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

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Abstract

The existence of a carbon premium remains debated, with conflicting evidence attributed to incomplete, noisy, or backward-looking data. We address this measurement challenge by introducing a dynamic, characteristics-driven carbon beta that conditions transition risk exposure on observable firm characteristics and market sentiment. Decomposing this measure for U.S. and European equities, we show that transition risk is anchored by historical Scope 1 emissions, yet is significantly reshaped by public controversies, corporate commitments, climate-related news, and ESG fund flows. We also document market foresight, as the beta today acts as a leading indicator of a firm's realized decarbonization over the next two years. Finally, we detect a significant and economically large carbon premium (4.8% annualized) emerging after the Paris Agreement that is undetectable when using raw emissions data. This suggests that investors price a sophisticated, time-varying information set rather than simple carbon footprints.

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 addressing a fundamental question: what information set do investors actually use to evaluate climate transition risk? Specifically, we investigate (i) which firm-level characteristics drive exposure to systematic transition risk, (ii) whether this exposure reflects backward-looking emissions or forward-looking signals about transition paths, and (iii) when such exposure is priced in the cross-section of stock returns.

To answer these questions, we develop a framework that disciplines and decomposes the carbon beta, transforming it from a noisy statistical estimate into an economically interpretable signal. Instead of treating the carbon beta as a reduced-form coefficient estimated solely from returns, we model it as a dynamic function of observable characteristics—including emissions, climate commitments, financial structure, and sentiment proxies such as climate news and ESG flows. This approach yields two key contributions. First, it provides the first characteristic-driven decomposition of carbon betas, allowing us to identify the economic channels through which transition risk enters asset prices. Second, it reconciles the emissions-based and beta-based literatures by retaining the forward-looking nature of market measures while filtering out statistical noise through firm fundamentals. As a result, our measure is both statistically robust and economically meaningful, enabling a sharper test of the existence and timing of a carbon premium.

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, climate risk exposure is distinct from traditional financial risks like leverage and profitability, suggesting 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 and statistical carbon betas, but clearly priced once transition risk reflects the comprehensive set of climate-related information available to investors.

Overall, our findings move the carbon premium 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 reassess the existence of a carbon premium.

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 risk exposure is quantified. Recognizing that historical emissions are a backward-looking proxy, researchers aim to develop forward-looking measures. As Giglio et al. (2021) mention in their review of the literature, 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 employ aggregate news-based or search volume indices to capture climate-related attention (Ardia et al., 2023; Choi et al., 2020; Engle et al., 2020). They 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) and 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.

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-

[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.

Brown (BB). The climate factor is then constructed monthly as:

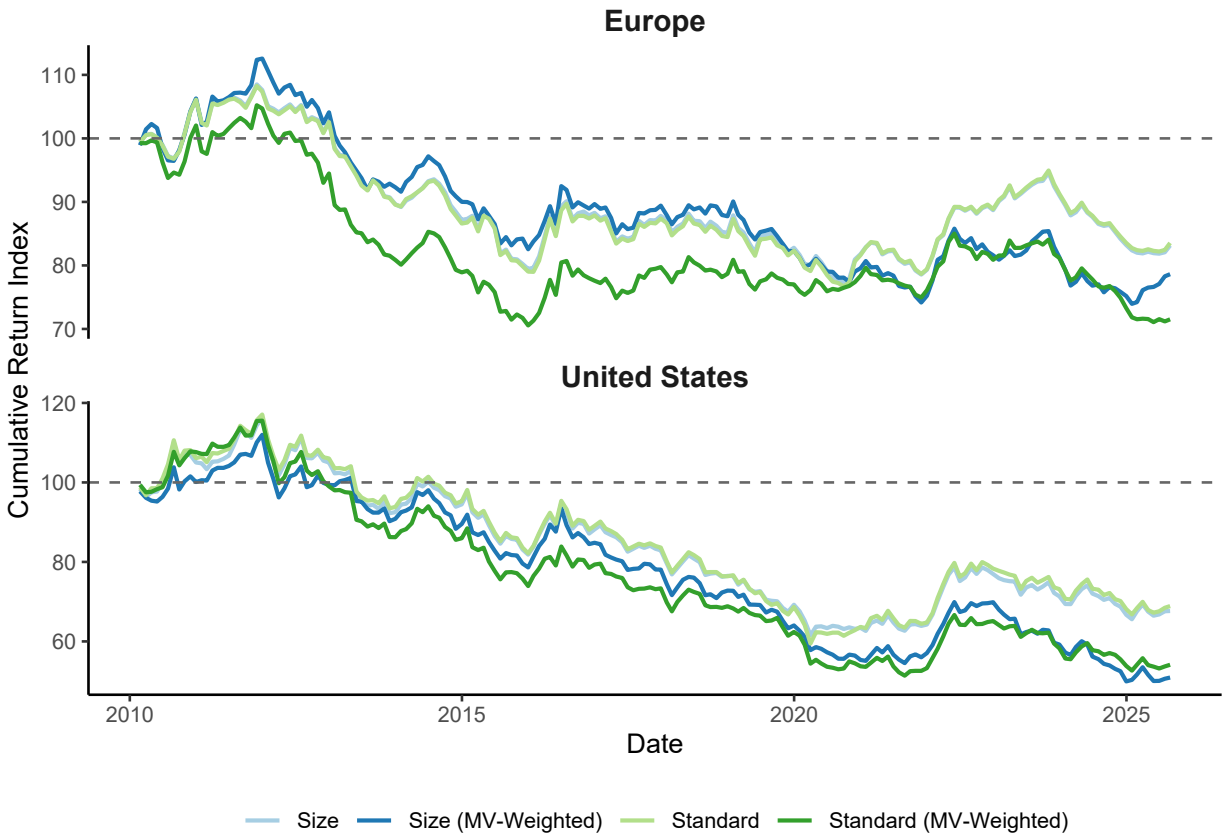
$$F_t^{\text{Climate}} = \frac{1}{2}(SB_t + BB_t) - \frac{1}{2}(SG_t + BG_t) \tag{1}$$

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 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 with 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 a 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. Lastly, our climate factor is relatively uncorrelated with the other factors used in the analysis, suggesting it captures sources of systematic risk otherwise not captured by the other factors[2].

