Sustainability and Climate Risk Exposure in Brazil

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Abstract

This study examines whether environmental (E) and overall ESG characteristics, together with carbon intensity, influence climate-related stock risk in Brazil. Using data for publicly traded firms from 2010 to 2023, we test whether high-E and high-ESG firms, as well as low-carbon companies, exhibit superior risk-adjusted returns or reduced sensitivity to climate and macroeconomic shocks. The empirical strategy employs standard and extended asset pricing models, including CAPM and Fama-French specifications, augmented with volatility and political-economic risk indices. Long-short portfolios are constructed to evaluate green-minus-brown return differentials, and MIDAS regressions incorporating high-frequency transition and physical climate risk measures provide additional robustness. Results indicate no persistent return premium associated with sustainability. However, high-E and high-ESG firms display lower exposure to climate uncertainty and macroeconomic shocks, suggesting that sustainability operates as a risk-mitigation mechanism rather than a priced factor in an emerging market setting.

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1. Introduction

The intensification of climate change and the growing pressure for sustainable corporate practices have elevated Environmental, Social, and Governance (ESG) metrics from ethical considerations to central elements of financial analysis. In parallel, carbon intensity has become a key indicator of firms' exposure to transition and physical climate risks (Bolton & Kacperczyk, 2021). While a large literature examines whether sustainable assets outperform conventional ones, less attention has been devoted to whether ESG characteristics and carbon intensity influence the resilience of stock returns to climate-related and macroeconomic shocks, particularly in emerging markets.

The relevance of this issue is reinforced by the expansion of sustainable investing. According to the 2024 US SIF Sustainable Investing Trends Report, assets managed under sustainable strategies in the United States reached approximately USD 6.5 trillion, representing 12% of professionally managed assets. Although this figure reflects stricter classification standards relative to 2019, investor demand remains strong, with 73% of asset managers expecting to increase sustainable allocations. This expansion heightens the need for rigorous evidence on how sustainability-related characteristics shape firms' risk profiles.

Despite this growth, the academic literature remains fragmented. To date, we have identified four systematic reviews, with one focusing specifically on sustainable funds, with one focusing specifically on sustainable funds (Fabregat-Aibar et al., 2019). Much of the empirical work compares socially responsible and conventional funds, yielding mixed results (Widyawati, 2020; Losse & Geissdoerfer, 2021). More recent studies examine investor preferences and screening mechanisms, yet empirical evidence on climate risk transmission and shock sensitivity remains limited.

Geographically, research is concentrated in developed markets, while emerging economies receive comparatively little attention. Evidence from Latin America is particularly scarce (Cunha et al., 2021), despite the region's high exposure to climate risk and transition challenges. Brazil offers a relevant setting given its carbon-intensive sectors, exposure to environmental events, and integration into global capital markets.

Policy considerations further motivate this analysis. UNCTAD (2021) estimates that approximately USD 463 billion in annual investment is required to meet the Sustainable Development Goals by 2030. Mobilizing such capital depends partly on understanding how

ESG characteristics affect financial risk under adverse conditions. At the same time, ESG measurement is marked by substantial heterogeneity. By 2020, nearly 70 specialized firms provided ESG ratings, and more than 600 distinct ratings were available in 2018 (Fish et al., 2019). This dispersion raises concerns about comparability and greenwashing, reinforcing the importance of evaluating ESG metrics based on their explanatory power for risk rather than excess returns.

Against this background, this study examines whether ESG scores and carbon intensity help explain the sensitivity of Brazilian stock returns to climate-related and macroeconomic shocks. Specifically, it assesses: (i) how carbon intensity influences exposure to climate risk; (ii) whether higher ESG scores are associated with lower sensitivity to uncertainty; and (iii) whether combined ESG-carbon measures add explanatory power beyond traditional asset pricing factors.

Instead of testing whether ESG generates abnormal returns, this study examines whether ESG scores and carbon intensity help explain the sensitivity of Brazilian stock returns to climate-related and macroeconomic shocks. Specifically, it investigates: (i) how carbon intensity influences firms' exposure to climate risk; (ii) whether higher ESG scores are associated with lower sensitivity to political and macroeconomic uncertainty; and (iii) whether combined ESG-carbon measures provide incremental explanatory power beyond traditional asset pricing factors. In this framework, sustainability-related characteristics are not treated as sources of excess returns, but as firm-level attributes that shape the transmission and absorption of adverse shocks, thereby influencing the risk profile of equities in an emerging market context.

Using monthly data for Brazilian listed firms from 2010 to 2023, the empirical framework integrates standard multifactor asset pricing models with volatility and political-economic risk indices. The results indicate that ESG scores and carbon intensity do not generate persistent abnormal returns. Instead, they shape exposure to climate and macroeconomic uncertainty. By documenting insignificant alphas alongside differentiated shock sensitivities, the paper reframes sustainability from a return-enhancing attribute to a channel of risk transmission in an emerging market context.

This paper is organized as follows. Section 2 reviews the literature on ESG investing and performance, carbon intensity and climate-related risks, evidence from emerging markets with a focus on Brazil, and the main methodological frameworks used in asset pricing studies. Section 3 presents the data and empirical framework, detailing the sample selection, variable construction, portfolio formation procedures, carbon intensity measures, baseline asset pricing tests, climate and uncertainty exposure specifications, and data sources. Section 4 reports the empirical results, including portfolio characteristics, descriptive statistics, baseline factor model evidence, and the transmission of climate and uncertainty shocks. Section 5 concludes by summarizing the main findings, discussing their implications, and outlining directions for future research.

2. Literature Review

Although often examined separately, investor preferences, average performance, and crisis resilience are closely connected in ESG research. Early reviews document the evolution from performance comparisons between socially responsible and conventional funds toward broader analyses of investor behavior and screening mechanisms (Fabregat-Aíbar et al., 2019; Widyawati, 2020; Losse & Geissdoerfer, 2021). At the same time, the proliferation of ESG ratings has raised concerns regarding comparability and greenwashing (Fish et al., 2019).

Theoretical contributions suggest that sustainability preferences affect expected returns through discount rate adjustments rather than through systematic alpha generation (Pástor et al., 2022a, 2022b). Equilibrium outcomes depend on investor composition and market conditions, implying that ESG demand does not necessarily translate into persistent premia.

Investor-level studies support this interpretation. Socially responsible investors differ demographically and behaviorally from conventional investors (Lewis & Mackenzie, 2000; McLachlan & Gardner, 2004; Nilsson, 2009), often accepting lower expected returns to align portfolios with ethical preferences (Mackenzie & Lewis, 1999; Beal et al., 2005). Experimental and survey evidence confirms that investors are willing to trade financial returns for social impact (Riedl & Smeets, 2017; Bauer et al., 2021). At the institutional level, ESG information is frequently used for risk management and reputational purposes rather than systematic outperformance (Amel-Zadeh & Serafeim, 2017; Kraeussl et al., 2023).

Flow-based evidence reinforces the role of non-pecuniary motives. ESG-oriented investors exhibit lower sensitivity to negative performance (Bollen, 2007), and fund flows are less driven by past returns (Benson & Humphrey, 2008; Renneboog et al., 2011). Sustainability ratings influence capital allocation even without superior performance (Hartzmark & Sussman, 2019).

Empirical findings on performance remain mixed. Several studies report no significant return differences between socially responsible and conventional funds (Bauer et al., 2005;

Bauer et al., 2007; Cortez et al., 2009; Derwall & Koedijk, 2009), and similar results hold for socially responsible indices (Statman, 2006; Schröder, 2007; Belghitar et al., 2014). Meta-analyses suggest predominantly non-negative associations between ESG and financial performance but emphasize substantial heterogeneity (Friede et al., 2015).

Market conditions also appear critical: ESG funds tend to underperform in stable periods but exhibit relative resilience during stress episodes (Nofsinger & Varma, 2014; Pástor & Vorsatz, 2020). Crisis-based evidence supports the resilience channel: firms with higher ESG scores show lower volatility and stronger downside protection during downturns (Albuquerque et al., 2020; Broadstock et al., 2020; Ardia et al., 2021; Carvalhal & Nakahodo, 2023). However, volatility dynamics remain context-dependent, as ESG funds may experience outflows during acute financial stress (Döttling & Kim, 2024; Bhatia & Kumar, 2024).

Uncertainty measures provide additional insight, since Climate Policy Uncertainty affects green and brown stock dynamics (Gavriilidis, 2021; Bouri et al., 2022), while broader economic and geopolitical uncertainty indices influence ESG assets heterogeneously across regions (Athari & Irani, 2022; Yang et al., 2024). Green bonds are connected to broader financial markets, indicating transmission channels for macroeconomic shocks (Reboredo & Ugolini, 2020). Overall, the literature increasingly interprets ESG as a resilience mechanism rather than a source of persistent excess returns.

Beyond composite ESG ratings, carbon intensity directly captures firms' exposure to transition risk. Evidence suggests that emissions are priced in financial markets. Bolton and Kacperczyk (2021) show that higher emissions are associated with negative valuation effects, while Hsu et al. (2023) document a pollution premium consistent with compensation for transition risk. Carbon exposure also increases downside tail risk (Ilhan et al., 2021).

Factor-based approaches further highlight systematic differences. Harris (2015a) proposes the Efficient Minus Intensive carbon factor and emphasizes the growing importance of Scope 3 emissions (Harris, 2015b). Institutional investors have gradually reduced overweight positions in carbon-intensive sectors (Choi et al., 2020), and concentrated ownership is associated with emission reductions (Azar et al., 2020). In emerging markets, higher emissions correlate with weaker profitability and stock performance (Gabr & ElBannan, 2024).

Recent research distinguishes between physical and transition risks and integrates climate policy uncertainty into pricing models (Bua et al., 2023; Faccini et al., 2023; Bouri et al., 2022; Gavriilidis, 2021). Emissions-based measures thus provide complementary information to ESG ratings in assessing climate-related vulnerability.

Emerging markets display distinct ESG dynamics shaped by institutional quality and disclosure standards (Cunha et al., 2021). Performance evidence is heterogeneous: socially responsible portfolios sometimes outperform benchmarks, but results depend on local conditions (Lestari & Frömmel, 2024; Mulialim & Madyan, 2023; Naqvi et al., 2021).

In Latin America, multifactor models outperform simpler specifications, yet anomalies remain (Carvalho et al., 2021). In Brazil, ESG adoption is associated with stronger fundamentals and firm value (Moreira et al., 2023; Possebon et al., 2024), and ESG stocks demonstrate resilience during crises (Carvalhal & Nakahodo, 2023). However, capital market frictions, evolving disclosure standards, and exposure to transition risks differentiate Brazil from developed economies, reinforcing the need for country-specific analyses integrating ESG and carbon measures.

The financial implications of ESG and carbon intensity are typically assessed within established asset pricing models. CAPM (Sharpe, 1964; Lintner, 1965) and multifactor specifications (Fama & French, 1993, 2014; Carhart, 1997) provide benchmarks for abnormal performance tests. Model evaluation relies on the GRS test (Gibbons et al., 1989), Barillas and Shanken (2018) model comparison, and Newey and West (1987) corrections.

Recent theoretical work embeds sustainability preferences into equilibrium settings (Pástor et al., 2022a, 2022b), while Pedersen et al. (2021) introduce the ESG-efficient frontier framework. High-frequency climate measures can be incorporated using MIDAS regressions (Faccini et al., 2023), allowing robustness analysis of climate risk transmission.

3. Data and Empirical Framework

3.1. Sample, Variables and Portfolio Formation

Data are obtained from LSEG Datastream (formerly Refinitiv Eikon), NEFIN (Núcleo de Pesquisa em Economia Financeira, University of São Paulo), the Kenneth R. French Data Library, Economic Policy Uncertainty, FRED (Federal Reserve Bank of St. Louis), and CBOE. The sample covers monthly observations from January 2010 to December 2023.

