	0.004	0.002	0.006
			(0.011)	(0.014)	(0.010)	(0.015)
CF x Analyst Coverage			0.005^{**}	0.004	0.005^{**}	0.004
			(0.002)	(0.003)	(0.002)	(0.003)
FE: Firm + Time	Yes	Yes	Yes	Yes	Yes	Yes
Controls: CF x Sector/Country	No	Yes	No	Yes	No	Yes
Observations	294,615	294,615	274,174	274,174	273,721	273,721
R^2	0.038	0.040	0.039	0.041	0.039	0.041
Adjusted R^2	0.027	0.029	0.028	0.030	0.028	0.030

Notes: The table investigates how financial policies, real activity, and attention proxies interact with the climate factor. All financial variables are lagged by 12 months. The sample includes monthly firm–level observations from 2010–2025. Standard errors are clustered by firm and time. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table A.5: Time-Series Evolution of the Carbon Beta

	Dependent variable: Stock Residuals							
	Trend				Paris Agreement			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Climate Factor (CF)	-0.471^{***}	-0.414	-0.537^{***}	-0.444	-0.410^{***}	-0.366	-0.402^{***}	-0.331
	(0.098)	(0.507)	(0.120)	(0.518)	(0.067)	(0.493)	(0.073)	(0.496)
CF x Log(CI)	0.131^{***}	0.059^{***}	0.147^{***}	0.065^{***}	0.130^{***}	0.058^{***}	0.128^{***}	0.050^{***}
	(0.008)	(0.010)	(0.016)	(0.018)	(0.008)	(0.010)	(0.012)	(0.015)
CF x Time Trend	0.002	-0.004	0.009	-0.001				
	(0.012)	(0.012)	(0.013)	(0.013)				
CF x Time Trend x Log(CI)			-0.002	-0.001				
			(0.002)	(0.002)				
CF x Post-Paris					-0.058	-0.105	-0.068	-0.145
					(0.134)	(0.133)	(0.141)	(0.141)
CF x Post-Paris x Log(CI)							0.003	0.010
							(0.014)	(0.015)
FE: Firm + Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls: CF x Sector/Country	No	Yes	No	Yes	No	Yes	No	Yes
Observations	295,280	295,280	295,280	295,280	295,280	295,280	295,280	295,280
R^2	0.038	0.040	0.038	0.040	0.038	0.040	0.038	0.040
Adjusted R^2	0.027	0.029	0.027	0.029	0.027	0.029	0.027	0.029

Notes: The table reports regressions testing whether the carbon beta evolves deterministically over time or around the Paris Agreement. The sample includes monthly observations for all firms in the dataset over 2010–2025. All models include firm and time fixed effects, with standard errors clustered by firm and month.

Table A.6: The Impact of Macroeconomic Risk Factors on the Carbon Beta

	Dependent variable: Stock Residuals							
	Yield Shocks				Volatility			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Climate Factor (CF)	−0.457***	−0.457	−0.455***	−0.454	−0.452***	−0.465	−0.454***	−0.467
	(0.092)	(0.522)	(0.093)	(0.523)	(0.087)	(0.517)	(0.088)	(0.517)
CF x Log(CI)	0.130***	0.060***	0.130***	0.059***	0.131***	0.059***	0.131***	0.060***
	(0.008)	(0.011)	(0.008)	(0.011)	(0.008)	(0.011)	(0.008)	(0.010)
CF x Yield Shock	0.266	0.253	0.182	0.164				
	(0.292)	(0.291)	(0.295)	(0.296)				
CF x Yield Shock x Log(CI)			0.022	0.023				
			(0.030)	(0.032)				
CF x Volatility Shock					−0.021	−0.023	−0.017	−0.020
					(0.021)	(0.021)	(0.023)	(0.022)
CF x Volatility Shock x Log(CI)							−0.001	−0.001
							(0.002)	(0.002)
FE: Firm + Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls: CF x Sector/Country	No	Yes	No	Yes	No	Yes	No	Yes
Observations	295,280	295,280	295,280	295,280	295,280	295,280	295,280	295,280
R^2	0.038	0.040	0.038	0.040	0.038	0.040	0.038	0.040
Adjusted R^2	0.027	0.029	0.027	0.029	0.027	0.030	0.027	0.030