[2]The Tables A.3, A.4 in the Appendix, not included here for brevity, report descriptive statistics and correlations for the factors across regions.

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)[3]. 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-

[3]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[4].

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, $\varepsilon_{i,t}$ (see 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:

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

[4]We provide a more detailed discussion of the DCC-GARCH framework employed in this paper in Appendix 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, the beta becomes an economically interpretable measure, directly linked to specific firm and market drivers. Our approach is distinct from purely statistical-based decomposition models, such as the Instrumented Principal Component Analysis (IPCA) framework (Kelly et al., 2019). While IPCA estimates latent factors and exposures simultaneously to maximize the explained variance of returns, its factors lack direct economic identification. By contrast, our framework conditions on an observable, ex-ante defined climate factor (F_t^{Climate}, see Equation 1). This ensures that the exposure we decompose is strictly a measure of sensitivity to climate transition risk, allowing us to isolate genuine climate exposure from other systematic risk factors.

2.4 Data

Our empirical analysis is based on firm-level and macro-financial datasets. The primary firm-level data are sourced from Refinitiv Datastream. We collect monthly total returns (i.e., including dividends) and accounting variables such as market capitalization, book value, sales, and total assets. The Refinitiv 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.1.

Our sample spans January 2010 through August 2025 and covers firms listed and domiciled in either the United States or Europe. We focus 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. First, we screen company names to remove non-equity entities misclassified in Datastream. Then, we 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[5], and including both continuing and delisted firms as of 2025. The sample is diversified across all major sectors.[6] 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.

We complement firm-level data with a comprehensive set of macroeconomic and financial variables (see Table A.2). 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

[5]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

[6]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.

(VIX for the U.S., V2X for Europe) also obtained from Datastream. We test stationarity of each time-series and convert 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-level heterogeneity even after controlling for the six Fama–French factors. By comparison, the underlying stock returns exhibit a standard deviation of 9%. 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. The difference between the median (27) and the mean intensity (213) is approximately tenfold, 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: carbon-intensity trends are slightly negative (–0.01 on average). 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 shows little variation between countries, with most developed economies grouped around 0.30. Finally, the time-series variables exhibit

patterns that are consistent with episodic climate attention. The climate factor has a 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 analyzed 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 Tables A.1 and A.2.

3 Empirical Results

This section estimates the characteristics-driven carbon beta, examining its economic drivers, dynamic behavior, and asset pricing implications. We begin by dissecting the cross-section of the carbon beta, testing whether it captures historical emissions, regulatory environments, and forward-looking corporate commitments. We then explore the time series dimension of the carbon beta, analyzing how it responds to regional climate and macroeconomic shocks. Finally, we perform asset pricing tests to determine whether this enhanced measure of carbon risk exposure is priced in the cross-section of returns.

3.1 Links between Emissions and the Carbon Beta

We begin by assessing the empirical link between firm-level emissions and exposure to transition shocks (carbon beta). Table 2 decomposes this relationship across emission scopes. In all specifications, we use a logarithmic carbon intensity as we find that it provides the most consistent and statistically significant positive relationship with the carbon beta.[7] The interaction terms between the climate risk factor and the emission Scopes 1 and 2 are positive and highly significant in the standalone scope specifications (Columns 1–4). 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 when sector and country fixed effects are included in the model specification (see Column 8). These results indicate that part of the relationship between emissions and carbon risk exposure is driven by sectoral and geographic heterogeneity rather than firm-specific exposure (e.g., Bolton and Kacperczyk, 2021, 2023). By contrast, Scope 3 intensity shows a negative and significant coefficient in

[7] Table A.9, available in Appendix, explores different functional forms for the relationship between emission intensity and the carbon beta. We find that 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 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.

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 likely due to the substantial measurement error affecting value-chain emissions, which rely on modeled data rather than reported measures (Aswani et al., 2024). A hypothesis would be that investors primarily price emissions under managerial control and measured with higher reliability. Based on this result and 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 (see Equation 6). 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 fixed effects. 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. Indeed, 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 regulations. 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 a positive and statistically significant coefficient associated with this triple interaction. 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 also the 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 5-6 examine the effect of country-level physical risk vulnerability on the carbon beta. 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 (see Equation 6). Carbon Pricing and Climate Change Performance indices are lagged by 12 months, while the Physical Risk exposure (ND-GAIN vulnerability 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 examine whether the carbon beta incorporates forward-looking qualitative information about firms' climate commitments, strategies, and public reputation. Table 4 decomposes climate-related corporate characteristics into three thematic groups: (i) formal commitments, (ii) internal governance processes, and (iii) public-reputation signals.