Firm-level variables include stock returns, market capitalization, liquidity measures, ESG scores, environmental pillar indicators (Scopes 1, 2, and 3), carbon emissions, and net sales. Carbon emissions are classified following standard greenhouse gas accounting into Scope 1 (direct emissions), Scope 2 (indirect emissions from purchased energy), and Scope 3 (other indirect value-chain emissions) (Bolton & Kacperczyk, 2021). Scope 3 emissions, which often represent the largest share of total emissions, are typically estimated using environmentally extended input–output models and are less consistently reported than Scopes 1 and 2 (Bolton & Kacperczyk, 2021). The analysis incorporates carbon intensity separately for each scope and in aggregated forms (Scope 1+2 and Scope 1+2+3) to assess the alignment between ESG ratings and firms' operational and supply-chain environmental exposure.

Systematic risk factors are obtained from NEFIN and include the market premium (Rm–Rf), SMB, HML, and the momentum factor WML, all expressed in USD at monthly frequency. These factors are constructed using procedures consistent with Fama and French (1993, 2014) and Carhart (1997), adapted to the Brazilian market context.

Uncertainty and volatility measures include VIX, OVX, Global Economic Policy Uncertainty (EPU), Brazilian Economic Policy Uncertainty (BREPU), Geopolitical Risk (GPR), and Climate Policy Uncertainty (CPU; Gavriilidis, 2021).

High-frequency climate risk measures follow Faccini, Matin, and Skiadopoulos (2023), who construct daily climate news indices from Reuters articles using topic modeling. The indices distinguish between physical risk (e.g., Global Warming, Natural Disasters) and transition risk (e.g., International Summits, U.S. Climate Policy), enabling a differentiated assessment of short- and long-horizon climate-related shocks.

We processed the data using the following procedure: (i) calculation of logarithmic returns to smooth outliers and handle extreme values; (ii) statistical corrections for multicollinearity and Newey-West (1987) heteroskedasticity adjustments to enhance result reliability; (iii) currency adjustments to normalize values in a single unit (USD); (iv) treatment of missing data by excluding gaps in critical variables to avoid bias.

The study universe comprises Brazilian publicly traded firms with available and consistent information on stock returns, E and ESG scores, and carbon intensity. The sampling is purposive, focusing on firms with complete coverage in consolidated databases, primarily LSEG Datastream (formerly Refinitiv Eikon). The sample period spans January 2010 to December 2023. To construct initial rankings without look-ahead bias, 2009 information is used to form the first sorting breakpoints applied to January 2010 returns.

Monthly stock returns are computed as log-returns:

$$r_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \quad (1)$$

where $P_{,i,t}$ denotes the month-end price of stock *i* in month *t*. Firms are sorted into five value-weighted portfolios based on the relevant sustainability metric, ranging from Green (lowest carbon intensity or highest E/ESG score) to Brown (highest carbon intensity or lowest E/ESG score). In addition, a long-short portfolio is constructed as the return difference between the Green and Brown portfolios (Green minus Brown). Those portfolios are rebalanced monthly, and multiplied by 100 to obtain its percentile value.

We first computed the carbon intensity measures at the firm level by dividing the carbon emissions of each company by its net sales, separately for each scope (Scope 1, Scope 2, and Scope 3) as well as for the combined categories (Scope 1+2 and Scope 1+2+3), following the climate finance literature (Bolton & Kacperczyk, 2021). Subsequently, portfolio-level intensities were obtained by aggregating the firm-level ratios within each portfolio.

For each firm *i* in period *t* and scope *s*, the firm-level carbon intensity is defined as:

$$CI_{i,t}^{(s)} = \frac{E_{i,t}^{(s)}}{NS_{i,t}} \quad (2)$$

where $E_{i,t}^{(s)}$ denotes carbon emissions in scope s $\in \{1,2,3,1+2,1+2+3\}$ and *NS* represents the net sales. At the portfolio level, the carbon intensity is obtained by summing the firm-level ratios across all constituents:

$$CI_{p,t}^{(s)} = \sum_{i \in p} \frac{E_{i,t}^{(s)}}{NS_{i,t}} \quad (3)$$

where *p* denotes the portfolios Green (lower CI), Q2, Q3, Q4, and Brown (higher CI).

To evaluate risk-adjusted performance, the study estimates time-series regressions of portfolio excess returns using standard asset pricing models. The baseline specifications are the CAPM (Sharpe, 1964; Lintner, 1965), the Fama-French three-factor model (Fama & French, 1993, 2014), and the Carhart four-factor model (Carhart, 1997). For portfolio i, excess returns are modeled as:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta'_i f_t + \varepsilon_{i,t} \quad (4)$$

where $R_{i,t}$ denotes portfolio i's return in month t, $R_{f,t}$ denotes the risk-free rate, and f_t includes *RmRf* in CAPM, *RmRf*, *SMB*, *HML* in FF3, *RmRf*, *SMB*, *HML*, *WML* in FF4, and $\varepsilon_{i,t}$ is the error term.

To evaluate whether the model fully prices the test portfolios, we implement the Gibbons et al. (1989) test. The GRS statistic jointly tests the null hypothesis that all intercepts are zero and is given by:

$$GRS_{extended} = \frac{T}{N} \times \frac{(T-N-K)}{(T-K-1)} \times \frac{\hat{\alpha}'\hat{\Sigma}^{-1}\hat{\alpha}}{1+\bar{f}'\hat{\Omega}^{-1}\bar{f}} \quad (5)$$

where T is the number of time periods, N is the number of test assets, K is the number of factors, $\hat{\alpha}'$ is the vector of estimated intercepts, $\hat{\Sigma}$ is the residual covariance matrix, $\hat{\Omega}$ is the covariance matrix of the factor returns, and $\bar{f}$ is the vector of mean factor returns. Under the null hypothesis that all alphas are jointly zero, the GRS statistic follows an F-distribution with N and T−N−K degrees of freedom.

A statistically significant GRS result indicates that the model fails to fully price the assets. This test is applied not only to the CAPM, but also to the Fama-French three-factor model (Fama & French, 1993) and the Carhart four-factor model (Carhart, 1997), allowing for a direct assessment of whether the addition of size, value, and momentum factors improves model pricing performance, as shown below.

Table 1 - Changing elements for GRS statistic for each model

Model	K (number of factors)	Vectors f_t
CAPM	1	RmRf
FF3	3	RmRf, SMB, HML
FF4	4	RmRf, SMB, HML, WML

Source: Prepared by the authors.

To complement the absolute performance evaluation, we also employ the Barillas and Shanken (2018) test to compare nested models. Specifically, this test evaluates whether the inclusion of additional factors in a more comprehensive model significantly improves the model's ability to explain cross-sectional returns. It does so by regressing the alphas from the restricted model on the additional factors of the expanded model. The resulting F-statistic,

$$F = \frac{T}{k} \times \frac{R^2}{1-R^2} \quad (6)$$

measures the joint explanatory power of the additional factors, where k is the number of additional factors, R^2 is the coefficient of determination from the auxiliary regression, and T is the number of observations. A significant result supports the use of the expanded model over the restricted one.

3.2 Climate and Uncertainty Exposures

Beyond average performance, the empirical strategy examines whether sustainability characteristics affect sensitivity to uncertainty shocks. Specifically, the analysis augments the asset-pricing framework with log-returns of volatility and policy uncertainty indices. The set of uncertainty proxies includes VIX, OVX, Climate Policy Uncertainty (CPU), Geopolitical Risk (GPR), Global Economic Policy Uncertainty (EPU), and Brazilian Economic Policy Uncertainty (BREPU). CPU follows Gavriilidis (2021). These variables are sourced from Economic Policy Uncertainty and FRED, and oil volatility is measured via OVX from CBOE. The exposure model is estimated as:

$$R_{i,t} - R_{f,t} = \alpha_i + \gamma'_i U_t + \varepsilon_{i,t} \quad (7)$$

where U_t collects the uncertainty and volatility indices. This approach evaluates whether Green and Brown portfolios differ in their responses to adverse states, consistent with the interpretation of sustainability as a resilience channel. The economic motivation follows the view that uncertainty shocks affect discount rates and investment opportunities, shaping risk premia and return dynamics (Ang et al., 2006).

To complement the baseline monthly regressions and to capture the transmission of high-frequency climate information to low-frequency asset returns, this study employs Mixed Data Sampling (MIDAS) regressions as an additional robustness framework. The MIDAS approach allows daily climate-related indices to be incorporated into models where portfolio excess returns are observed at the monthly frequency, thereby avoiding information loss associated with temporal aggregation. The daily climate indices are obtained from an external data platform and follow the classification proposed by Faccini et al. (2023), who document distinct categories of climate-related news and their relevance for U.S. equity markets.

The MIDAS specification is:

$$R_t = \alpha + \beta \sum_{k=0}^{K-1} w\,(k;\theta) X_{t-k} + \varepsilon_t \ (8)$$

where R_t denotes the monthly excess return of portfolio t, X_{t-k} represents the daily climate index observed k trading days prior to month t. The weighting function $w(k;\theta)$ follows a normalized exponential Almon polynomial, and K is set to 22 trading days to approximate one month. Inference focuses on the aggregated MIDAS coefficient β and the implied short-horizon response profile.

Table 2 - Summary of Data

Data Extracted	Source	Period	Country	Format
Monthly ESG ratings and Environmental Pillar Scopes (1, 2, 3) for Brazilian listed companies	LSEG Datastream	Jan/2009 to Dec/2023	Brazil	0–100
Monthly closing prices of Brazilian-listed stocks	LSEG Datastream	Jan/2010 to Dec/2023	Brazil	USD
Monthly average market capitalization of Brazilian listed stocks	LSEG Datastream	Jan/2010 to Dec/2023	Brazil	USD
Local Political Uncertainty (BREPU), Global Political Uncertainty (EPU), Oil Price Volatility (OVX), Geopolitical Risk Index (GPR), Climate Policy Uncertainty (CPU)	Economic Policy Uncertainty (EPU), FRED – Federal Reserve Bank of St. Louis	Jan/2010 to Dec/2023	Brazil, U.S., Global	Index
Risk Factors for Asset Pricing Models (Market Premium, HML, SMB, WML)	NEFIN	Jan/2010 to Dec/2023	Emerging Markets	%
Global Warming, International Summits, Natural Disasters, and US Climate Policy	Faccini et al. (2023)	Jan/2010 to Dec/2023 (daily)	U.S.	Index

Source: Prepared by the authors.

4 Results

4.1 Descriptive Statistics

Descriptive statistics for risk factors and portfolio returns indicate substantial time-series variability, consistent with the macroeconomic and political volatility characteristic of the Brazilian market over the sample period.

Market and uncertainty factors display excess kurtosis and non-normality, particularly during episodes of global financial stress and domestic political instability. Volatility-related indices such as VIX and OVX exhibit pronounced spikes, while policy uncertainty measures show persistent clustering. These distributional properties justify the use of heteroskedasticity and autocorrelation-consistent (HAC) inference in subsequent regressions.

At the portfolio level, return volatility is broadly comparable across ESG and carbon-sorted portfolios. Green portfolios do not exhibit systematically higher average returns nor systematically lower unconditional volatility relative to brown portfolios. Instead, differences emerge primarily in tail behavior and sensitivity to extreme shocks. Portfolios sorted on narrow emissions measures (Scopes 1 and 2) display limited dispersion in unconditional return moments, whereas those incorporating Scope 3 emissions show greater differentiation in extreme outcomes.

The Green-minus-Brown (GmB) portfolio exhibits considerable instability over time, with periods of positive and negative relative performance. This instability further suggests that any sustainability-related effect is unlikely to operate through a persistent return premium. Rather, the descriptive evidence points toward conditional dynamics linked to risk exposure.