Notes: The table reports the interaction between the climate factor and macro-financial shocks, including yield curve movements and volatility shocks. The sample spans 2010–2025 at monthly frequency. Each observation corresponds to a firm-month with Firm and Time fixed effects. The sample includes monthly observations for all firms in the dataset over 2010–2025. Robust standard errors, clustered at the firm and time level, are in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table A.7: The Impact of Energy Shocks on the Carbon Beta

	Dependent variable: Stock Residuals							
	Copper shocks				Oil shocks			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Climate Factor (CF)	−0.451***	−0.451	−0.449***	−0.452	−0.438***	−0.439	−0.436***	−0.438
	(0.089)	(0.518)	(0.089)	(0.520)	(0.085)	(0.515)	(0.084)	(0.515)
CF x Log(CI)	0.130***	0.059***	0.130***	0.059***	0.130***	0.059***	0.130***	0.059***
	(0.008)	(0.011)	(0.008)	(0.010)	(0.008)	(0.011)	(0.008)	(0.011)
CF x Copper Shock	0.944	1.087	0.115	0.280				
	(2.015)	(1.981)	(2.126)	(2.090)				
CF x Copper Shock x Log(CI)			0.213*	0.207				
			(0.125)	(0.125)				
CF x Oil Shock					1.115	1.164	0.959	1.030
					(1.302)	(1.278)	(1.346)	(1.317)
CF x Oil Shock x Log(CI)							0.041	0.036
							(0.080)	(0.089)
FE: Firm + Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls: CF x Sector/Country	No	Yes	No	Yes	No	Yes	No	Yes
Observations	295,280	295,280	295,280	295,280	295,280	295,280	295,280	295,280
R^2	0.038	0.040	0.038	0.040	0.038	0.040	0.038	0.040
Adjusted R^2	0.027	0.029	0.027	0.029	0.027	0.030	0.027	0.029

Notes: The table reports panel regressions assessing the effect of contemporaneous commodity-price shocks on the carbon beta. The sample consists of firm–month observations from January 2010 to December 2025. All models include Firm and Time fixed effects, with even columns adding CF × Sector/Country controls. Standard errors are clustered by firm and time.

4.2 Variable Definition

Table A.8: Variable Definitions: Firm-Level Characteristics

Variable	Description	Source
Key Variables		
Residual	Stock total excess return orthogonalized against FF5 factors + Momentum.	Authors
Stock Return	Monthly logarithmic stock total excess return.	Datastream
Climate Factor	Long-short portfolio based on firm carbon intensity.	Authors
Financial Characteristics		
Log(Market Value)	Log of market capitalization (USD millions).	Datastream
Book-to-Market	Ratio of book equity to market equity.	Datastream
Return on Equity	Net income divided by the book value of equity.	Datastream
Cash Ratio	Cash and equivalents divided by total assets.	Datastream
Leverage	Total debt divided by total assets.	Datastream
Idiosyncratic Vol.	SD of residuals (12-month window).	Authors
Investment Ratio	Capital expenditures divided by total assets.	Datastream
Log(PPE)	Log of net Property, Plant, and Equipment.	Datastream
Log(Turnover)	Log of share turnover rate (volume / market cap).	Datastream
Analyst Coverage	Number of analysts providing earnings estimates.	I/B/E/S
Climate Characteristics		
Log(Carbon Intensity)	Log of (Scope 1+2 emissions / Revenue).	Refinitiv ESG
CI Trend (Past/Fut.)	Percentage change in carbon intensity over various windows.	Authors
Scope 1, 2, 3 Int.	Log of (Scope X emissions / Revenue).	Refinitiv ESG
Emission Target	Dummy: 1 if firm has emission reduction targets.	Refinitiv ESG
Env. Controversies	Dummy: 1 if firm has environmental media controversies.	Refinitiv ESG
Renewable Energy	Dummy: 1 if firm uses renewable energy.	Refinitiv ESG
Emission Policy	Dummy: 1 if firm has a formal emission reduction policy.	Refinitiv ESG
Internal C-Price	Dummy: 1 if firm uses an internal carbon price.	Refinitiv ESG
Climate Awareness	Dummy: 1 if firm has a policy on climate change risks/opps.	Refinitiv ESG
Env. Team	Dummy: 1 if firm has a dedicated environmental management team.	Refinitiv ESG

