Disaggregated ESG Risk in European Asset Pricing Based on ESG Leaders Data

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Abstract

Background: This study investigates the conditional pricing of environmental, social, governance (ESG)-related risk exposures – specifically ESG, carbon intensity, and controversy – using portfolio-level data from firms in the Morgan Stanley Capital International Europe ESG Leaders Index (2018–2024). The sample comprises nine sector-neutral portfolios, double-sorted by ESG and Controversy scores, ensuring balanced exposure across Europe's leading ESG-rated firms.

Aim: This study evaluates how factor decomposition, macro-regime sensitivity, and time-varying risk exposure affect ESG integration in multifactor pricing models. It also assesses the effectiveness of Kalman filtering in stabilizing ESG beta estimates under data limitations.

Methodology: A two-stage Fama-MacBeth approach estimates ESG, carbon, and controversy betas using rolling regressions and Kalman filtering. These betas are then incorporated into fixed-effect panel regressions with macroeconomic volatility controls and regime interaction terms for the 2020–2021 regulatory and financial stress periods.

Results: Disaggregated E, S, and G exposures exhibit significant positive return premia, particularly under stress. Carbon and controversy factors display conditional pricing effects that intensify under transition regimes. Kalman filtering yields smoother, more interpretable beta estimates than rolling regression, enhancing model robustness.

Recommendation: ESG pricing models should incorporate factor decomposition, regime dynamics, and dynamic beta estimation, particularly Kalman filters – when working with quarterly or constrained datasets. Replicating this approach using data from multiple professional ESG providers would be valuable to assess the robustness of the pricing effects under rating divergence and disclosure heterogeneity.

Practical relevance/social implications: This study offers a replicable framework for ESG researchers and investment practitioners seeking to identify time-varying, regime-sensitive, sustainable premiums for asset pricing.

Originality/value: This study is among the first to combine ESG factor decomposition with Kalman-filtered beta estimation in a regime-augmented panel model using European portfolio data. Unlike the dominant United States-focused literature, it applies double-sorted, sector-neutral portfolios based on ESG and controversy scores. The findings demonstrate that robust ESG pricing signals can be uncovered even in small, high-quality European samples when the models are specified dynamically and contextually.

Keywords

ESG factors, Asset Pricing, European Market, ESG leaders, Carbon intensity, Controversy exposure

JEL Codes

G12, G11, Q56, C23

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Introduction

The integration of environmental, social, and governance (ESG) considerations into asset pricing models has become central to sustainable finance. Over the past two decades, scholars and practitioners have debated ESG's role in expected returns, interpreting it variously as a priced risk factor (Gregory et al., 2020; Ciciretti et al., 2023), a reflection of investor preferences (Pástor et al., 2021; Avramov et al., 2022), or a signal of firm quality and strategic advantage (Khan et al., 2016; Nagy et al., 2016). Despite the proliferation of ESG-focused models, empirical findings remain inconsistent and sensitive to methodology, factor construction, and market context (Friede et al., 2015; Blitz & Fabozzi, 2017; Berg et al., 2022).

Recent literature emphasizes that ESG factor pricing is highly conditional, often intensifying during crises or regulatory transitions (Albuquerque et al., 2020; Ramelli & Wagner, 2020). Component-level analysis may reveal more stable signals than aggregate ESG scores (Ciciretti et al., 2023; Dobrick et al., 2025). Reputational risks from ESG controversies are increasingly recognized as distinct priced exposures, particularly under heightened uncertainty (Ilhan et al., 2021; Chen et al, 2020) In parallel, carbon transition risk has emerged as a separate risk premium, driven by climate-policy developments, particularly in markets with stringent disclosure or emission-reduction mandates (Bolton & Kacperczyk, 2021; Bauer et al., 2022; Aswani et al., 2024). Therefore, this study aims to evaluate the impact of factor decomposition, macro-regime sensitivity, and time-varying risk exposure on ESG integration into multifactor pricing models.

Based on empirical design choices and findings, this study evaluates the following hypotheses:

H1 – Empirical ESG Premium Hypothesis: Exposure to disaggregated ESG components is associated with positive return premia, particularly during periods of macrofinancial stress.