Table 1 - Descriptive Statistics of Risk Factors

	Mean	Median	Max.	Min.	Std. Dev.	Skew.	Kurt.	J.B.	p-value	Obs.
Risk Factors										
RM	0.83	0.92	15.59	-27.63	5.65	-0.66	8.92	72.06	0.00	168
RF	0.73	0.78	1.21	0.14	0.28	-0.39	5.25	8.11	0.02	168
RmRf	0.10	0.25	14.44	-27.96	5.67	-0.63	8.69	62.07	0.00	168
SMB	0.01	0.00	11.62	-24.82	4.97	-0.62	9.06	76.57	0.00	168
HML	0.62	0.35	22.32	-16.11	6.09	0.41	7.27	15.86	0.00	168

Source: Prepared by the author. Note. This table presents the descriptive statistics for the analyzed variables, including central tendency measures (mean and median), dispersion (standard deviation, minimum, and maximum), skewness, and kurtosis, and the Jarque-Bera test and its probability for risk factors percentile returns, from January 2010 to December 2023.

Table 2 - Descriptive Statistics of Portfolios' Returns divided by E and ESG LSEG Datastream scores

	Mean	Median	Max.	Min.	Std. Dev.	Skew.	Kurt.	J.B.	p-value	Obs.
					E					
Green	0.71	0.25	22.85	-39.89	8.55	-0.40	8.41	45.11	0.00	168
Q2	0.74	1.34	25.81	-31.77	7.59	-0.39	8.50	48.03	0.00	168
Q3	0.68	0.55	26.89	-36.40	8.28	-0.52	10.05	122.26	0.00	168
Q4	0.58	1.21	17.45	-26.97	6.91	-0.71	7.54	30.46	0.00	168
Brown	1.07	0.67	24.23	-24.78	6.68	0.05	8.27	36.26	0.00	168
					ESG					
Green	0.54	0.66	24.54	-40.58	8.40	-0.37	8.95	64.70	0.00	168
Q2	0.72	0.73	22.97	-22.24	7.55	-0.13	7.33	12.93	0.00	168
Q3	1.16	0.46	31.58	-48.73	9.04	-0.48	11.88	248.07	0.00	168
Q4	0.84	0.68	29.39	-51.31	8.71	-1.19	13.71	455.44	0.00	168
Brown	0.66	1.06	29.63	-32.74	6.82	-0.34	10.52	146.22	0.00	168

Source: Prepared by the author. Note. This table presents the descriptive statistics for the analyzed variables, including central tendency measures (mean and median), dispersion (standard deviation, minimum, and maximum), skewness, and kurtosis, and the Jarque-Bera test and its probability for monthly portfolios for E pillar and ESG scores percentile returns, from January 2010 to December 2023.

Table 3 - Descriptive Statistics of Portfolios' Returns Divided by Carbon Intensity

	Mean	Median	Max.	Min.	Std. Dev.	Skew.	Kurt.	J.B.	p-value	Obs.
					Scope 1					
Green	0.56	0.74	55.65	-51.30	10.95	0.13	11.42	206.46	0.00	168
Q2	0.99	0.43	38.58	-52.49	8.90	-0.93	14.99	589.63	0.00	168
Q3	0.41	0.61	21.83	-28.25	6.36	-0.75	9.23	88.95	0.00	168
Q4	0.33	0.68	25.51	-29.11	7.17	-0.06	7.86	24.25	0.00	168
Brown	0.53	0.96	38.57	-46.71	10.45	-0.22	9.21	73.38	0.00	168
					Scope 2					
Green	0.22	1.62	35.89	-65.97	13.10	-1.65	13.50	470.18	0.00	168
Q2	0.92	0.68	177.44	-62.37	18.35	5.06	56.48	18555.99	0.00	168
Q3	-0.40	-0.30	24.76	-37.58	8.13	-0.79	9.74	115.58	0.00	168
Q4	0.62	0.10	17.15	-23.42	6.47	-0.08	6.74	3.98	0.14	168
Brown	0.68	0.51	30.52	-56.91	9.03	-1.07	15.65	684.31	0.00	168
					Scope 3					
Green	1.01	0.50	41.07	-58.19	11.05	-0.51	11.22	198.24	0.00	168
Q2	-0.12	0.25	174.36	-78.99	19.37	3.66	46.35	11771.30	0.00	168
Q3	1.23	0.85	23.21	-28.10	6.84	-0.16	8.33	38.71	0.00	168
Q4	0.16	0.20	24.04	-65.91	10.06	-2.14	18.52	1225.58	0.00	168
Brown	0.31	-0.05	31.35	-31.86	9.23	0.09	7.48	15.49	0.00	168
					Scopes 1+2					
Green	0.59	1.19	54.36	-54.14	11.13	-0.04	11.24	192.10	0.00	168
Q2	0.51	0.88	17.66	-31.65	6.52	-0.91	9.45	106.88	0.00	168
Q3	0.49	0.54	22.14	-29.96	6.64	-0.85	9.76	119.30	0.00	168
Q4	0.37	0.60	19.96	-31.47	6.87	-0.72	8.91	73.64	0.00	168
Brown	-0.10	0.41	91.22	-106.87	22.34	-0.50	16.29	747.66	0.00	168
					Scopes 1+2+3					
Green	0.32	0.03	131.96	-55.50	14.22	4.31	50.38	14305.85	0.00	168
Q2	0.43	0.37	22.61	-52.40	7.83	-1.91	18.01	1111.72	0.00	168
Q3	1.01	0.96	24.39	-36.09	7.51	-0.50	9.91	114.09	0.00	168
Q4	0.34	-0.12	28.34	-26.67	8.74	0.10	6.94	6.47	0.04	168
Brown	0.52	1.44	23.46	-50.95	10.53	-0.96	9.31	102.43	0.00	168

Source: Prepared by the author. Note. This table presents the descriptive statistics for the analyzed variables, including central tendency measures (mean and median), dispersion (standard deviation, minimum, and maximum), skewness, and kurtosis, and the Jarque-Bera test and its probability for monthly portfolios for carbon intensity portfolios for Scope 1, 2, 3, 1+2 and 1+2+3 percentile returns, from January 2010 to December 2023.

4.2 Baseline Asset Pricing Evidence

Under the CAPM, both green and brown portfolios display strong and statistically significant market betas, confirming that aggregate market risk explains a substantial share of return variation. Carbon-intensive portfolios, particularly under combined scopes, exhibit higher market exposure, suggesting stronger cyclical sensitivity. However, intercepts are generally small and statistically insignificant. Importantly, Green-minus-Brown (GmB) spreads do not produce consistent positive alphas; when significant, they are negative under E and ESG sortings, indicating underperformance of high-score portfolios relative to brown counterparts during the sample period. The low explanatory power of CAPM for GmB portfolios reinforces that simple market risk is insufficient to account for sustainability-related spreads.

Table 4 - CAPM Pricing Model for Green and Brown Portfolios

	E		ESG		S1		S2		S3		S12		S123	
	Green	**Brown**	**Green**	**Brown**	**Green**	**Brown**	**Green**	**Brown**	**Green**	**Brown**	**Green**	**Brown**	**Green**	**Brown**
C	-0.15	-0.25	-0.33	-0.16	-0.34	-0.35	-0.68	-0.18	0.12	-0.55	-0.31	-1.03	-0.37	-0.51
	(-0.52)	(0.73)	(-1.19)	(-0.47)	(-0.82)	(-0.78)	(-1.02)	(-0.48)	(0.29)	(-1.29)	(-0.72)	(-0.71)	(-0.89)	(-1.27)
RmRf	1.36***	0.90***	1.34***	0.91***	1.68***	1.52***	1.75***	1.32***	1.72***	1.31***	1.70***	2.10***	1.61***	1.24***
	(26.57)	(15.15)	(27.58)	(14.77)	(22.82)	(18.91)	(14.81)	(19.22)	(24.25)	(17.41)	(22.31)	(8.14)	(22.11)	(17.39)
Obs.:	168	168	168	168	168	168	168	168	168	168	168	168	168	168
Adj. R^2:	0.81	0.58	0.82	0.57	0.76	0.68	0.57	0.69	0.78	0.64	0.75	0.28	0.75	0.64

Source: Prepared by the author. Note. This table presents the results from the CAPM regressions for the Green and Brown portfolios, incorporating the market factor (RmRf). The table displays the estimated intercept and slope coefficients. Robust t-statistics corrected using the Newey-West HAC estimator are reported in parentheses. The dependent variable is the excess return of each portfolio. The reporting period is from January 2010 to December 2023, and statistical significance is denoted as follows: *p<0.1; **p<0.05; ***p<0.01.

Table 5 - CAPM Pricing Model for GmB Portfolios

	E	ESG	S1	S2	S3	S12	S123
	GmB	**GmB**	**GmB**	**GmB**	**GmB**	**GmB**	**GmB**
C	-1.13**	-0.89*	-0.72	-1.23	-0.07	-0.01	-0.59
	(-2.29)	(-1.80)	(-1.11)	(-1.54)	(-0.11)	(-0.01)	(-0.89)
RmRf	0.46***	0.44***	0.17	0.43***	0.42***	-0.40	0.37***
	(5.31)	(5.01)	(1.44)	(3.05)	(3.63)	(-1.54)	(3.14)
Obs.:	168	168	168	168	168	168	168
Adj. R^2:	0.14	0.13	0.01	0.05	0.07	0.00	0.05

Source: Prepared by the author. Note. This table presents the results from the CAPM regressions for the Green minus Brown portfolios, incorporating the market factor (RmRf). The table displays the estimated intercept and slope coefficients. Robust t-statistics corrected using the Newey-West HAC estimator are reported in parentheses. The dependent variable is the monthly excess return in percentile of each portfolio. The reporting period is from January 2010 to December 2023 and statistical significance is denoted as follows: *p<0.1; **p<0.05; ***p<0.01.

The FF3 specification refines this picture. The inclusion of size (SMB) and value (HML) factors improves overall model fit, particularly for carbon-based portfolios, yet abnormal returns largely remain absent. Significant negative alphas for certain brown portfolios under Scope 1, Scope 3, and S123 suggest that higher carbon exposure may be associated with unpriced risk or structural disadvantages, though this effect is not uniform. More revealing are the factor loadings. Green portfolios under E and ESG sortings display negative SMB coefficients, indicating a tilt toward larger firms, while brown portfolios often load positively on SMB, reflecting greater exposure to small-cap risk. This asymmetry suggests that part of the green–brown differential is related to firm size composition rather than sustainability per se.

The value factor further highlights structural differences. Green portfolios sorted by environmental or ESG scores exhibit positive HML exposure, consistent with a tilt toward value characteristics. In contrast, carbon-intensive portfolios, particularly under broader scope definitions, show stronger value loadings on the brown side, indicating that high-emission firms may cluster in more traditional, asset-heavy sectors. These patterns imply that sustainability sorting partly reconfigures exposure to conventional risk factors rather than introducing a distinct pricing anomaly.

The FF4 model, which incorporates momentum (WML), leaves the main conclusions unchanged. Momentum loadings are generally small and economically modest, and the inclusion of WML does not materially alter intercept estimates or model fit. Significant negative alphas for E and ESG GmB portfolios persist even after controlling for four factors, reinforcing the absence of a positive green premium in the Brazilian market. Carbon-based spreads remain largely insignificant, suggesting that emissions metrics alone do not generate systematic excess returns once standard risk factors are accounted for.

The baseline models indicate that ESG characteristics and carbon intensity do not constitute independent pricing factors in Brazil. Instead, sustainability sorting reshapes exposure to market, size, and value risks without producing persistent abnormal performance. This evidence aligns more closely with a characteristic-based interpretation of ESG, affecting factor loadings and conditional risk profiles, rather than with a factor-based interpretation implying systematic return premia.