Columns 1–2 show that formal commitments, including emission targets, emission policies, and renewable energy usage, do not have a statistically significant standalone impact on the carbon beta, despite a negative sign. This suggests that formal pledges alone are insufficient to convince investors of lower transition risk. Likewise, internal governance tools, such as internal carbon pricing, environmental teams, and climate awareness indicators, are statistically insignificant in the simple specification (Columns 3–4). Interestingly, when all qualitative characteristics are jointly considered (Columns 7–8), environmental teams and climate-awareness indicators become positive and significant. This pattern suggests that the market does not view these internal structures as an effective way of mitigating risk, a hypothesis we explore further below.

Conversely, Columns 5–6 show that environmental controversies lead to significant and substantial increases in carbon beta. These effects persist in the full specification (Columns 7–8), making public reputation the only qualitative signal that is consistently reflected in risk exposure. This finding indicates that investors view reputational damage as a significant predictor of transition vulnerability.

To interpret the absence of standalone pricing effects for formal commitments and internal governance variables in Table 4, Table 5 examines how these characteristics relate to firms' baseline emission profiles and realized decarbonization dynamics. Column 1 shows that all commitment and governance indicators are strongly positively associated with current carbon intensity. This indicates that such characteristics are disproportionately adopted by firms that are already highly carbon-intensive and therefore structurally more exposed to transition risk. At the same time, Columns 2–4 show that some commitment-related

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

The table reports coefficient estimates (see Equation 6) 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.

variables, particularly renewable energy adoption and emission-reduction targets, are significantly associated with lower future carbon-intensity growth. This indicates that these commitments do contain forward-looking information about firms' realized decarbonization efforts. These results imply that commitment variables carry two opposing information components: they are adopted primarily by firms with high baseline exposure (which mechanically increases the carbon beta), yet they also predict subsequent reductions in emissions (which would lower future exposure). These channels operate in opposite directions and therefore rationalize why formal commitments do not exhibit statistically significant standalone effects on the carbon beta in Table 4. By contrast, internal governance indicators show no systematic relationship with realized future decarbonization while remaining strongly correlated with current emission intensity. This implies that these governance variables primarily signal high present exposure rather than credible future abatement, explaining why they only become priced conditionally in the full joint model.

We complement our analysis of the predictive power of our measure, providing a test of the information horizon embedded in the carbon beta (Table 6). While the level of historical emissions remains 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 show positive and significant coefficients. The positive sign implies that firms increasing their emissions intensity (a positive trend) face higher betas, while those successfully decarbonizing (a negative trend) benefit from lower risk exposure. Importantly, the coefficient on the future trend is not only highly statistically significant but is also economically larger (0.15) than both the past (0.04) and current (0.09) trend coefficients. This provides evidence of market foresight: 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 acts as a leading indicator, capturing investors' expectations about a firm's ability to adapt to a

Table 5: 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 relation 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 9). 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.

low-carbon economy.

Table 6: Carbon Beta and 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 examines whether the carbon beta incorporates information from past, current, and future emissions trends (see Equation 6). 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.

Collectively, these results show that the carbon beta is not only a backward-looking emissions proxy but also a credibility-sensitive and forward-looking measure of transition exposure. Although markets do not appear to consider stated intentions in isolation, the carbon beta successfully discriminates between firms based on current and future emission trends. Moreover, investors respond strongly to tangible reputational signals that can materially impact legal and demand conditions. This finding complements Bingler et al. (2024) by providing empirical evidence that only credible initiatives are effectively accounted for in market-based transition risk assessments.

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 prof-

itability, 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.

Appendix Table A.10 examines the interaction between the climate factor and standard firm-level measures of financial vulnerability. Once we control for firm-level carbon intensity, we find that leverage, profitability, cash holdings, and idiosyncratic volatility do not significantly interact with the climate factor. This absence of pricing effects suggests that investors do not view transition risk as a by-product of financial strength, but rather as a distinct exposure linked to firms' carbon footprint.

Two financial characteristics nevertheless emerge once we expand the analysis beyond standard vulnerability measures. Appendix Table A.10 first examines a broad set of firm-level financial characteristics jointly with carbon intensity. In this setting, firm size enters with a positive and statistically significant coefficient in the fully controlled specification. Larger firms exhibit greater sensitivity to climate transition shocks, consistent with the idea that, for a given level of carbon intensity, they generate a larger absolute contribution to global emissions and therefore attract heightened regulatory, reputational, and investor scrutiny.

Appendix Table A.11 then isolates the role of investment intensity. Firms with higher investment ratios display higher carbon betas in specifications that exclude Sector/Country interactions. 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 exposure varies with shifts in investor attention and market sentiment. As in all previous specifications, our empirical framework includes time fixed effects, which absorb any variation that is common across all firms at a given point in time. Consequently, the impact of these aggregate drivers, such as climate-related news, can only be identified through their interactions with the regional climate transition factors. By leveraging the differential variation between our U.S. and European climate factors, our model design ensures that our findings are not driven by global confounding factors.

Table 7 reveals that spikes in climate-related news significantly amplify the carbon beta. This finding is consistent with the framework of Pástor et al. (2021, 2022) and the empirical evidence in Ardia et al. (2023), which show that an increase in climate change concerns results in a reduction of the net cash flows and an increase of the discount rate of brown firms. The mechanism is intuitive: when climate issues dominate the news, investors update expectations about the probability of (and firm exposure to) adverse climate scenarios. This includes stricter regulations and carbon pricing, but also broader market risks such as shifts in consumer demand and potential litigation. These sudden revisions in cash flow forecasts and investor preferences increase the covariance between stock returns and the climate factor, making firms more exposed to future climate shocks. Interestingly, we observe no exception for low-carbon firms, suggesting that they are not expected to act as a potential hedge against these shocks. This implies that attention spikes trigger a global increase in perceived transition risk, rather than a flight-to-safety toward low-carbon assets.