H2 – Conditional Reputational Risk Hypothesis: ESG controversy exposure does not consistently predict return penalties under baseline conditions but may exhibit negative pricing effects during regulatory or market stress regimes.

H3 – Conditional Carbon Risk Hypothesis: Carbon intensity is not significantly priced in stable periods but becomes negatively associated with returns under policy transitions, suggesting the emergence of a carbon transition penalty.

This study contributes to the evolving ESG asset pricing literature by decomposing ESG-related risk exposures into three key components – ESG performance, controversial risk, and carbon intensity – and testing their pricing implications in the European equity market. A two-stage Fama-MacBeth estimation framework is applied to sector-neutral portfolios based on firms from the Morgan Stanley Capital International (MSCI) Europe ESG Leaders Index (2018–2024). Factor betas are estimated using rolling regressions and Kalman filters, with a regime interaction structure capturing the 2020–2021 period of heightened systemic stress and ESG policy acceleration.

The remainder of the paper is structured as follows. Section 1 presents the theoretical foundations of ESG pricing models, covering both conceptual frameworks and methodological challenges. Section 2 outlines the core hypotheses concerning ESG, controversies, and carbon-related return premia. Section 3 describes the data, variables, and model specifications, including regime-sensitive extensions. Section 4 presents empirical results, and Section 5 discusses their implications, focusing on the conditional nature of ESG pricing and its interpretation. Finally, Section 6 summarizes the key findings and outlines the directions for future research and model development.

1 Theoretical framework and literature

1.1 Conceptual Framework: ESG in asset pricing theory

In recent years, ESG factors have gained prominence in asset-pricing theory; however, their roles remain conceptually fragmented. ESG has been interpreted as a source of nonfinancial risk, reflection of investor preferences, signal of firm quality, and driver of strategic alpha. These interpretations reflect broader debates in financial economics regarding how intangible, often non-pecuniary, information is incorporated into asset valuation.

ESG integration in asset pricing theory has evolved across multiple frameworks. In traditional models like CAPM and Fama-French, ESG is added as a priced factor alongside size, value, and momentum (Gregory et al., 2020; Naffa & Fain, 2022) but often suffers from multicollinearity and weak significance. Arbitrage-based approaches (Pedersen et al., 2021; Pollard et al., 2017) offer greater flexibility by not assuming equilibrium, allow ESG risk exposure to vary across sectors and time. Conversely, behavioral asset-pricing frameworks emphasize investor preferences, ESG sentiment, and non-financial utility as key drivers of asset selection (Pástor et al., 2021; Avramov et al., 2022). These models suggest that ESG-related demand shifts driven by sustainability-focused investors can result in persistent price effects without traditional risk compensation. ESG preferences can be formalized through an augmented utility function that incorporates both traditional risk-return trade-offs and ESG-related preferences. These preferences can be formalized through a utility function that balances financial risk-return with ESG-related utility, as shown below:

$$U_j = E[r_p] - \frac{\lambda_j}{2} Var(r_p) + \theta_{j,t} \cdot \bar{s} - \gamma_{j,t} \cdot \overline{CONT} \tag{1.1}$$

Where U_j represents the utility of investor j; λ_j represents the investor-specific risk aversion coefficient; $\bar{s}$ represents the portfolio-level ESG score; $\overline{CONT}$ denotes the portfolio-level exposure to ESG controversies; $\theta_{j,t}$ and $\gamma_{j,t}$ are time-varying ESG preference strength and controversy aversion, respectively. This formulation shows how investors balance financial returns with ESG utility, accepting lower expected returns in exchange for sustainability or reputational quality. Future model extensions could introduce investor segmentation by varying $\theta_{j,t}$ and $\gamma_{j,t}$ across investor types, reflecting heterogeneous ESG preferences and regulatory constraints.

Similarly, intertemporal consumption models and stochastic discount factormodels incorporate ESG into marginal utility, linking it to climate risk, sustainability, and consumption smoothing (Ilhan et al., 2021; Zerbib, 2022). However, these models often rely on high-frequency data or complex parameterization, limiting their empirical use.