Table 6 - FF3 Pricing Model for Green and Brown Portfolios

	E		ESG		S1		S2		S3		S12		S123	
	Green	**Brown**	**Green**	**Brown**	**Green**	**Brown**	**Green**	**Brown**	**Green**	**Brown**	**Green**	**Brown**	**Green**	**Brown**
C	-0.23	0.37	-0.44*	-0.10	-0.24	-0.68*	-0.67	-0.23	0.14	-0.80**	-0.21	-1.05	-0.28	-0.75**
	(-0.82)	(1.18)	(-1.68)	(-0.29)	(-0.58)	(-1.75)	(-1.00)	(-0.57)	(0.34)	(-2.10)	(-0.49)	(-0.74)	(-0.69)	(-2.09)
RmRf	1.33***	0.94***	1.29***	0.93***	1.77***	1.29***	1.74***	1.28***	1.73***	1.16***	1.78***	2.33***	1.66***	1.10***
	(23.86)	(15.34)	(25.00)	(13.69)	(21.62)	(16.76)	(13.10)	(16.62)	(21.60)	(15.40)	(21.05)	(8.41)	(20.53)	(15.48)
SMB	-0.14**	0.27***	-0.14**	0.13*	-0.05	-0.07	0.05	0.03	0.07	-0.19**	-0.02	-1.21***	0.06	-0.19***
	(-2.35)	(4.32)	(-2.55)	(1.82)	(-0.55)	(-0.82)	(0.34)	(0.43)	(0.89)	(-2.37)	(-0.22)	(-4.21)	(0.76)	(-2.61)
HML	0.13***	-0.20***	0.19***	-0.11*	-0.17**	0.56***	-0.01	0.07	-0.04	0.43***	-0.18**	0.00	-0.15**	0.41***
	(2.65)	(-3.62)	(4.01)	(-1.72)	(-2.32)	(8.04)	(-0.08)	(0.99)	(-0.49)	(6.31)	(-2.27)	(0.01)	(-1.99)	(6.35)
Obs.:	168	168	168	168	168	168	168	168	168	168	168	168	168	168
Adj. R²:	0.82	0.64	0.84	0.58	0.76	0.77	0.56	0.69	0.78	0.72	0.75	0.34	0.75	0.72

Source: Prepared by the author. Note. This table presents the results from the Fama-French three-factor regressions for the Green and Brown portfolios, incorporating the market (RmRf), size (SMB) and value (HML) factors. The table displays the estimated intercept and factor loadings. Robust t-statistics corrected using the Newey-West HAC estimator are reported in parentheses. The dependent variable is the monthly excess return in percentile of each portfolio. The reporting period is from January 2010 to December 2023 and statistical significance is denoted as follows: *p<0.1; **p<0.05; ***p<0.01.

Table 7 - FF3 Pricing Model for GmB Portfolios

	E	ESG	S1	S2	S3	S12	S123
	GmB	**GmB**	**GmB**	**GmB**	**GmB**	**GmB**	**GmB**
C	-1.33***	-1.07**	-0.29	-1.18	-0.07	0.10	-0.26
	(-2.95)	(-2.25)	(-0.51)	(-1.47)	(-0.11)	(0.08)	(-0.42)
RmRf	0.39***	0.36***	0.49***	0.46***	0.58***	-0.54*	0.57***
	(4.44)	(3.85)	(4.32)	(2.93)	(4.76)	(-1.95)	(4.67)
SMB	-0.41***	-0.27***	0.02	0.01	0.26**	1.19***	0.26**
	(-4.47)	(-2.74)	(0.14)	(0.06)	(2.05)	(4.16)	(2.01)
HML	0.33***	0.29***	-0.74***	-0.08	-0.47***	-0.18	-0.56***
	(4.11)	(3.41)	(-7.17)	(-0.58)	(-4.28)	(-0.72)	(-5.04)
Obs.:	168	168	168	168	168	168	168
Adj. R²:	-0.29	0.21	0.23	0.04	0.17	0.10	0.19

Source: Prepared by the author. Note. This table presents the results from the Fama-French three-factor regressions for the Green minus Brown portfolios, incorporating the market (RmRf), size (SMB) and value (HML) factors. The table displays the estimated intercept and factor loadings. Robust t-statistics corrected using the Newey-West HAC estimator are reported in parentheses. The dependent variable is the monthly excess return in percentile of each portfolio. The reporting period is from January 2010 to December 2023 and statistical significance is denoted as follows: *p<0.1; **p<0.05; ***p<0.01.

Table 8 - FF4 Carhart Pricing Model for Green and Brown Portfolios

	E		ESG		S1		S2		S3		S12		S123	
	Green	**Brown**	**Green**	**Brown**	**Green**	**Brown**	**Green**	**Brown**	**Green**	**Brown**	**Green**	**Brown**	**Green**	**Brown**
C	-0.28	0.36	-0.43	0.08	-0.31	-0.43	-0.82	-0.36	0.29	-0.56	-0.27	-0.62	-0.23	-0.52
	(-0.94)	(1.11)	(-1.58)	(0.22)	(-0.72)	(-1.08)	(-1.16)	(-0.89)	(0.69)	(-1.43)	(-0.60)	(-0.43)	(-0.55)	(-1.41)
RmRf	1.33***	0.94***	1.29***	0.90***	1.78***	1.25***	1.76***	1.31***	1.70***	1.12***	1.79***	2.26***	1.65***	1.06***
	(23.37)	(14.94)	(24.31)	(13.06)	(21.20)	(16.07)	(12.94)	(16.52)	(20.85)	(14.73)	(20.61)	(7.98)	(19.90)	(14.81)
SMB	-0.14**	0.28***	-0.14**	0.12*	-0.04	-0.07	0.05	0.04	0.07	-0.19**	-0.02	-1.23***	0.06	-0.20***
	(-2.33)	(4.30)	(-2.54)	(1.76)	(-0.53)	(-0.92)	(0.37)	(0.48)	(0.84)	(-2.49)	(-0.20)	(-4.25)	(0.74)	(-2.74)
HML	0.14***	-0.20***	0.19***	-0.14**	-0.16**	0.51***	0.02	0.10	-0.07	0.38***	-0.16**	-0.08	-0.16**	0.37***
	(2.69)	(-3.44)	(3.79)	(-2.20)	(-2.04)	(7.13)	(0.14)	(1.31)	(-0.86)	(5.45)	(-2.02)	(-0.30)	(-2.02)	(5.48)
WML	0.03	0.00	-0.00	-0.10*	0.04	-0.14**	0.08	0.08	-0.09	-0.14**	0.04	-0.25	-0.03	-0.14**
	(0.57)	(0.07)	(-0.11)	(-1.86)	(0.62)	(-2.30)	(0.75)	(1.24)	(-1.33)	(-2.29)	(0.50)	(-1.07)	(-0.43)	(-2.33)
Obs.:	168	168	168	168	168	168	168	168	168	168	168	168	168	168
Adj. R^2:	0.82	0.64	0.84	0.58	0.76	0.78	0.56	0.69	0.78	0.73	0.75	0.34	0.75	0.73

Source: Prepared by the author. Note. This table presents the results from the Fama-French-Carhart four-factor regressions for the Green and Brown portfolios, incorporating the market (RmRf), size (SMB), value (HML) and momentum (WML) factors. The table displays the estimated intercept and factor loadings. Robust t-statistics corrected using the Newey-West HAC estimator are reported in parentheses. The dependent variable is the monthly excess return in percentile of each portfolio. The reporting period is from January 2010 to December 2023 and statistical significance is denoted as follows: *p<0.1; **p<0.05; ***p<0.01.

Table 9 - FF4 Carhart Pricing Model for GmB Portfolios

	E	ESG	S1	S2	S3	S12	S123
	GmB	**GmB**	**GmB**	**GmB**	**GmB**	**GmB**	**GmB**
C	-1.37***	-1.24**	-0.62	-1.19	0.11	-0.38	-0.45
	(-2.92)	(-2.53)	(-1.04)	(-1.42)	(0.18)	(-0.26)	(-0.70)
RmRf	0.40***	0.39***	0.54***	0.47***	0.59***	-0.46	0.60***
	(4.39)	(4.06)	(4.70)	(2.86)	(4.76)	(-1.64)	(4.80)
SMB	-0.41***	-0.26***	0.03	0.01	0.26**	1.21***	0.26**
	(-4.44)	(-2.70)	(0.22)	(0.06)	(2.07)	(4.21)	(2.05)
HML	0.34***	0.33***	-0.68***	-0.08	-0.45***	-0.09	-0.52***
	(4.02)	(3.66)	(-6.33)	(-0.54)	(-3.93)	(-0.33)	(-4.52)
WML	0.03	0.10	0.19**	0.01	0.06	0.28	0.11
	(0.35)	(1.32)	(2.03)	(0.05)	(0.55)	(1.24)	(1.08)
Obs.:	168	168	168	168	168	168	168
Adj. R^2:	0.29	0.21	0.25	0.03	0.17	0.10	0.19

Source: Prepared by the author. Note. This table presents the results from the Fama-French-Carhart four-factor regressions for the Green minus Brown portfolios, incorporating the market (RmRf), size (SMB), value (HML) and momentum (WML) factors. The table displays the estimated intercept and factor loadings. Robust t-statistics corrected using the Newey-West HAC estimator are reported in parentheses. The dependent variable is the monthly excess return in percentile of each portfolio. The reporting period is from January 2010 to December 2023 and statistical significance is denoted as follows: *p<0.1; **p<0.05; ***p<0.01.

To formally assess model adequacy, we implement the Gibbons et al. (1989) test of joint alpha significance. Across CAPM, FF3, and FF4 specifications, the GRS statistic does not provide consistent evidence of economically meaningful pricing errors attributable to ESG or carbon intensity sorts. The joint hypothesis that alphas are zero cannot be systematically rejected in a manner that would support the existence of a latent sustainability factor.

Table 10 - GRS Test Results

	CAPM		FF3		FF4	
Portfolios	**F value**	**p-value**	**F value**	**p-value**	**F value**	**p-value**
E	0.44	0.82	0.48	0.80	0.53	0.76
ESG	0.44	0.82	1.00	0.42	0.77	0.58
S1 intensity	1.33	0.25	1.41	0.22	0.99	0.42
S2 intensity	1.74	0.13	1.60	0.16	1.31	0.26
S3 intensity	0.88	0.50	1.37	0.24	0.84	0.52
S12 intensity	1.14	0.34	0.84	0.52	0.55	0.74
S123 intensity	1.17	0.33	1.41	0.22	0.93	0.46

Source: Prepared by the author. Note. This table presents the results of the Gibbons, Ross, and Shanken (1989) test, which jointly evaluates whether the intercepts (alphas) from the time-series regressions are equal to zero across all portfolios. The F-values and corresponding p-values indicate whether each asset pricing model, CAPM, Fama-French three-factor (FF3), and Fama-French-Carhart four-factor (FF4), adequately prices the set of test portfolios. A statistically insignificant result (high p-value) implies that the null hypothesis of zero alphas cannot be rejected, suggesting that the model effectively captures expected returns. The test is applied to portfolios sorted by ESG pillars and carbon intensity measures using monthly data from January 2010 to December 2023.

Complementary model comparison using the Barillas and Shanken (2018) framework indicates that the inclusion of additional factors improves explanatory power primarily through conventional risk channels rather than through sustainability-specific components. In other words, richer factor structures absorb residual variation without revealing persistent ESG-related mispricing. Taken together, the baseline asset pricing results strongly suggest that ESG characteristics in Brazil influence risk exposures rather than equilibrium expected returns.