Conversely, ESG fund inflows are associated with a statistically significant decline in the carbon beta (Table 7). At first glance, this result appears counterintuitive, as large-scale portfolio reallocations from brown to green assets should increase the performance

differential, thereby strengthening the comovement between stocks and the transition risk factor. However, we interpret this decline through three offsetting channels. First, the lack of consensus on green definitions means that ESG flows are not perfectly aligned with carbon intensity (i.e., carbon-intensive firms can have strong social and governance scores), which disperses the selling pressure and dilutes the carbon signal. Second, demand-based inflows can drive asset prices independently of fundamental news (Pástor et al., 2021; Pedersen et al., 2021; Van der Beck, 2025). These flows can therefore disconnect stock returns from specific climate shocks, dampening the carbon beta. Finally, strong ESG inflows may lower the cost of capital for green initiatives, making the transition to a low-carbon economy more realistic and achievable. This abundance of financing ultimately reduces the perceived severity of future transition shocks, leading to a global decrease in transition risk exposure.

Table 7: 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 (see Equation 6). All regressions include Firm and Time fixed effects, with even columns adding CF × 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.

To further assess the dynamic properties of climate risk exposure beyond short-term attention and demand shocks, we conduct a set of additional analyses that examine longer-

term evolution and macro-financial drivers. For readability and to maintain focus on the core mechanisms, these results are reported in the Appendix and summarized here. Appendix Table A.12 examines whether the carbon beta exhibits a deterministic time trend or a structural break following the Paris Agreement. We find little evidence of either. The coefficients on both the linear time trend and the post-Paris indicator are statistically insignificant, suggesting that exposure to transition risk has neither increased steadily over time nor shifted permanently after 2015. Instead, the dynamics of the carbon beta appear to be episodic, characterized by discrete bursts of attention and changes in investor preferences rather than a smooth evolution.

We further investigate the role of macroeconomic and commodity-market conditions. Appendix Tables A.13–A.14 show that shocks to interest rates, market volatility, and energy prices do not exert a statistically significant effect on the carbon beta. These null results should be interpreted with two caveats. First, our identification strategy, which exploits differential responses between U.S. and European climate factors, may absorb global shocks that affect both regions simultaneously. Second, because the analysis relies on monthly innovations, it captures short-run sensitivity rather than slow-moving or regime-dependent effects. Consequently, while transitory macroeconomic and commodity shocks do not appear to drive short-term variation in transition risk exposure, we cannot rule out that persistent changes in macroeconomic or energy-price environments influence the longer-run level of the carbon beta.

3.5 Carbon Beta Prediction

We now shift from explaining variations in climate transition exposure to constructing a predictive specification for the firm-level carbon beta. The goal of this section is to assess whether the drivers identified in the previous analyses can be combined into a forward-looking model that captures how investors evaluate and update transition risk exposure. Unlike the explanatory regressions above, the predictive specification adopts two deliberate

restrictions to ensure that the model relies exclusively on the information set available to investors at time t. First, we exclude interactions between the climate factor and sector or country fixed effects. Since these fixed effects represent average exposures estimated over the full sample, including them would introduce a look-ahead bias by incorporating future information into current estimates. Second, we exclude contemporaneous and future decarbonization trends, relying instead on lagged firm-level characteristics. We make an exception for high-frequency market variables, namely climate news shocks and ESG fund flows (e.g., EPFR), which are observable in real-time (e.g., daily or weekly) and thus plausible drivers of investor perceptions within the same month.

Table 8 reports the results of this predictive approach across four specifications. Column 1 estimates the unconditional average carbon beta across the full sample. The coefficient is positive but statistically insignificant, confirming that the average firm does not exhibit systematic exposure to transition risk absent conditioning information. Column 2 introduces the interaction with carbon emission intensity. The coefficient is positive and highly significant, which underscores that historical emissions are the primary anchor of risk exposure. Column 3 expands the model to include forward-looking climate characteristics, such as emission reduction commitments. Finally, Column 4 presents the forward-looking and dynamic model, incorporating both firm-level characteristics and time-varying market signals. 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[8].

The final model, presented in Column 4, 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), amplifies with controversies and climate news shocks, and is compressed by ESG fund flows. Importantly,

[8]The relatively low R^2 values are expected in this setting, as the dependent variable is the orthogonalized stock return, which by construction removes the explanatory power of standard risk factors. The objective of the model is not to maximize return fit, but to isolate and predict the climate-specific component of transition risk exposure.

corporate commitments, specifically emission targets and the use of renewable energy, gain statistical significance in this final dynamic framework. This reinforces the finding (non-significant in Table 4) that these climate 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. By defining the time-varying beta ($\beta_{i,t}^{\text{Climate}}$) as a clean function of the observable characteristics, we ensure that the measure used for the carbon premium estimation is an economically interpretable predictor of transition risk exposure.

Figure 2 compares the distributions of our estimated characteristic-driven carbon betas across the different specifications. First, we observe that the forward-looking beta (Column 3) exhibits a slightly larger dispersion than the backward-looking measure (Column 2), although the difference is moderate. This confirms that while historical emissions remain the primary anchor of transition risk exposure, forward-looking characteristics allow investors to refine their assessments. Second, accounting for high-frequency predictors in the fully dynamic model (Column 4) leads to a much wider distribution. This significant increase in dispersion reflects the fact that the time series of carbon betas are quite volatile, responding rapidly to contemporaneous climate news and sentiment.