Others interpret ESG as a source of strategic alpha, reflecting firm-specific advantages like reputational capital, management quality, and long-term orientation – factors not fully captured by traditional models (Jensen, 1968; Khan et al., 2016; Nagy et al., 2016). ESG exposure in this view can drive persistent outperformance, especially in less-regulated or under-researched markets.

Recent empirical studies show that ESG pricing is regime-dependent, with premiums intensifying or reversing during crises or regulatory transitions (Albuquerque et al., 2020; Ramelli & Wagner, 2020). This motivates the use of regime-sensitive specifications and interaction terms, which are central to this study's design. To capture complex ESG-return relationships, recent work has introduced machine learning and nonlinear models (Feng et al., 2022; Chen et al., 2020), though these approaches trade off interpretability and transparency.

Despite growing interest, empirical evidence on ESG pricing remains mixed, often due to methodological variation, context sensitivity, and data limitations. ESG ratings diverge significantly across providers, introducing measurement noise (Berg et al., 2022), and frequently correlate with firm characteristics like size and profitability, leading to multicollinearity risks in multifactor models (Nagy et al., 2016). While meta-analyses report numerous positive findings (Friede et al., 2015), other studies highlight weak explanatory power (Blitz & Fabozzi, 2017) or note that ESG preferences may lower expected returns without improving model predictability (Pástor et al., 2022). ESG significance also tends to spike during crises and regulatory transitions (e.g., COVID-19, EU taxonomy), underscoring its regime-dependent nature. These challenges, along with ESG's dual interpretation as both a priced risk and a reflection of investor preferences, point to the need for more adaptive, context-sensitive modeling frameworks capable of isolating conditional ESG effects.

Against this background, the study adopts a simplified multifactor framework based on the Fama–MacBeth two-stage regression, treating ESG, carbon, and controversy as systematic exposures. Regime interaction terms are included to capture time-varying pricing effects, balancing empirical tractability with the need to reflect conditional ESG dynamics. The contribution lies in combining a classification framework with empirical ESG factor decomposition, integrating climate and reputational risks. While earlier models omitted heterogeneity and regime effects, the extended specification incorporates interaction terms to capture regime-dependent pricing, in line with recent studies (Albuquerque et al., 2020; Pástor et al., 2021).

1.2 Empirical literature - ESG factors in asset pricing

Integrating ESG into asset valuation presents several methodological challenges, notably in factor selection, data consistency, and market sensitivity. This study focuses on three core ESG-related factors: a decomposed ESG index, a controversy indicator, and a carbon factor – each with distinct empirical significance across markets.

Aggregated ESG scores have been widely used but show inconsistent explanatory power, especially when not disaggregated into E, S, and G components (Gregory et al., 2020; Naffa & Fain, 2022). Correlations with firm quality and profitability raise multicollinearity risks in standard multifactor models (Nagy et al., 2016; Khan et al., 2016). Moreover, ESG rating divergence across providers introduces measurement noise (Berg et al., 2022). These limitations have shifted the literature toward ESG decomposition, which improves stability and interpretability of pricing signals, especially in European and U.S. markets. Lioui & Tarelli (2022) confirm that factor construction critically affects valuation outcomes, underscoring the need for methodological precision. Theoretically, ESG can also reflect investor preferences rather than risk, aligning with Cornell's (2021) view that ESG demand is shaped by utility maximization beyond financial returns.

ESG controversy is increasingly recognized as a distinct pricing risk. Bang et al. (2023) and Chen et al. (2020) show that controversy indices capturing reputational and governance incidents significantly explain return variation in U.S. and global markets. Firms with high controversy exposure often require a risk premium due to reputational loss, especially under regulatory pressure or social tension – supporting the inclusion of controversy factors in dynamic ESG valuation models.