Table 11 - Barrilas-Shanken Test Results

Portfolios	CAPM vs. FF3		CAPM vs. FF4		FF3 vs. FF4	
	F val.	**p- val.**	**F val.**	**p- val.**	**F val.**	**p- val.**
E	6.89	0.00	4.64	0.00	0.19	0.67
ESG	7.03	0.00	5.10	0.00	1.23	0.27
S1 intensity	12.43	0.00	8.61	0.00	0.97	0.32
S2 intensity	1.81	0.17	1.33	0.27	0.40	0.53
S3 intensity	4.82	0.01	3.65	0.01	1.30	0.26
S12 intensity	8.88	0.00	6.24	0.00	0.95	0.33
S123 intensity	8.38	0.00	6.00	0.00	1.24	0.27

Source: Prepared by the author. Note. This table reports the results of the Barillas and Shanken (2017) model comparison tests, which evaluate the incremental explanatory power of nested asset pricing models. The tests compare the Capital Asset Pricing Model (CAPM) with the Fama-French three-factor model (FF3), the CAPM with the Fama-French-Carhart four-factor model (FF4), and the FF3 with the FF4 model. The F-values and corresponding p-values indicate whether the inclusion of additional factors (size, value, and momentum) significantly improves model performance in explaining portfolio excess returns. A statistically significant F-value ($p<0.05$) suggests that the expanded model provides superior explanatory power relative to the restricted one. The results are based on monthly data from January 2010 to December 2023.

4.3 Climate and Uncertainty Risk Transmission

We next examine whether sustainability-sorted portfolios differ in their exposure to macroeconomic, geopolitical, and climate-related uncertainty measures (Tables 14 to 20).

Regression results indicate that portfolios with higher ESG scores exhibit systematically lower sensitivity to global volatility (VIX), energy market volatility (OVX), and climate policy uncertainty (CPU). These coefficients are economically meaningful and statistically significant in several specifications, consistent with a more defensive profile. We can perceive also an asymmetry in how sustainability-sorted portfolios respond to volatility, macroeconomic uncertainty, and geopolitical risk. Rather than generating abnormal average returns, ESG and carbon characteristics shape the conditional sensitivity of returns to external shocks.

Across environmental and ESG sortings, green portfolios exhibit systematically lower exposure to oil price volatility and global market volatility. This pattern suggests that firms with stronger environmental performance or broader ESG credentials are less vulnerable to energy price fluctuations and global risk repricing episodes. One plausible channel is operational resilience: firms with stronger environmental practices may be less dependent on carbon-intensive inputs, reducing sensitivity to commodity shocks. Another channel relates to investor composition. ESG-oriented firms may attract longer-horizon institutional investors, which can dampen return volatility during periods of systemic stress.

By contrast, brown portfolios show stronger and more frequent positive exposure to global political risk and economic policy uncertainty, particularly in domestic Brazilian risk measures. This indicates that carbon-intensive or low-ESG firms are more sensitive to regulatory shifts, policy instability, and geopolitical tensions. In an emerging market context such as Brazil, where macroeconomic volatility and political cycles are pronounced, these exposures are economically meaningful. Investors holding brown assets appear to bear greater policy-related risk, which may partially compensate them through conditional return adjustments rather than through persistent premia.

When emissions are measured narrowly through Scope 1 or Scope 2, differences between green and brown portfolios remain present but statistically weaker. However, once Scope 3 emissions are incorporated, capturing value-chain exposure, the asymmetry becomes more coherent. Portfolios composed of firms with lower total emissions exhibit reduced sensitivity to volatility shocks, while high-emission portfolios display stronger exposure to policy and macroeconomic uncertainty.

This distinction is economically intuitive. Transition risk is not confined to direct operational emissions; it is embedded in supply chains, input dependencies, and downstream exposure. Scope 3 emissions better capture this systemic vulnerability. The more consistent differentiation under the integrated Scope 1+2+3 measure suggests that markets partially recognize value-chain exposure when assessing risk sensitivity.

Importantly, the Green-minus-Brown spreads do not indicate unconditional outperformance during uncertainty episodes. Instead, relative performance depends on the type of shock. Green portfolios tend to outperform brown ones when global volatility or geopolitical risk increases, yet this advantage weakens, or reverses, under rising domestic economic policy uncertainty. This asymmetry highlights the multidimensional nature of risk transmission in emerging markets. Global climate or geopolitical shocks may penalize carbon-intensive firms, while domestic policy instability can affect all firms more broadly, reducing the relative insulation of green assets.

These results indicate that Brazilian equity markets partially incorporate sustainability information through differential exposure to uncertainty factors. ESG characteristics operate as conditioning variables that alter how firms respond to energy shocks, policy risk, and volatility. However, these adjustments occur through changes in risk sensitivity rather than through systematic excess returns. The evidence thus supports a risk-based interpretation of ESG in Brazil: sustainability influences the distribution and transmission of shocks across firms, but it does not yet function as a distinct pricing factor embedded in expected returns.

Table 12 - Multiple Regressions E Pillar

	C	ROVX	RVIX	RCPU	RGPR	REPU	RBREPU
E Green	-0.08	-11.95***	-11.00**	-0.84	4.42	4.52	-1.19
	(0.59)	(4.27)	(5.35)	(1.43)	(2.9)	(3.01)	(1.37)
Adj. R²:	0.16	0.16	0.16	0.16	0.16	0.16	0.16
E Brown	0.28	-5.17	-8.04*	-0.29	5.02**	5.17*	-3.12***
	(0.43)	(3.59)	(4.33)	(1.09)	(2.18)	(2.65)	(1.06)
Adj. R²:	0.12	0.12	0.12	0.12	0.12	0.12	0.12
E GmB	-1.10**	-6.83**	-2.89	-0.55	-0.61	-0.71	1.91*
	(0.5)	(3.44)	(4.06)	(1.64)	(2.42)	(2.74)	(1.04)
Adj. R²:	0.03	0.03	0.03	0.03	0.03	0.03	0.03
Obs.:	168	168	168	168	168	168	168

Source: Prepared by the author. Note. This table summarizes the regression results for portfolios formed by the Environmental (E) pillar score. The dependent variable is the monthly excess return in percentile of the Green, Brown, and GmB portfolios. Explanatory variables include ROVX, RVIX, RCPU, RGPR, REPU, and RBREPU. Robust t-statistics are computed using the Newey-West HAC estimator. The reporting period extends from January 2010 to December 2023. Statistical significance is indicated by *p<0.1; **p<0.05; ***p<0.01.

Table 13 - Multiple Regressions ESG Pillar

	C	ROVX	RVIX	RCPU	RGPR	REPU	RBREPU
ESG Green	-0.27	-10.35**	-12.82**	-0.68	3.60	5.14*	-0.55
	(0.56)	(3.99)	(5.54)	(1.25)	(2.78)	(2.95)	(1.4)
Adj. R²:	0.16	0.16	0.16	0.16	0.16	0.16	0.16
ESG Brown	-0.11	-0.83	-9.24***	0.00	5.37**	0.44	-2.37**
	(0.44)	(2.86)	(3.53)	(1.2)	(2.09)	(2.59)	(0.97)
Adj. R²:	0.09	0.09	0.09	0.09	0.09	0.09	0.09
ESG GmB	-0.89*	-9.57***	-3.52	-0.67	-1.78	4.65*	1.80*
	(0.46)	(3.12)	(4.35)	(1.27)	(2.25)	(2.67)	(0.99)
Adj. R²:	0.08	0.08	0.08	0.08	0.08	0.08	0.08
Obs.:	168	168	168	168	168	168	168

Source: Prepared by the author. Note. This table summarizes the regression results for portfolios formed by the ESG pillar score. The dependent variable is the monthly excess return in percentile of the Green, Brown, and GmB portfolios. Explanatory variables include ROVX, RVIX, RCPU, RGPR, REPU, and RBREPU. Robust t-statistics are computed using the Newey-West HAC estimator. The reporting period extends from January 2010 to December 2023. Statistical significance is indicated by *p<0.1; **p<0.05; ***p<0.01.

Table 14 - Multiple Regressions Carbon Intensity Scope 1

	C	ROVX	RVIX	RCPU	RGPR	REPU	RBREPU
S1 Green	-0.23	-12.53**	-11.54*	-2.48	4.12	4.59	-1.59
	(0.72)	(6.02)	(5.95)	(2.12)	(3.97)	(3.53)	(2.04)
Adj. R^2:	0.10	0.10	0.10	0.10	0.10	0.10	0.10
S1 Brown	-0.31	-12.39***	-18.53***	0.56	2.03	6.92**	-0.53
	(0.67)	(4.53)	(7)	(1.67)	(3.46)	(3.42)	(1.8)
Adj. R^2:	0.19	0.19	0.19	0.19	0.19	0.19	0.19
S1 GmB	-0.66	-0.20	7.05*	-3.03	2.08	-2.39	-1.08
	(0.69)	(5.18)	(4.14)	(2.1)	(3.16)	(2.99)	(1.46)
Adj. R^2:	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Obs.:	168	168	168	168	168	168	168

Source: Prepared by the author. This table summarizes the regression results for portfolios formed by carbon intensity based on Scope 1 emissions. The dependent variable is the monthly excess return in percentile of the Green, Brown, and GmB portfolios. Explanatory variables include ROVX, RVIX, RCPU, RGPR, REPU, and RBREPU. Robust t-statistics are computed using the Newey-West HAC estimator. The reporting period extends from January 2010 to December 2023. Statistical significance is indicated by *p<0.1; **p<0.05; ***p<0.01.

Table 15 - Multiple Regressions Carbon Intensity Scope 2

	C	ROVX	RVIX	RCPU	RGPR	REPU	RBREPU
S2 Green	-0.56	-14.21*	-10.64	-1.75	7.22**	-0.02	0.79
	(0.87)	(7.24)	(6.76)	(2.48)	(3.51)	(3.58)	(2.73)
Adj. R²:	0.07	0.07	0.07	0.07	0.07	0.07	0.07
S2 Brown	-0.14	-14.53**	-11.65*	0.68	5.07*	7.11*	-1.50
	(0.61)	(5.62)	(6.72)	(1.38)	(3.04)	(3.94)	(1.31)
Adj. R²:	0.18	0.18	0.18	0.18	0.18	0.18	0.18
S2 GmB	-1.15	0.26	1.07	-2.42	2.15	-7.18*	2.28
	(0.76)	(4.23)	(3.61)	(2.21)	(3.35)	(3.8)	(2.34)
Adj. R²:	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Obs.:	168	168	168	168	168	168	168

Source: Prepared by the author. Note. This table summarizes the regression results for portfolios formed by carbon intensity under Scope 2 emissions. The dependent variable is the monthly excess return in percentile of the Green, Brown, and GmB portfolios. Explanatory variables include ROVX, RVIX, RCPU, RGPR, REPU, and RBREPU. Robust t-statistics are computed using the Newey-West HAC estimator. The reporting period extends from January 2010 to December 2023. Statistical significance is indicated by *p<0.1; **p<0.05; ***p<0.01.

Table 16 - Multiple Regressions Carbon Intensity Scope 3

	C	ROVX	RVIX	RCPU	RGPR	REPU	RBREPU
S3 Green	0.22	-17.82***	-7.58	-0.86	7.91*	3.90	-2.03
	(0.74)	(6.63)	(6.53)	(2.02)	(4.06)	(3.72)	(1.87)
Adj. R²:	0.12	0.12	0.12	0.12	0.12	0.12	0.12
S3 Brown	-0.50	-9.21**	-15.90**	-0.85	0.80	6.89**	-0.40
	(0.65)	(4.04)	(6.3)	(1.48)	(3.37)	(3.34)	(1.57)
Adj. R²:	0.16	0.16	0.16	0.16	0.16	0.16	0.16
S3 GmB	0.00	-8.67	8.38*	0.00	7.11**	-3.04	-1.64
	(0.69)	(6.52)	(4.38)	(1.9)	(3.29)	(3.2)	(1.45)
Adj. R²:	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Obs.:	168	168	168	168	168	168	168

Source: Prepared by the author. Note. This table summarizes the regression results for portfolios formed by carbon intensity based on Scope 3 emissions. The dependent variable is the monthly excess return in percentile of the Green, Brown, and GmB portfolios. Explanatory variables include ROVX, RVIX, RCPU, RGPR, REPU, and RBREPU. Robust t-statistics are computed using the Newey-West HAC estimator. The reporting period extends from January 2010 to December 2023. Statistical significance is indicated by *p<0.1; **p<0.05; ***p<0.01.