Figure 3 displays the time-series evolution of the dynamic carbon beta (Column 4). While the long-term median exposure remains close to zero, the interquartile and 1st–99th percentile ranges show wide dispersion, consistent with Figure 2. However, the median exposure demonstrates clear time variation in response to shifting market sentiment. Most notably, we observe a sustained period of negative median carbon betas from 2018 to 2021. This trend aligns with the surge in ESG fund inflows documented during this period, combined with limited climate news coverage during the COVID-19 episode. These dynamics confirm that the stock market's reaction to climate shocks is state-dependent, fluctuating with the intensity of information flows and capital reallocation.

Finally, we benchmark our characteristic-driven estimates against standard statistical

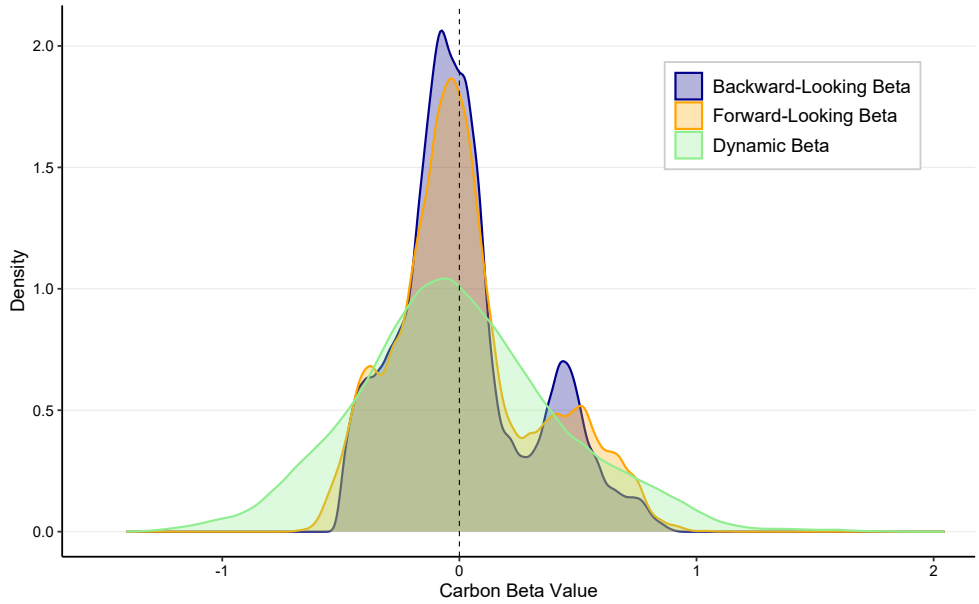
Table 8: Drivers of the Dynamic Carbon Beta-Full Model

	Dependent variable: Stock Residuals			
	Backward-Looking		Forward-Looking	Dynamic Beta
	(1)	(2)	(3)	(4)
Climate Factor (CF)	0.027	−0.677***	−0.902***	−0.902***
	(0.076)	(0.097)	(0.191)	(0.172)
CF x Log(CI)		0.063***	0.045***	0.041***
		(0.010)	(0.013)	(0.013)
CF x Sectoral CI		0.133***	0.134***	0.142***
		(0.019)	(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	0.039	0.042	0.044
Adjusted R^2	0.019	0.028	0.030	0.032

Notes: This table reports the parameter estimates for the conditional carbon beta ($\beta_{i,t}^{\text{Climate}}$) across four cumulative specifications. The models progressively incorporate economic drivers, culminating in the fully dynamic specification (Column 4), which integrates lagged carbon intensity, firm characteristics, and real-time market signals (ESG Flows and Climate News Shocks). Sectoral CI is defined as the average log carbon intensity (t-24) within the firm's sector. All models include firm and time fixed effects. The sample covers the period 2010–2025. Standard errors are clustered at both the firm and time levels. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

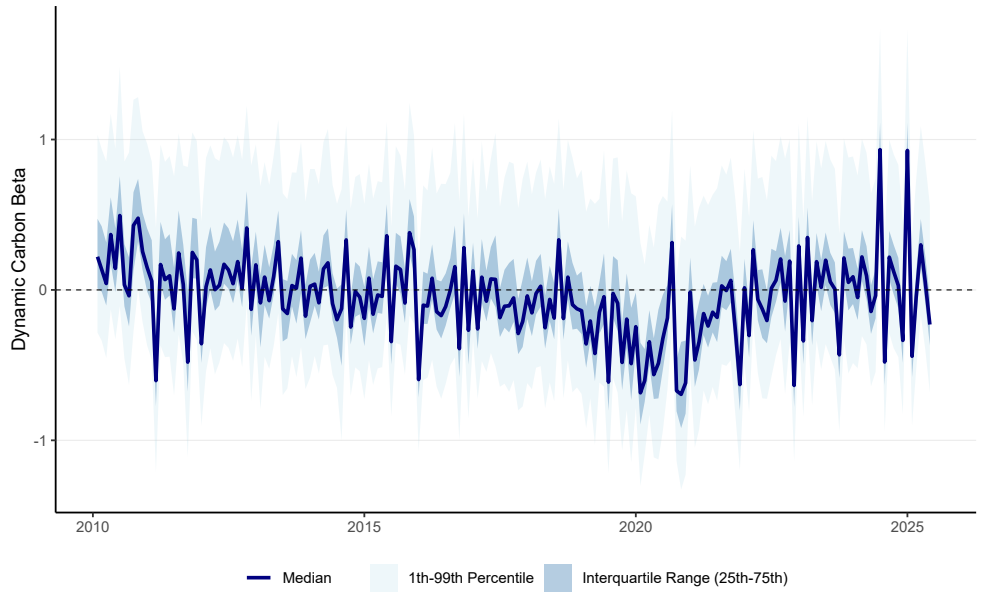
measures derived from static and rolling regressions. Table A.5 confirms a positive correlation, ranging from 0.25 to 0.55, between our model-implied betas and the statistical benchmarks, validating that our approach captures the same fundamental risk exposure. However, Figure A.1 and the descriptive statistics in Table A.6 reveal that our framework achieves significant noise reduction. As shown in the summary statistics, the rolling statistical beta is plagued by outliers, with values ranging from -9.2 to 12.2. In contrast, the fully dynamic model produces a more disciplined distribution (ranging from -1.4 to 2.0) that retains meaningful economic variation while filtering out the estimation error inherent in short-window regressions. This confirms that our characteristics-based approach successfully disciplines the carbon beta, providing a robust signal for asset pricing tests.