The carbon factor is increasingly validated as a distinct climate risk premium, particularly in European markets. Carbon-intensive firms tend to earn higher returns as compensation for transition risk (Bolton & Kacperczyk, 2021). Aswani et al. (2024) find that self-reported emissions drive pricing more strongly than third-party assessments. Carbon premia are most pronounced in jurisdictions with stringent climate policies and disclosure rules (Bauer et al., 2022). Ardia et al. (2023) further support this by showing return differentials between green and brown assets, reinforcing the case for including carbon in asset pricing models.

1.3 Overview of methodological challenges

Contemporary models of ESG integration into asset valuations demonstrate significant theoretical and empirical limitations that have remained unresolved. Despite various approaches, including ESG as an additional risk, investor preference, information signal, or strategic alpha source, most models face recurring problems that call into question the reliability and interpretability of their results.

Inconsistency of ESG ratings remains a critical issue. ESG scores vary significantly across providers (MSCI, Sustainalytics, Refinitiv, S&P), leading to low inter-provider correlation and distorted return estimates (Berg et al., 2022; Gibson Brandon et al., 2021; Tian et al., 2025). Market reactions also vary depending on the rating source (Luo et al., 2023; Serafeim, 2022). To mitigate this, the present study relies on a single provider (S&P Capital IQ), though even single-source consistency is not guaranteed.

Multicollinearity with traditional factors. ESG ratings often correlate with firm fundamentals like size, investment, and profitability (Nagy et al., 2016), causing multicollinearity, coefficient instability, and reduced statistical power. This overlap can obscure ESG's independent pricing effect.

Endogeneity of ESG measures. A further challenge arises from potential endogeneity between ESG performance and financial outcomes. Firms with strong valuations may invest more in sustainability initiatives, while improved ESG profiles can, in turn, enhance market valuation and financing conditions. This bidirectional relationship complicates causal inference and may bias estimated ESG premia if not addressed. Studies typically mitigate this through fixed effects, lagged variables, or ex-ante factor construction, although full identification remains difficult and context-dependent.

Temporary instability of ESG premiums. ESG factors often lack stable significance. Studies show that ESG premiums are weak or insignificant in normal markets but become more pronounced during crises, regulatory shifts, or periods of public pressure (Albuquerque et al., 2020; Ramelli & Wagner, 2020). This instability underscores the need for regime-sensitive modelling – an element frequently omitted in basic frameworks.

Theoretical duality of ESG interpretation. ESG is interpreted as both a risk factor and reflection of investment preferences (Pástor et al., 2021). This duality makes it difficult to specify models and complicates the interpretation of alpha. If ESG is a preference, rising prices of ESG assets may reduce expected returns, which contradicts traditional perspectives on risk premiums.

Weak identification and low reproducibility. Many models experience weak identification of ESG factors. The results often depend on the database, country, sector, or ESG score calculation method. The transferability and reproducibility of these results across samples and periods remain a serious limitation. Models often demonstrate sensitivity to the choice of specifications, which reduces confidence in the stability of their conclusions.

Institutional and political dependence. ESG premiums are shaped by local institutional factors, including regulatory frameworks, green taxonomy implementation, and political context (Pedersen et al., 2021). National climate policy has a stronger influence on carbon risk premiums than international agreements lacking domestic enforcement (Bolton & Kacperczyk, 2021). ESG disclosure quality and transparency also affect firms' access to financing (Guo et al., 2024). Notably, carbon premiums tend to be lower in countries with strong democratic institutions and rule of law (Bolton & Kacperczyk, 2021). Market responses to events like the Paris Agreement underscore that political and regulatory shifts significantly influence ESG pricing, reinforcing the need for regime-sensitive, institutionally grounded models. This regulatory dynamic culminated in the European Union's sustainable finance framework – anchored in the EU Green Deal, the Sustainable Finance Disclosure Regulation (SFDR 2019/2088), and the Corporate Sustainability Reporting Directive (CSRD 2022/2464 amending Directive 2013/34/EU) – which together institutionalized ESG disclosure and risk integration. The 2020–2021 transition period analysed in this study aligns with these legislative milestones, capturing the onset of standardized ESG reporting and supervisory expectations across the European market.