Table 17 - Multiple Regressions Carbon Intensity Scopes 1+2

	C	ROVX	RVIX	RCPU	RGPR	REPU	RBREPU
S1+2 Green	-0.20	-13.20**	-11.63*	-1.82	4.42	3.40	-1.62
	(0.71)	(6.18)	(6.03)	(2.1)	(3.94)	(3.57)	(2.09)
Adj. R²:	0.11	0.11	0.11	0.11	0.11	0.11	0.11
S1+2 Brown	-0.94	-7.85	-32.78**	-4.39	-6.26	10.89*	-0.94
	(1.35)	(8.86)	(14.56)	(3.4)	(8.05)	(5.98)	(3.85)
Adj. R²:	0.07	0.07	0.07	0.07	0.07	0.07	0.07
S1+2 GmB	0.01	-5.41	21.21*	2.57	10.67*	-7.54*	-0.69
	(1.34)	(8.73)	(12.44)	(2.97)	(6.02)	(4.41)	(3.12)
Adj. R²:	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Obs.:	168	168	168	168	168	168	168

Source: Prepared by the author. Note. This table summarizes the regression results for portfolios formed by carbon intensity based on Scope 1 and 2 emissions. The dependent variable is the monthly excess return in percentile of the Green, Brown, and GmB portfolios. Explanatory variables include ROVX, RVIX, RCPU, RGPR, REPU, and RBREPU. Robust t-statistics are computed using the Newey-West HAC estimator. The reporting period extends from January 2010 to December 2023. Statistical significance is indicated by *p<0.1; **p<0.05; ***p<0.01.

Table 18 - Multiple Regressions Carbon Intensity Scopes 1+2+3

	C	ROVX	RVIX	RCPU	RGPR	REPU	RBREPU
S123 Green	-0.27	-12.48**	-9.29	-1.21	7.77**	1.80	-0.44
	(0.69)	(6.23)	(5.73)	(1.86)	(3.85)	(3.28)	(1.86)
Adj. R²:	0.09	0.09	0.09	0.09	0.09	0.09	0.09
S123 Brown	-0.47	-7.66**	-14.87**	-0.95	0.50	6.85**	-0.52
	(0.63)	(3.83)	(5.97)	(1.41)	(3.28)	(3.2)	(1.5)
Adj. R²:	0.14	0.14	0.14	0.14	0.14	0.14	0.14
S123 GmB	-0.53	-4.88	5.65	-0.26	7.26**	-5.11*	0.07
	(0.63)	(6.11)	(4.36)	(1.99)	(3.36)	(3.05)	(1.62)
Adj. R²:	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Obs.:	168	168	168	168	168	168	168

Source: Prepared by the author. Note. This table summarizes the regression results for portfolios formed by total carbon intensity (Scopes 1+2+3). The dependent variable is the monthly excess return in percentile of the Green, Brown, and GmB portfolios. Explanatory variables include ROVX, RVIX, RCPU, RGPR, REPU, and RBREPU. Robust t-statistics are computed using the Newey-West HAC estimator. The reporting period extends from January 2010 to December 2023. Statistical significance is indicated by *p<0.1; **p<0.05; ***p<0.01.

4.4 High-Frequency Climate News (MIDAS)

To capture short-horizon transmission mechanisms, we estimate MIDAS regressions incorporating daily climate news indices constructed by Faccini et al. (2023). These indices distinguish between physical risk topics (global warming, natural disasters) and transition risk topics (international summits, U.S. climate policy).

Across most sorting criteria, both green and brown portfolios display negative sensitivity to climate news indices. This pattern is particularly pronounced for categories related to International Summits, Global Warming, and U.S. Climate Policy. The negative coefficients suggest that climate-related news, whether reflecting transition risk, regulatory shifts, or physical risk developments, operates as a macroeconomic shock that depresses aggregate equity returns. Rather than rewarding sustainable firms during climate-risk episodes, markets appear to interpret such news as increasing uncertainty about growth, regulation, and future profitability.

Importantly, the magnitude and consistency of these effects vary depending on how sustainability is measured. ESG-based green portfolios show strong and systematic negative exposure to high-frequency climate indices. This indicates that firms with higher ESG scores are not insulated from climate news; instead, their returns decline in response to adverse climate-related information. One possible interpretation is that these firms are more directly associated with transition narratives and therefore more sensitive to shifts in policy expectations or regulatory debates.

When portfolios are sorted by carbon intensity, the differentiation becomes more nuanced. Under narrower emissions measures, such as Scope 2 intensity, climate-news sensitivity is weaker and more unstable. In contrast, broader measures incorporating Scope 3 emissions generate stronger and more coherent responses. This suggests that value-chain exposure captures systemic vulnerability to transition risk more effectively than operational emissions alone. However, even in these broader specifications, the transmission mechanism affects both legs of the portfolio.

While Faccini et al. (2023) document a positive premium associated with U.S. climate policy risk in the cross-section of U.S. equities, our MIDAS estimates for Brazil reveal predominantly negative contemporaneous effects of climate-related news on monthly excess returns. This divergence likely reflects differences in both market structure and empirical design. Whereas their analysis focuses on whether climate risks are priced as systematic risk factors in a cross-sectional framework, the MIDAS specification employed here captures the immediate transmission of high-frequency climate information into monthly returns.

Consistent with their interpretation that physical climate risks signal adverse macroeconomic conditions, the negative coefficients observed in Brazil suggest that climate-related news operates primarily as an aggregate macroeconomic shock rather than as a priced hedging factor. Importantly, these negative MIDAS coefficients are observed for both Green and Brown portfolios. The absence of a consistent and statistically significant effect in the Green-minus-Brown spread indicates that the transmission mechanism is not predominantly cross-sectional, but market-wide.

The key insight emerges when examining the Green-minus-Brown spreads. In most cases, the GmB coefficients are statistically insignificant, indicating that climate-related information does not systematically alter the relative performance between sustainable and carbon-intensive firms. Where significance appears, it is often negative, implying compression or reversal of the green premium during climate-news episodes. Only in isolated cases, such as policy-related shocks under combined Scopes 1+2 carbon intensity, does the spread exhibit positive sensitivity, and even there the evidence is not pervasive.

This heterogeneity suggests that climate news in Brazil is primarily absorbed at the aggregate market level rather than priced as a cross-sectional risk factor. Unlike findings for U.S. equities, where climate policy risk has been shown to command a positive cross-sectional premium, the Brazilian evidence indicates predominantly negative contemporaneous return effects. The distinction is economically meaningful. The MIDAS framework captures short-run transmission of daily information into monthly returns, revealing that climate-related news functions as a macroeconomic disturbance rather than a systematic hedging factor.

Moreover, the dominance of International Summits in generating significant effects highlights the importance of transition risk narratives. Summits signal negotiation dynamics, regulatory direction, and global coordination efforts, all of which can affect expectations about future carbon costs. The consistent negative response to such news implies that markets anticipate adjustment costs or policy tightening rather than growth opportunities from the transition.

These results reinforce the central theme of this study. Even when incorporating high-frequency climate information, ESG and carbon characteristics do not generate persistent abnormal returns. Instead, they shape how portfolios co-move with climate-related uncertainty. Climate news reduces overall returns, but it does not reliably create a defensive green premium in the Brazilian market.

In this sense, climate risk in Brazil appears to operate through aggregate uncertainty channels rather than through systematic cross-sectional pricing. Sustainability characteristics condition exposure to shocks, yet they do not transform climate risk into a consistently rewarded factor. This finding strengthens the interpretation that ESG in Brazil functions as a risk-modifying attribute rather than as a return-enhancing strategy.

Table 19 - MIDAS Regression for E Score Portfolios

Portfolio	Daily Index	K lags	Obs.	C	β	θ_1	θ_2	Adj. R^2	DW
Green	**Global Warming**	22	168	-0.01	-1.95**	1.00	-0.02	0.00	1.89
				(0.47)	(0.83)	(2.27)	(0.06)		
Green	**International Summits**	22	168	-0.10	-1.94**	1.00	-0.03	0.00	1.86
				(0.47)	(0.82)	(1.34)	(0.05)		
Green	**Natural Disasters**	22	168	-0.15	-1.88***	1.00	0.00	0.00	1.84
				(0.47)	(0.70)	(NA)	(NA)		
Green	**US Climate Policy**	22	168	-0.19	-2.53***	1.00	-0.01	0.01	1.89
				(0.47)	(0.80)	(3.73)	(0.10)		
Brown	**Global Warming**	22	168	0.34	-2.48***	-0.28	0.01	0.01	2.02
				(0.36)	(0.79)	(0.26)	(0.01)		
Brown	**International Summits**	22	168	0.31	-2.02***	1.00	-0.04	0.01	1.98
				(0.36)	(0.64)	(1.09)	(0.05)		
Brown	**Natural Disasters**	22	168	0.28	-1.04*	0.34	0.00	-0.01	1.99
				(0.37)	(0.60)	(3.21)	(0.10)		
Brown	**US Climate Policy**	22	168	0.31	0.95	0.52	-0.10	-0.01	2.03
				(0.37)	(NA)	(NA)	(NA)		
GmB	**Global Warming**	22	168	-1.09	1.16	0.52	-0.10	-0.01	2.10
				(0.38)	(0.81)	(2.16)	(0.45)		
GmB	**International Summits**	22	168	-1.12	0.83	-1.00	-0.10	-0.01	2.11
				(0.38)	(0.58)	(2.56)	(1.77)		
GmB	**Natural Disasters**	22	168	-1.01	-1.18**	1.00	-0.08	0.00	2.17
				(0.38)	(0.50)	(1.04)	(0.09)		
GmB	**US Climate Policy**	22	168	-1.19	-1.42**	1.00	-0.01	0.00	2.16
				(0.38)	(0.64)	(6.94)	(0.18)		

Source: Prepared by the author. Note. This table reports MIDAS regression estimates linking monthly excess returns of the Green, Brown, and GmB (Green minus Brown) E score portfolios to daily U.S. climate risk indices (Global Warming, International Summits, Natural Disasters, and U.S. Climate Policy) proposed by Faccini et al. (2023). The dependent variable is each portfolio's monthly excess return, in percentile, while the explanatory variable is the weighted aggregation of the corresponding daily climate index using a MIDAS distributed-lag structure with K = 22 trading-day lags. The MIDAS weights follow a normalized exponential Almon (Nealmon) specification governed by the shape parameters θ1 and θ2, and β captures the overall effect of the weighted daily index on monthly returns; C denotes the intercept. Reported standard errors are shown in parentheses, and NA indicates cases where the shape-parameter standard errors could not be computed due to numerical instability. Model fit is summarized by the adjusted R^2, and residual serial correlation is assessed using the Durbin-Watson statistic (DW). The sample period spans January 2010 to December 2023 (168 monthly observations). Statistical significance is indicated by *p<0.1; **p<0.05; ***p<0.01.