Table A.9: Variable Definitions: Country and Time-Varying Factors

Variable	Description	Source
Country-Level Characteristics		
Carbon Price Index	Country-level index of carbon pricing stringency.	ILB
Climate Score	Germanwatch Climate Change Performance Index.	Germanwatch
ND-GAIN Vuln.	Country-level index of climate change vulnerability.	ND-GAIN
Time-Varying Factors		
Climate News Shock	Monthly AR(1) residual of the MCCC index.	Ardia et al.
ESG Flow Diff.	Monthly net flows into ESG funds minus non-ESG funds.	EPFR
Oil Return	Monthly return of Crude Oil price.	S&P GSCI
Copper Return	Monthly return of Copper price.	S&P GSCI
Yield Shock	Monthly change in 10-year government bond yield.	Datastream
Implied Volatility	VIX (US) or V2X (Europe) index level.	Datastream
Post-Paris	Dummy: 1 for months after December 2015.	Authors
Time Trend	Linear time index measured in years from sample start.	Authors

Table A.10: Descriptive Statistics for Regional Climate and Fama-French Factors

Factor	N	Mean	SD	Min	P25	Median	P75	Max
Panel A: European Factors								
CF	186	-0.001	0.016	-0.040	-0.013	-0.002	0.009	0.065
MKT	186	0.006	0.050	-0.154	-0.026	0.007	0.042	0.166
SMB	186	0.000	0.017	-0.051	-0.011	0.000	0.012	0.047
HML	186	0.000	0.028	-0.113	-0.018	-0.002	0.017	0.121
RMW	186	0.002	0.016	-0.054	-0.008	0.003	0.012	0.038
CMA	186	0.000	0.015	-0.044	-0.009	0.000	0.009	0.052
WML	186	0.009	0.031	-0.184	-0.006	0.009	0.025	0.089
Panel B: U.S. Factors								
CF	186	-0.002	0.023	-0.062	-0.017	-0.003	0.014	0.067
MKT	186	0.011	0.044	-0.134	-0.015	0.015	0.035	0.136
SMB	186	-0.001	0.027	-0.082	-0.019	-0.001	0.015	0.083
HML	186	-0.001	0.033	-0.138	-0.019	-0.004	0.015	0.129
RMW	186	0.003	0.020	-0.048	-0.012	0.003	0.014	0.072
CMA	186	0.000	0.021	-0.071	-0.015	-0.001	0.013	0.077
WML	186	0.003	0.035	-0.162	-0.017	0.004	0.025	0.100

Notes: This table presents descriptive statistics for monthly factor returns. The sample includes monthly observations for all firms in the dataset over 2010–2025. CF represents the climate factor estimated in Equation 1.

Table A.11: Correlation Matrix: European Climate Factor vs. Fama-French Factors

Factor	CF	MKT	SMB	HML	RMW	CMA	WML
CF	1.00	−0.05	0.01	0.06	0.16	0.18	0.00
MKT	−0.05	1.00	0.08	0.28	−0.23	−0.12	−0.42
SMB	0.01	0.08	1.00	−0.01	−0.07	−0.16	−0.02
HML	0.06	0.28	−0.01	1.00	−0.79	0.69	−0.48
RMW	0.16	−0.23	−0.07	−0.79	1.00	−0.55	0.38
CMA	0.18	−0.12	−0.16	0.69	−0.55	1.00	−0.14
WML	0.00	−0.42	−0.02	−0.48	0.38	−0.14	1.00

Notes: This table presents the correlation matrix between the European climate factor (CF), estimated in Equation 1, and the five European Fama-French and momentum factors based on monthly returns from 2010 to 2025.

Table A.12: Correlation Matrix: U.S. Climate Factor vs. Fama-French Factors

Factor	CF	MKT	SMB	HML	RMW	CMA	WML
CF	1.00	−0.20	−0.02	0.29	0.26	0.37	−0.02
MKT	−0.20	1.00	0.36	0.06	−0.12	−0.13	−0.32
SMB	−0.02	0.36	1.00	0.30	−0.39	0.04	−0.32
HML	0.29	0.06	0.30	1.00	0.07	0.62	−0.28
RMW	0.26	−0.12	−0.39	0.07	1.00	0.13	0.00
CMA	0.37	−0.13	0.04	0.62	0.13	1.00	0.03
WML	−0.02	−0.32	−0.32	−0.28	0.00	0.03	1.00

Notes: This table presents the correlation matrix between the US climate factor (CF), estimated in Equation 1, and the five European Fama-French and momentum factors based on monthly returns from 2010 to 2025.