Despite theoretical progress, ESG pricing models still face key limitations – namely, rating inconsistency, multicollinearity, temporal instability, theoretical ambiguity, and low reproducibility. These issues call for hybrid, adaptive models that account for regime effects, data quality, and institutional variation. This study addresses several of these challenges by using a single data provider (S&P Capital IQ), decomposing ESG components, treating controversy and carbon as distinct priced factors, and incorporating regime interactions. This improves robustness and enhances the interpretability of ESG pricing effects.

2 Data and variable justification

2.1 Data sample based on S&P capital IQ

This study utilizes S&P Capital IQ Pro[1] as the primary data source, in line with industry practice among analysts, valuation experts, and risk managers. The platform offers high-quality, consistent ESG and financial data. A key challenge was identifying relevant firms for the European market, which lacks a predefined target universe. To resolve this, the

1 *S&P Capital IQ Pro is an analytics platform from S&P Global that provides access to a wide range of financial, market and ESG data, including MSCI ratings, asset returns, market indices, and macroeconomic variables. https://www.spglobal.com/market-intelligence/en/solutions/products/sp-capital-iq-pro*

study selects constituents of the MSCI Europe ESG Leaders Index, a transparent, sector-balanced benchmark featuring large- and mid-cap firms with strong ESG reporting and regulatory alignment. This ensures compatibility with Capital IQ's structure, minimizes data gaps, and provides historical ESG scores and carbon emissions at the firm level.[2]

The sample is not representative of the entire European market but serves as a high-quality panel for testing ESG pricing models in a controlled, observable environment. Due to limited ESG and carbon disclosure prior to 2017, the multicounty design is constrained. The final dataset comprises nine factor-mimicking portfolios from MSCI Europe ESG Leaders (Q1 2018–Q4 2024), based on firms with consistent index inclusion and complete ESG and carbon data. ESG pricing studies often rely on portfolio-level returns rather than individual firm data (Lioui & Tarelli, 2022; Gregory et al., 2020; Pástor et al., 2021; Giese et al., 2019). This approach – focused on factor portfolio construction – offers a robust and methodologically consistent framework. The use of a smaller but curated portfolio panel aligns with best practices and confirms that ESG return premia can be analysed without requiring large firm-level cross-sections.

2.2 Variables definition and data sources

This empirical model uses four key variables, each capturing an important aspect of ESG-driven asset pricing. Their selection is based on both academic literature and practical considerations of data availability and analytical relevance (Table 1).

Total return: It represents the quarterly return on an asset, including both changes in market price and dividends received. This acts as a dependent variable and reflects the total benefits received by investors. The use of total returns aligns with standard asset-pricing methodologies (Fama and French, 1992; Pástor et al., 2021; Mohanty & Ivanov 2021), enabling a direct assessment of the various risk factors' contributions in explaining returns.

Beta market (β_{Market})**:** It reflects the sensitivity of an asset's return to overall market movements and is a core variable in classical asset pricing models such as CAPM and Fama-French (Fama & French, 1992). It is consistently included in ESG-linked asset-pricing research to control for systematic risk and isolate ESG-specific effects (Mohanty & Ivanov,

2 *Attempting to build a broader dataset outside the MSCI ESG Leaders Index would not guarantee the availability of historical ESG data. Moreover, consistent reporting of carbon emissions represents additional challenge. DitchCarbon is used to source information on initially selected companies from MSCI ESG Leaders Index. Therefore, such an approach could likely increase the number of firms with incomplete reporting, particularly in the early years (2015–2016), where ESG disclosure was limited and S&P data coverage was thinner. Additionally, the costs of expanding the dataset – given the pay-per-point structure of many ESG data vendors – could introduce significant financial and practical constraints, without assurance of sector balance or methodological consistent. Therefore, selecting the MSCI Europe ESG Leaders Index is not only conceptually aligned with market standards but also a pragmatic data-driven decision that ensures long-term ESG reporting consistency and data quality, enabling the construction of a balanced panel without artificial data imputation or speculative firm selection.*

2021; Pástor et al., 2021). Gregory et al. (2020), Geczy et al. (2021), Mohanasundaram (2024), and Dobrick et al. (2025) retain market beta as a critical factor in their ESG-augmented models, confirming its continued significance and explanatory power. Across these studies, market beta remains essential for accurately capturing the portion of asset returns driven by general market risk, even when ESG factors are introduced.