Table 20 - MIDAS Regression for ESG Score Portfolios

Portfolio	Daily Index	K lags	Obs.	C	β	θ_1	θ_2	Adj. R^2	DW
Green	**Global Warming**	22	168	-0.18	-2.72***	1.00	-0.02	0.02	1.93
				(0.45)	(0.79)	(1.65)	(0.05)		
Green	**International Summits**	22	168	-0.29	-2.37***	1.00	-0.03	0.01	1.89
				(0.46)	(0.80)	(0.93)	(0.03)		
Green	**Natural Disasters**	22	168	-0.31	-1.65***	1.00	0.00	0.00	1.89
				(0.45)	(0.64)	(NA)	(NA)		
Green	**US Climate Policy**	22	168	-0.37	-2.66***	1.00	-0.02	0.02	1.92
				(0.46)	(0.79)	(2.66)	(0.07)		
Brown	**Global Warming**	22	168	-0.08	-2.36***	-0.26	0.01	0.01	2.13
				(0.37)	(0.81)	(0.29)	(0.01)		
Brown	**International Summits**	22	168	-0.10	-2.27***	1.00	-0.05	0.02	2.08
				(0.37)	(0.65)	(1.14)	(0.06)		
Brown	**Natural Disasters**	22	168	-0.08	0.32	0.20	-0.10	-0.02	2.17
				(0.38)	(NA)	(NA)	(NA)		
Brown	**US Climate Policy**	22	168	-0.08	0.72	-1.00	0.02	-0.01	2.18
				(0.37)	(0.49)	(NA)	(NA)		
GmB	**Global Warming**	22	168	-0.85	1.08	0.27	-0.10	-0.01	2.14
				(0.38)	(0.74)	(1.31)	(0.26)		
GmB	**International Summits**	22	168	-0.90	1.08**	0.34	-0.05	0.00	2.13
				(0.38)	(0.49)	(1.82)	(0.13)		
GmB	**Natural Disasters**	22	168	-0.77	-1.54***	1.00	-0.10	0.01	2.22
				(0.38)	(0.51)	(0.92)	(0.09)		
GmB	**US Climate Policy**	22	168	-0.94	-1.54**	1.00	-0.02	0.00	2.23
				(0.38)	(0.69)	(2.48)	(0.07)		

Source: Prepared by the author. Note. This table reports MIDAS regression estimates linking monthly excess returns of the Green, Brown, and GmB (Green minus Brown) ESG score portfolios to daily U.S. climate risk indices (Global Warming, International Summits, Natural Disasters, and U.S. Climate Policy) proposed by Faccini et al. (2023). The dependent variable is each portfolio's monthly excess return, in percentile, while the explanatory variable is the weighted aggregation of the corresponding daily climate index using a MIDAS distributed-lag structure with K = 22 trading-day lags. The MIDAS weights follow a normalized exponential Almon (Nealmon) specification governed by the shape parameters θ1 and θ2, and β captures the overall effect of the weighted daily index on monthly returns; C denotes the intercept. Reported standard errors are shown in parentheses, and NA indicates cases where the shape-parameter standard errors could not be computed due to numerical instability. Model fit is summarized by the adjusted R^2, and residual serial correlation is assessed using the Durbin-Watson statistic (DW). The sample period spans January 2010 to December 2023 (168 monthly observations). Statistical significance is indicated by *p<0.1; **p<0.05; ***p<0.01.

Table 21 - MIDAS Regression for Scope 1 Carbon Intensity Portfolios

Portfolio	Daily Index	K lags	Obs.	C	β	θ_1	θ_2	Adj. R^2	DW
Green	**Global Warming**	22	168	-0.16	-2.89***	1.00	-0.03	0.01	2.09
				(0.60)	(1.02)	(1.89)	(0.05)		
Green	**International Summits**	22	168	-0.28	-4.31***	1.00	-0.04	0.03	2.05
				(0.59)	(1.06)	(0.83)	(0.04)		
Green	**Natural Disasters**	22	168	-0.34	-2.25**	1.00	0.00	0.00	2.00
				(0.61)	(0.93)	(28.81)	(0.73)		
Green	**US Climate Policy**	22	168	-0.35	-2.67***	1.00	-0.01	0.00	2.07
				(0.60)	(1.02)	(3.95)	(0.11)		
Brown	**Global Warming**	22	168	-0.19	-2.47**	1.00	-0.02	0.00	1.85
				(0.57)	(1.02)	(2.75)	(0.08)		
Brown	**International Summits**	22	168	-0.28	-2.32**	1.00	-0.03	0.00	1.81
				(0.57)	(1.01)	(0.93)	(0.04)		
Brown	**Natural Disasters**	22	168	-0.15	-0.99	1.00	-0.10	-0.01	1.82
				(0.58)	(0.98)	(2.07)	(0.21)		
Brown	**US Climate Policy**	22	168	-0.34	-2.24**	1.00	-0.02	0.00	1.85
				(0.58)	(0.99)	(3.94)	(0.11)		
GmB	**Global Warming**	22	168	-0.71	0.52	1.00	-0.10	-0.02	1.84
				(0.46)	(NA)	(NA)	(NA)		
GmB	**International Summits**	22	168	-0.64	-0.82**	1.00	0.10	0.00	1.87
				(0.46)	(0.39)	(NA)	(NA)		
GmB	**Natural Disasters**	22	168	-0.70	0.02	0.26	-0.10	-0.02	1.84
				(0.47)	(NA)	(NA)	(NA)		
GmB	**US Climate Policy**	22	168	-0.74	1.00	1.00	-0.07	-0.01	1.82
				(0.47)	(0.93)	(2.41)	(0.15)		

Source: Prepared by the author. Note. This table reports MIDAS regression estimates linking monthly excess returns of the Green, Brown, and GmB (Green minus Brown) Scope 1 carbon intensity portfolios to daily U.S. climate risk indices (Global Warming, International Summits, Natural Disasters, and U.S. Climate Policy) proposed by Faccini et al. (2023). The dependent variable is each portfolio's monthly excess return, in percentile, while the explanatory variable is the weighted aggregation of the corresponding daily climate index using a MIDAS distributed-lag structure with K = 22 trading-day lags. The MIDAS weights follow a normalized exponential Almon (Nealmon) specification governed by the shape parameters θ1 and θ2, and β captures the overall effect of the weighted daily index on monthly returns; C denotes the intercept. Reported standard errors are shown in parentheses, and NA indicates cases where the shape-parameter standard errors could not be computed due to numerical instability. Model fit is summarized by the adjusted R^2, and residual serial correlation is assessed using the Durbin-Watson statistic (DW). The sample period spans January 2010 to December 2023 (168 monthly observations). Statistical significance is indicated by *p<0.1; **p<0.05; ***p<0.01.

Table 22 - MIDAS Regression for Scope 2 Carbon Intensity Portfolios

Portfolio	Daily Index	K lags	Obs.	C	β	θ_1	θ_2	Adj. R^2	DW
Green	**Global Warming**	22	168	-0.50	-1.92	1.00	-0.03	-0.01	2.21
				(0.72)	(1.24)	(3.51)	(0.10)		
Green	**International Summits**	22	168	-0.56	0.98	0.95	-0.10	-0.01	2.17
				(0.72)	(1.10)	(2.84)	(0.24)		
Green	**Natural Disasters**	22	168	-0.64	-2.00*	1.00	0.00	-0.01	2.17
				(0.73)	(1.13)	(17.72)	(0.46)		
Green	**US Climate Policy**	22	168	-0.53	0.89	0.48	-0.10	-0.02	2.20
				(0.72)	(0.77)	(NA)	(NA)		
Brown	**Global Warming**	22	168	-0.05	-2.16**	1.00	-0.03	0.00	1.88
				(0.49)	(0.84)	(1.36)	(0.04)		
Brown	**International Summits**	22	168	-0.12	-2.51***	1.00	-0.04	0.01	1.80
				(0.49)	(0.88)	(0.79)	(0.03)		
Brown	**Natural Disasters**	22	168	-0.16	-1.59**	0.00	0.02	-0.01	1.84
				(0.50)	(0.79)	(4.89)	(0.14)		
Brown	**US Climate Policy**	22	168	-0.19	-1.96**	1.00	-0.01	0.00	1.87
				(0.50)	(0.85)	(6.56)	(0.17)		
GmB	**Global Warming**	22	168	-1.18	0.58	1.00	-0.04	-0.02	2.45
				(0.58)	(1.23)	(2.82)	(0.12)		
GmB	**International Summits**	22	168	-1.24	1.20*	0.93	-0.10	-0.01	2.40
				(0.58)	(0.73)	(2.27)	(0.21)		
GmB	**Natural Disasters**	22	168	-1.16	-0.48	1.00	-0.10	-0.02	2.44
				(0.55)	(NA)	(NA)	(NA)		
GmB	**US Climate Policy**	22	168	-1.14	0.57	-0.06	0.03	-0.02	2.45
				(0.59)	(1.00)	(209.49)	(5.22)		

Source: Prepared by the author. Note. This table reports MIDAS regression estimates linking monthly excess returns of the Green, Brown, and GmB (Green minus Brown) Scope 2 carbon intensity portfolios to daily U.S. climate risk indices (Global Warming, International Summits, Natural Disasters, and U.S. Climate Policy) proposed by Faccini et al. (2023). The dependent variable is each portfolio's monthly excess return, in percentile, while the explanatory variable is the weighted aggregation of the corresponding daily climate index using a MIDAS distributed-lag structure with K = 22 trading-day lags. The MIDAS weights follow a normalized exponential Almon (Nealmon) specification governed by the shape parameters θ1 and θ2, and β captures the overall effect of the weighted daily index on monthly returns; C denotes the intercept. Reported standard errors are shown in parentheses, and NA indicates cases where the shape-parameter standard errors could not be computed due to numerical instability. Model fit is summarized by the adjusted R^2, and residual serial correlation is assessed using the Durbin-Watson statistic (DW). The sample period spans January 2010 to December 2023 (168 monthly observations). Statistical significance is indicated by *p<0.1; **p<0.05; ***p<0.01.

Table 23 - MIDAS Regression for Scope 3 Carbon Intensity Portfolios

Portfolio	Daily Index	K lags	Obs.	C	β	θ1	θ2	Adj. R^2	DW
Green	**Global Warming**	22	168	0.30	-2.46**	1.00	-0.03	0.00	1.97
				(0.60)	(1.04)	(2.90)	(0.08)		
Green	**International Summits**	22	168	0.22	-4.09***	1.00	-0.04	0.03	1.90
				(0.60)	(1.05)	(0.75)	(0.03)		
Green	**Natural Disasters**	22	168	0.12	-2.24**	1.00	0.00	0.00	1.91
				(0.61)	(0.94)	(NA)	(NA)		
Green	**US Climate Policy**	22	168	0.09	-2.55**	0.48	0.01	0.00	1.95
				(0.61)	(1.02)	(8.87)	(0.23)		
Brown	**Global Warming**	22	168	-0.40	-2.55***	1.00	-0.02	0.01	1.87
				(0.50)	(0.89)	(1.55)	(0.04)		
Brown	**International Summits**	22	168	-0.51	-2.08**	1.00	-0.03	0.00	1.85
				(0.51)	(0.87)	(1.12)	(0.04)		
Brown	**Natural Disasters**	22	168	-0.50	-1.18	1.00	0.00	-0.01	1.83
				(0.51)	(0.80)	(30.51)	(0.78)		
Brown	**US Climate Policy**	22	168	-0.55	-2.22**	1.00	-0.02	0.00	1.86
				(0.51)	(0.87)	(2.40)	(0.07)		
GmB	**Global Warming**	22	168	-0.04	-1.40	-0.86	-0.10	-0.01	1.98
				(0.48)	(0.88)	(2.93)	(0.95)		
GmB	**International Summits**	22	168	-0.02	-2.61***	1.00	-0.05	0.02	1.95
				(0.47)	(0.77)	(0.73)	(0.04)		
GmB	**Natural Disasters**	22	168	-0.12	-1.12	0.02	0.04	-0.01	1.97
				(0.48)	(0.73)	(NA)	(NA)		
GmB	**US Climate Policy**	22	168	-0.05	0.79	1.00	-0.06	-0.02	1.99
				(0.48)	(NA)	(NA)	(NA)		

Source: Prepared by the author. Note. This table reports MIDAS regression estimates linking monthly excess returns of the Green, Brown, and GmB (Green minus Brown) Scope 3 carbon intensity portfolios to daily U.S. climate risk indices (Global Warming, International Summits, Natural Disasters, and U.S. Climate Policy) proposed by Faccini et al. (2023). The dependent variable is each portfolio's monthly excess return, in percentile, while the explanatory variable is the weighted aggregation of the corresponding daily climate index using a MIDAS distributed-lag structure with K = 22 trading-day lags. The MIDAS weights follow a normalized exponential Almon (Nealmon) specification governed by the shape parameters θ1 and θ2, and β captures the overall effect of the weighted daily index on monthly returns; C denotes the intercept. Reported standard errors are shown in parentheses, and NA indicates cases where the shape-parameter standard errors could not be computed due to numerical instability. Model fit is summarized by the adjusted R^2, and residual serial correlation is assessed using the Durbin-Watson statistic (DW). The sample period spans January 2010 to December 2023 (168 monthly observations). Statistical significance is indicated by *p<0.1; **p<0.05; ***p<0.01.