Figure 2: Carbon Beta Density



Note: The figure compares the distributions of the backward-looking, forward-looking, and fully dynamic carbon betas for 3,029 U.S. and European firms over the period 2010-2025. The betas are computed using the parameters displayed in Table 8 (Columns 2-4).

Figure 3: Carbon Beta Dynamics



Note: This figure shows the time-series evolution of the carbon beta computed from the coefficients estimated in the full model (see Table 8, Column 4). The beta captures the conditional exposure of firm-level residual returns to the climate factor. The line reports the median exposure across firms at each point in time. Shaded areas show 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. While theoretical models posit a positive risk premium for firms exposed to transition risk (Pástor et al., 2021), empirical evidence remains mixed, with findings often sensitive to the choice of risk proxy and sample period.

Table 9 presents panel regressions of monthly stock returns on alternative measures of transition risk. We first estimate each specification using the maximum number of observations available for that specific measure. To facilitate the comparison of economic magnitudes, all independent variables are standardized to unit variance.

We observe that traditional metrics fail to capture a risk premium. For raw carbon emission intensities (Columns 1–2), the coefficients are statistically insignificant over the full sample and we observe no regime shift following the Paris Agreement. This confirms that

raw emission intensities alone are insufficient to explain cross-sectional variation in returns, even during periods of heightened climate awareness. Similarly, the backward-looking beta (Columns 3–4), which conditions solely on historical firm and sector-level emissions, fails to generate a statistically significant premium.

In contrast, a premium begins to emerge when using the forward-looking beta (Columns 5–6), which incorporates corporate commitments and governance signals. The interaction term with the post-Paris indicator is positive and marginally significant. This result is strengthened further in the fully dynamic beta specification (Columns 7–8). The post-Paris interaction is statistically significant at the 5% level with a larger standardized coefficient than simpler proxies. Economically, this magnitude implies that a one-standard-deviation increase in dynamic transition risk exposure is associated with an annualized risk premium of approximately 4.8%. This suggests that the market specifically prices the component of risk that reflects real-time sentiment and fund flows, which static measures fail to capture.

To strictly test whether our measure captures information that is independent of raw emissions, Table A.7 reports a horse race specification estimated using the intersection sample. Columns 1–2 show that, within this specific sample, carbon emissions carry a marginally significant premium post-Paris. However, this signal is fragile. When the dynamic beta is introduced into the joint specification (Columns 5–6), the coefficient associated with carbon intensity becomes statistically insignificant and changes sign. In contrast, the premium associated with the dynamic beta increases in magnitude and remains statistically significant. This result suggests that the historical carbon emissions are a noisy proxy for the dynamic transition risk captured by our measure. Investors do not appear to price the level of pollution per se; rather, they price the time-varying risk exposure that pollution implies.

Finally, we assess whether our characteristic-based approach offers an improvement over statistical carbon betas. In Appendix Table A.8, we perform a similar comparison against a carbon beta estimated using a 36-month rolling window. We find that the rolling beta is associated with a negative premium prior to 2015, followed by a net post-Paris premium close

Table 9: Carbon Premium Analysis: Static vs. Dynamic Betas

	Dependent variable: Monthly Stock Return (log)							
	Log(CI) (Baseline Proxy)		Backward-Looking Beta		Forward-Looking Beta		Dynamic Beta	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(CI)	0.0004	−0.001						
	(0.001)	(0.001)						
Log(CI) × Post-Paris (PP)		0.002						
		(0.001)						
Carbon Beta (Baseline)			0.002	0.0003				
			(0.001)	(0.002)				
CB (Baseline) × PP				0.002				
				(0.001)				
CB (Forward)					0.0003	−0.002		
					(0.001)	(0.002)		
CB (Forward) × PP						0.002*		
						(0.001)		
CB (Dynamic)							0.002	−0.001
							(0.002)	(0.003)
CB (Dynamic) × PP								0.004**
								(0.002)
Financial Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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 the cross-section of monthly logarithmic stock returns. We compare the pricing ability of four alternative climate risk measures: Log(Carbon Intensity) (Columns 1–2); a Backward-Looking Beta (Columns 3–4), estimated from Table 8 coefficients; a Forward-Looking Beta (Columns 5–6), derived from firm and country characteristics (Table 8); and our fully Dynamic Beta (Columns 7–8), based on all time-varying market and corporate signals (Table 8). Each model is estimated using the maximum available sample for that specific measure. Financial controls include: Size, Book-to-market, Leverage, Momentum, Investment ratio, Profitability (ROE), Log PPE, and Idiosyncratic volatility. All models include 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. Standardized regression coefficients are reported. Robust standard errors, clustered at the firm and time level, are in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

to zero. This is likely due to the noise inherent in short-window estimation. In contrast, the premium associated with the characteristic-based dynamic beta remains significant when controlling for the statistical carbon beta. This confirms that anchoring the beta to fundamentals effectively filters out estimation noise, isolating the component of transition risk that is systematically priced by the market.