4.3 Methodological Details on the DCC-GARCH Estimation

Standard implementations of the CAPM and multi-factor models often assume time-invariant factor loadings. A large literature, however, shows that risk exposures vary with market conditions and information sets, implying that betas should be treated as conditional rather than constant (Bollerslev et al., 1988; Jagannathan and Wang, 1996; Bauer et al., 2010; Engle, 2016; Bali et al., 2017). Time variation arises because volatilities and correlations are persistent and investors' marginal utility is state-dependent (Fama and French, 1988).

To obtain conditional betas for the orthogonalization step in the main text, we estimate Dynamic Conditional Betas using the DCC-GARCH model of Engle (2002). Let $r_{i,t}$ denote the excess return on firm i and let f_t denote the $k \times 1$ vector of standard Fama–French factor returns (Market, SMB, HML, RMW, CMA, and Momentum). Stack these into the $(k+1) \times 1$ vector

$$z_t \equiv \begin{pmatrix} r_{i,t} \\ f_t \end{pmatrix}, \qquad z_t \mid \Omega_{t-1} \sim \mathcal{N}(\mu_t, H_t),$$

where Ω_{t-1} denotes the information available at $t-1$ and H_t is the conditional covariance matrix. We partition H_t as

$$H_t = \begin{pmatrix} H_{rr,t} & H_{rf,t} \\ H_{fr,t} & H_{ff,t} \end{pmatrix},$$

where $H_{rf,t}$ is a $1 \times k$ conditional covariance vector and $H_{ff,t}$ is the $k \times k$ conditional covariance matrix of the factors.

The conditional beta of firm i with respect to the factor vector is given by the conditional projection coefficient:

$$\beta_{i,t} = H_{rf,t} H_{ff,t}^{-1}. \tag{7}$$

In the univariate case (single factor), this reduces to the familiar ratio of conditional covariance to conditional variance.

To estimate H_t, we use the DCC decomposition:

$$H_t = D_t R_t D_t, \tag{8}$$

where $D_t = \text{diag}(\sigma_{1,t}, \ldots, \sigma_{k+1,t})$ collects conditional standard deviations from univariate GARCH(1,1) models, and R_t is the dynamic correlation matrix. Letting $\tilde{u}_t = D_t^{-1}(z_t - \mu_t)$ denote standardized residuals, the correlation dynamics evolve as

$$Q_t = (1 - \alpha - \beta)\,\bar{Q} \;+\; \alpha\,\tilde{u}_{t-1}\tilde{u}_{t-1}^{\top} \;+\; \beta\,Q_{t-1}, \tag{9}$$

$$R_t = \text{diag}(Q_t)^{-1/2}\,Q_t\,\text{diag}(Q_t)^{-1/2}, \tag{10}$$

with $\bar{Q}$ the unconditional correlation matrix of $\tilde{u}_t$, and parameters (α, β) satisfying $\alpha, \beta \geq 0$ and $\alpha + \beta < 1$ for stationarity. Estimation proceeds by quasi-maximum likelihood in two steps: (i) univariate GARCH margins, (ii) correlation dynamics.

Once $\beta_{i,t}$ is obtained via (7), we compute the orthogonalized return used in the main analysis as:

$$\varepsilon_{i,t} = r_{i,t} - \left(\alpha_i + \beta_{i,t}' f_t\right), \tag{11}$$

where α_i is a firm fixed effect. The residual $\varepsilon_{i,t}$ represents the component of returns unexplained by standard systematic factors and is the dependent variable in the carbon beta decomposition.

Relative to rolling-window OLS, the DCC approach avoids arbitrary window-length choices and captures volatility clustering and correlation persistence in a coherent multivariate structure. Relative to state-space models, it requires fewer parametric assumptions while still delivering high-frequency time variation in the conditional betas.