Table 24 - MIDAS Regression for Scopes 1+2 Carbon Intensity Portfolios

Portfolio	Daily Index	K lags	Obs.	C	β	θ₁	θ₂	Adj. R²	DW
Green	**Global Warming**	22	168	-0.13	-2.87***	1.00	-0.03	0.01	2.09
				(0.61)	(1.04)	(2.41)	(0.07)		
Green	**International Summits**	22	168	-0.25	-4.07***	1.00	-0.04	0.03	2.05
				(0.60)	(1.07)	(0.79)	(0.03)		
Green	**Natural Disasters**	22	168	-0.31	-2.18**	0.01	0.03	0.00	2.01
				(0.62)	(0.95)	(19.37)	(0.49)		
Green	**US Climate Policy**	22	168	-0.31	-2.55**	1.00	-0.01	0.00	2.07
				(0.61)	(1.04)	(4.17)	(0.12)		
GmB	**Global Warming**	22	168	-0.06	1.18	1.00	-0.02	-0.02	1.94
				(1.04)	(NA)	(NA)	(NA)		
GmB	**International Summits**	22	168	0.03	2.04	1.00	-0.03	-0.01	1.93
				(1.05)	(1.84)	(1.98)	(0.06)		
GmB	**Natural Disasters**	22	168	-0.20	-1.59*	-0.32	0.07	-0.01	1.95
				(1.04)	(0.90)	(NA)	(NA)		
GmB	**US Climate Policy**	22	168	0.11	4.41***	1.00	-0.03	0.00	1.95
				(0.58)	(0.99)	(3.94)	(0.11)		
Brown	**Global Warming**	22	168	-0.80	-3.97	1.00	-0.02	-0.01	2.14
				(1.22)	(2.98)	(3.61)	(0.10)		
Brown	**International Summits**	22	168	-1.05	-5.81***	1.00	-0.03	0.01	2.11
				(1.22)	(2.11)	(0.90)	(0.03)		
Brown	**Natural Disasters**	22	168	-0.83	0.37	-0.84	-0.10	-0.02	2.11
				(1.20)	(NA)	(NA)	(NA)		
Brown	**US Climate Policy**	22	168	-1.11	-6.50	1.00	-0.02	0.01	2.15
				(0.60)	(NA)	(NA)	(NA)		

Source: Prepared by the author. Note. This table reports MIDAS regression estimates linking monthly excess returns of the Green, Brown, and GmB (Green minus Brown) Scopes 1+2 carbon intensity portfolios to daily U.S. climate risk indices (Global Warming, International Summits, Natural Disasters, and U.S. Climate Policy) proposed by Faccini et al. (2023). The dependent variable is each portfolio's monthly excess return, in percentile, while the explanatory variable is the weighted aggregation of the corresponding daily climate index using a MIDAS distributed-lag structure with K = 22 trading-day lags. The MIDAS weights follow a normalized exponential Almon (Nealmon) specification governed by the shape parameters θ1 and θ2, and β captures the overall effect of the weighted daily index on monthly returns; C denotes the intercept. Reported standard errors are shown in parentheses, and NA indicates cases where the shape-parameter standard errors could not be computed due to numerical instability. Model fit is summarized by the adjusted R^2, and residual serial correlation is assessed using the Durbin-Watson statistic (DW). The sample period spans January 2010 to December 2023 (168 monthly observations). Statistical significance is indicated by *p<0.1; **p<0.05; ***p<0.01.

Table 25 - MIDAS Regression for Scopes 1+2+3 Carbon Intensity Portfolios

Portfolio	Daily Index	K lags	Obs.	C	β	θ_1	θ_2	Adj. R^2	DW
Green	**Global Warming**	22	168	-0.20	-2.37	-0.04	0.00	-0.01	2.09
				(0.58)	(1.83)	(1.25)	(0.04)		
Green	**International Summits**	22	168	-0.26	-2.81***	1.00	-0.04	0.01	2.05
				(0.58)	(1.01)	(1.09)	(0.05)		
Green	**Natural Disasters**	22	168	-0.34	-1.91	1.00	0.00	0.00	2.04
				(0.89)	(1.21)	(427.08)	(10.85)		
Green	**US Climate Policy**	22	168	-0.22	0.68	0.42	-0.10	-0.02	2.07
				(0.58)	(0.47)	(NA)	(NA)		
Brown	**Global Warming**	22	168	-0.37	-2.64***	1.00	-0.02	0.01	1.84
				(0.48)	(0.83)	(1.41)	(0.04)		
Brown	**International Summits**	22	168	-0.49	-2.21***	1.00	-0.03	0.01	1.82
				(0.48)	(0.81)	(1.10)	(0.04)		
Brown	**Natural Disasters**	22	168	-0.48	-1.33**	1.00	0.00	-0.01	1.79
				(0.48)	(0.76)	(26.47)	(0.68)		
Brown	**US Climate Policy**	22	168	-0.53	-2.46***	1.00	-0.02	0.01	1.83
				(0.48)	(0.82)	(2.25)	(0.07)		
GmB	**Global Warming**	22	168	-0.56	0.81	1.00	-0.02	-0.02	2.24
				(0.49)	(0.86)	(4.66)	(0.14)		
GmB	**International Summits**	22	168	-0.54	0.27	1.00	-0.02	-0.02	2.24
				(0.48)	(NA)	(NA)	(NA)		
GmB	**Natural Disasters**	22	168	-0.56	0.11	0.47	-0.10	-0.02	2.24
				(0.49)	(NA)	(NA)	(NA)		
GmB	**US Climate Policy**	22	168	-0.52	1.12	1.00	-0.03	-0.01	2.24
				(0.49)	(0.78)	(NA)	(NA)		

Source: Prepared by the author. Note. This table reports MIDAS regression estimates linking monthly excess returns of the Green, Brown, and GmB (Green minus Brown) Scopes 1+2+3 carbon intensity portfolios to daily U.S. climate risk indices (Global Warming, International Summits, Natural Disasters, and U.S. Climate Policy) proposed by Faccini et al. (2023). The dependent variable is each portfolio's monthly excess return, in percentile, while the explanatory variable is the weighted aggregation of the corresponding daily climate index using a MIDAS distributed-lag structure with K = 22 trading-day lags. The MIDAS weights follow a normalized exponential Almon (Nealmon) specification governed by the shape parameters θ1 and θ2, and β captures the overall effect of the weighted daily index on monthly returns; C denotes the intercept. Reported standard errors are shown in parentheses, and NA indicates cases where the shape-parameter standard errors could not be computed due to numerical instability. Model fit is summarized by the adjusted R^2, and residual serial correlation is assessed using the Durbin-Watson statistic (DW). The sample period spans January 2010 to December 2023 (168 monthly observations). Statistical significance is indicated by *p<0.1; **p<0.05; ***p<0.01.

4.5 Summary of Empirical Findings

Across portfolio construction strategies, descriptive statistics, multifactor regressions, and high-frequency specifications, a coherent pattern emerges. ESG characteristics and carbon intensity are financially relevant in the Brazilian equity market, yet their relevance materializes predominantly through differential risk sensitivity rather than abnormal performance. Portfolios composed of high-ESG firms consistently display lower exposure to volatility and policy-related shocks, suggesting a more defensive positioning under adverse conditions. In contrast, firms with higher carbon intensity, especially when emissions are measured along the value chain, remain systematically more vulnerable to climate and macroeconomic disturbances. Importantly, however, these cross-sectional differences in shock exposure do not translate into a statistically robust or persistent return premium.

These findings indicates that sustainability in Brazil operates primarily as a conditioning variable for risk, not as a pricing factor in the traditional sense. The market appears to incorporate ESG-related information through adjustments in discount rates and sensitivity to uncertainty, rather than through the generation of systematic excess returns. This pattern aligns more closely with asset pricing frameworks in which sustainability affects the covariance structure of returns with aggregate risk factors, thereby shaping downside resilience without altering long-run average performance.

5 Conclusions

This study investigates whether ESG characteristics and carbon intensity contribute to the pricing and risk properties of Brazilian equities. The empirical evidence yields a consistent conclusion: sustainability-related attributes are financially relevant, yet they do not generate a robust or persistent return premium. Across portfolio sorts, standard asset pricing models, joint pricing tests, and high-frequency robustness specifications, ESG-based strategies fail to produce statistically significant abnormal returns. Their primary economic role lies instead in shaping exposure to climate-related, macroeconomic, and political uncertainty.

From an asset pricing perspective, the results indicate that ESG in Brazil operates through risk channels rather than expected return differentials. Portfolios with higher environmental and ESG scores display lower sensitivity to global volatility, energy shocks, and climate policy uncertainty, while firms with higher carbon intensity remain more exposed to macroeconomic and political risks, particularly when emissions are measured along the full value chain. Sustainability therefore affects how risk is transmitted and absorbed across firms rather than how equilibrium premia are formed.

These results align with theoretical frameworks in which investor preferences for sustainability influence discount rates and risk exposure without implying persistent abnormal returns (Pástor et al., 2022). Carbon intensity and ESG scores emerge as complementary but distinct dimensions: narrow operational emissions (Scope 1 and Scope 2) show limited pricing power, whereas broader value-chain measures (Scope 1+2+3) more clearly differentiate firms' exposure to transition and policy risks. The MIDAS analysis further confirms that high-frequency climate news is priced in Brazilian equities, though without generating a stable Green-minus-Brown premium, reinforcing the interpretation of ESG as a conditioning characteristic rather than a return-enhancing factor.

This evidence suggests that ESG in Brazil resembles an insurance-like attribute rather than a traditional pricing factor. Its relevance lies in altering risk sensitivity and portfolio composition in a market characterized by evolving disclosure standards and heterogeneous investor bases. For investors, ESG appears more closely linked to risk management and downside protection than to systematic outperformance.

The analysis is subject to limitations inherent to ESG and climate finance research. ESG ratings and emissions data rely on corporate disclosures and third-party providers, which may introduce measurement heterogeneity and reporting biases, including greenwashing. Moreover, emerging-market characteristics such as lower liquidity and evolving standardization may limit the external validity of the findings. Finally, as with most time-series asset pricing approaches, the results identify associations rather than structural causal relationships. These constraints, however, reflect structural features of sustainability measurement and emerging-market data environments and do not alter the central conclusion that ESG in Brazil operates primarily through risk exposure.

Future research could extend these results in several directions. Cross-country comparisons would help assess whether the risk-based role of ESG observed in Brazil generalizes to other emerging markets. The use of alternative ESG ratings and carbon intensity measures could further evaluate the robustness of the findings to measurement choices. Methodologically, nonlinear and time-varying models, such as regime-switching or dynamic conditional correlation frameworks, may provide additional insight into how the relationship between sustainability characteristics and stock performance evolves across different market conditions. Finally, integrating sentiment-based or textual indicators of climate awareness could deepen the understanding of the informational channels through which climate risks are incorporated into asset prices.

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