Overall, the emergence of a post-Paris carbon premium validates the relevance of the dynamic, characteristic-driven carbon beta in asset-pricing. Transition risk is priced when measured through a forward-looking exposure that integrates firm-specific signals (e.g., commitments) and market sentiment (e.g., news and flows). Raw emissions and statistical betas 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 relying exclusively on static emissions (which are backward-looking) or standard time-series carbon betas (which are statistically noisy and opaque) provides an incomplete picture of risk. We bridge this gap by developing a dynamic, characteristics-driven model to construct a robust and economically interpretable measure of the carbon beta. Our framework serves as a mechanism to optimally combine diverse climate signals, thereby capturing the multidimensional information set that investors actually use to assess transition risk exposure.

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), suggesting that investors perceive climate

transition as a distinct risk 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 enhanced measure helps solve 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 emissions, 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

Variable Definition

Table A.1: 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.2: 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.	Authors

Factor Statistics

Table A.3: 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: The 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.4: Correlation Matrix: Climate Factor vs. Fama-French Factors

Factor	CF	MKT	SMB	HML	RMW	CMA	WML
Panel A: European Factors							
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
Panel B: U.S. Factors							
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 matrices between the Climate Factor (CF), estimated in Equation 1, and the five Fama-French and momentum factors. Panel A reports correlations for the European sample, and Panel B reports correlations for the U.S. sample. All factors are based on monthly returns from 2010 to 2025.

Carbon Beta Comparison

Table A.5: Correlation Matrix of Carbon Beta Estimates

Variable	(1)	(2)	(3)	(4)	(5)
(1) Static Statistical Beta	1.00				
(2) Rolling Statistical Beta	0.57	1.00			
(3) Predicted Beta (Backward-Looking)	0.54	0.31	1.00		
(4) Predicted Beta (Forward-Looking)	0.55	0.32	0.96	1.00	
(5) Predicted Beta (Full Dynamic)	0.40	0.25	0.64	0.68	1.00

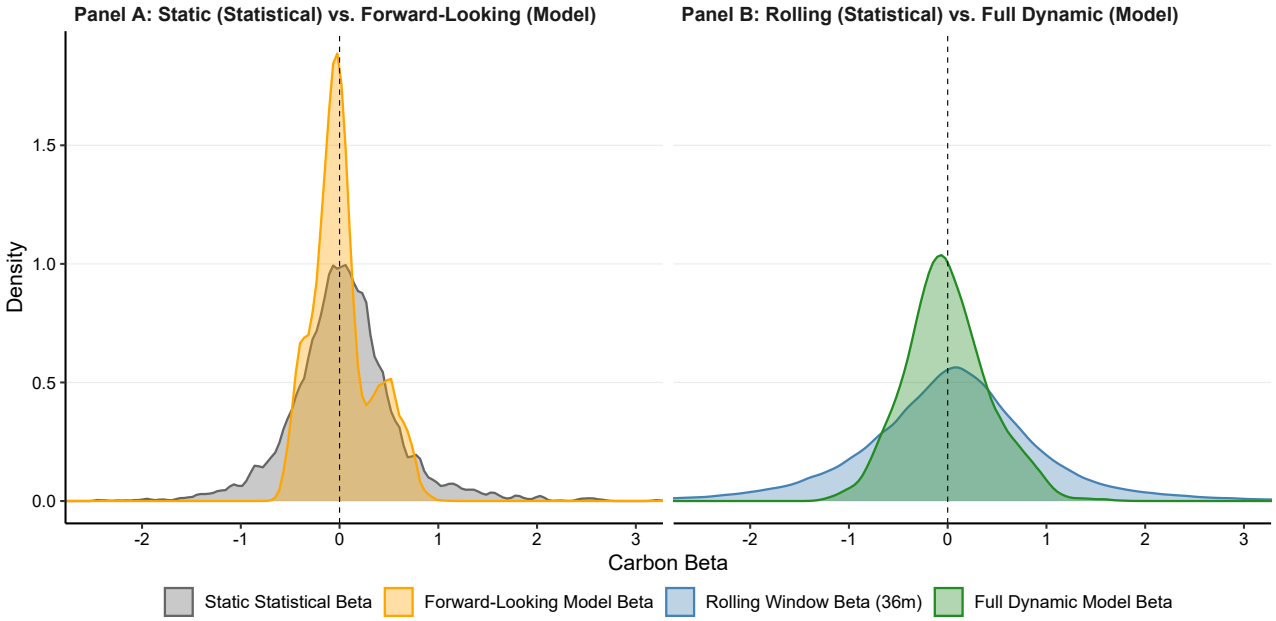
Notes: This table reports the Pearson correlation coefficients between the different carbon beta measures. Static statistical beta and rolling statistical beta (36-month window) are estimated by regressing the residual return on the climate risk factor. Predicted betas correspond to the characteristic-based models: backward-looking (Column 2), forward-looking (Column 3), and full dynamic (Column 4) in Table 8.

Table A.6: Descriptive Statistics of Carbon Beta Estimates

Measure	Mean	Min	P25	Median	P75	Max
Panel A: Statistical Benchmarks						
Static Statistical Beta	0.04	-2.45	-0.25	0.03	0.31	3.21
Rolling Statistical Beta (36m)	0.03	-9.20	-0.48	0.05	0.54	12.21
Panel B: Characteristic-Based Models						
Predicted Beta (Backward-Looking)	0.02	-0.51	-0.16	-0.03	0.13	0.91
Predicted Beta (Forward-Looking)	0.03	-0.69	-0.17	-0.02	0.17	1.13
Predicted Beta (Full Dynamic)	-0.01	-1.40	-0.29	-0.03	0.26	2.05

Note: This table reports summary statistics for the different carbon beta measures. Statistical Benchmarks (Panel A) are estimated by regressing residual returns on the climate factor using either the full sample (Static) or a 36-month rolling window (Rolling). Characteristic-Based Models (Panel B) correspond to the predicted values from the specifications in Table 8: Backward-Looking (Column 2), Forward-Looking (Column 3), and Full Dynamic (Column 4).

Figure A.1: Carbon Beta Comparison



Note: This figure presents the kernel density estimates of the characteristics-based carbon betas compared to statistical benchmarks. Panel A compares the distribution of the static statistical beta (estimated over the full sample) against the forward-looking model beta (Table 8, Column 3). Panel B compares the rolling statistical beta (estimated using a 36-month rolling window) against the full dynamic model beta (Table 8, Column 4). The statistical betas are obtained by regressing the residual returns on the regional climate risk factor.

Table A.7: Carbon Premium Analysis: Emissions vs. Dynamic Beta

	Dependent variable: Monthly Stock Return (log)					
	Backward-looking		Forward-looking		Horse Race	
	(1)	(2)	(3)	(4)	(5)	(6)
Log(CI)	0.0002	−0.001			−0.001	0.001
	(0.001)	(0.001)			(0.001)	(0.002)
Log(CI) × Post-Paris		0.002*				−0.002
		(0.001)				(0.002)
Dynamic Beta			0.003	−0.001	0.003	−0.001
			(0.002)	(0.003)	(0.003)	(0.004)
Dynamic Beta × Post-Paris				0.004**		0.005*
				(0.002)		(0.003)
Financial Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE: Time	Yes	Yes	Yes	Yes	Yes	Yes
FE: Sector	Yes	Yes	Yes	Yes	Yes	Yes
Observations	231,579	231,579	231,579	231,579	231,579	231,579
R^2	0.321	0.321	0.321	0.321	0.321	0.321
Adjusted R^2	0.320	0.320	0.320	0.320	0.320	0.320

Notes: This table tests the pricing of climate risk in the cross-section of stock returns using the intersection sample of firm-month observations available for both backward and forward-looking measures ($N = 231,579$). Columns 1-2 estimate the carbon premium using Log(Carbon Intensity) as a proxy for transition risk exposure. Columns 3-4 use the Dynamic Beta computed from Table 8 coefficients. Columns 5-6 present the "Horse Race" specification, including both measures simultaneously. Financial controls include: Size, Book-to-market, Leverage, Momentum, Investment ratio, Profitability (ROE), Log PPE, and Idiosyncratic volatility. All models include Time and Sector fixed effects. The Post-Paris indicator equals one for months after December 2015. The sample includes monthly observations for all firms in the dataset over 2010–2025. Standardized regression coefficients are reported. 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.8: Methodological Robustness: Rolling Statistical Beta vs. Dynamic Beta

	Dependent variable: Monthly Stock Return (log)					
	Rolling Statistical Beta		Dynamic Beta		Horse Race	
	(1)	(2)	(3)	(4)	(5)	(6)
Rolling Beta	0.0003	−0.005**			0.0003	−0.004**
	(0.001)	(0.002)			(0.001)	(0.002)
Rolling Beta × Post-Paris		0.006**				0.005**
		(0.002)				(0.002)
Dynamic Beta			0.003	−0.001	0.003	0.0005
			(0.003)	(0.003)	(0.003)	(0.003)
Dynamic Beta × Post-Paris				0.005**		0.003*
				(0.002)		(0.002)
Financial Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE: Time	Yes	Yes	Yes	Yes	Yes	Yes
FE: Sector	Yes	Yes	Yes	Yes	Yes	Yes
Observations	213,301	213,301	213,301	213,301	213,301	213,301
R^2	0.310	0.310	0.310	0.310	0.310	0.310
Adjusted R^2	0.309	0.309	0.309	0.309	0.309	0.309

Notes: This table compares the pricing performance of a standard statistical benchmark against our characteristic-driven measure. Rolling Statistical Beta is estimated using a 36-month rolling regression of stock returns on the climate factor. Dynamic Beta is our characteristics-based measure computed from Table 8 coefficients. Financial controls include: Size, Book-to-market, Leverage, Momentum, Investment ratio, Profitability (ROE), Log PPE, and Idiosyncratic volatility. The sample includes monthly observations for all firms in the dataset over 2010–2025. Standardized regression coefficients are reported. Robust standard errors, clustered at the firm and time level, are in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Additional Results

Table A.9: 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 (see Equation 6). 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.10: 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 (see Equation 6). 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.11: 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 (see Equation 6). 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.12: 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 (see Equation 6). 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.13: 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 (see Equation 6). 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.14: 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 (see Equation 6). The sample consists of firm–month observations from January 2010 to August 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.

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

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

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

with $\bar{Q}$ the unconditional correlation matrix of $\tilde{u}_t$, and parameters (α, λ) satisfying $\alpha, \lambda \geq 0$ and $\alpha + \lambda < 1$ 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:

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

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.