Table 1: Description of variables used in the empirical model

Variable	**Description**	**Calculation method / source**
Total Return	Quarterly return on the asset, including price movements and dividends	Calculation based on market data, S&P Capital IQ Pro
Beta_ Market	Sensitivity of the asset's return to a market index	Rolling regression on yields MSCI Europe
Risk-Free Rate	Three-month EURIBOR rate reflecting risk-free yields	European Interbank Market Data, ECB Statistical Data Warehouse[3]
Beta_ESG (E/S/G)	Sensitivity to the ESG factor reflecting the sustainability of companies	Returns of portfolios sorted by ESG, S&P Capital IQ Pro
Beta Controversy	Sensitivity to negative information about ESG (scandals, violations, etc.)	Portfolio returns sorted by level of controversy; Systainalytics,[4] Corporate and Investor reporting
Beta Carbon	Sensitivity to carbon intensity (emissions-adjusted exposure)	Assigned based on reported carbon emissions (scope 1-3)[5] provided by DitchCarbon at no financial cost in support of academic research, and used as an explanatory factor in second-stage panel regressions; not used in portfolio sorting
Policy Dummy	Dummy variable for relevant regulatory or policy events impacting ESG	Author-encoded based on the timeline of major EU climate and ESG policy events[6]

3 *European Central Bank. (n.d.). ECB Statistical Data Warehouse. https://sdw.ecb.europa.eu/*

4 *Sustainalytics is a leading ESG analytics company owned by Morningstar. It provides ESG risk ratings and assessments for companies around the world, https://www.sustainalytics.com/*

5 *Due to inconsistent availability of emissions intensity data (e.g., carbon emissions per unit of revenue), the author uses absolute emission values and applies cross-sectional normalization within each year to construct a comparable carbon score ranging from 0 to 1:*

$$cs_{i,t} = Emissions_{i,t} - \min_{j}(Emissions_{j,t} / max(Emissions_{j,t}) - min(Emissions_{j,t}).$$

This score reflects the relative carbon footprint of firm i in year t, where higher scores indicate higher emissions relative to industry peers. For firms with missing or incomplete emissions data, a static carbon proxy (such as the DitchCarbon rating) may be used to preserve cross-sectional coverage. For firms with partial carbon reporting histories, missing intermediate years were imputed using Huber regression, which provides a robust trend estimation that is resistant to outliers while maintaining sensitivity to underlying emission trajectories. This approach ensures a continuous and comparably scaled carbon score series across the entire sample period.

6 *The policy dummy is constructed to capture the impact of key European ESG regulatory and policy milestones. Events encoded include: (1) the release of the HLEG Final Report on 31/01/2018, which laid the foun-*

Macro-financial Control Variables	Controls for market volatility, systemic stress, and energy shocks	VSTOXX (volatility), CISS (systemic stress), and Brent oil prices (energy shocks); sourced from ECB and market data

Source: Author calculations based on data from S&P Capital IQ Pro, Sustainalytics, DitchCarbon, ECB Statistical Data Warehouse, and market sources as detailed in the table.

Beta ESG factor (β_{ESG})**:** This factor measures the sensitivity of asset returns to portfolios sorted by ESG scores. It allows testing for a potential "resilience premium" and captures whether ESG acts as a priced risk or a preference channel (Pástor et al., 2021; Chen et al., 2020). Empirical applications by Gregory et al. (2020), Geczy et al. (2021), and Dobrick et al. (2025) confirm ESG betas as valid factors beyond traditional risks. Chen et al. (2020) develop sentiment-driven ESG betas, while Kumar (2023) finds alpha enhancement in regional markets, with weaker effects in global portfolios. ESG betas remain significant in regional studies, including India (Mohanasundaram, 2024). Overall, ESG betas reflect investor preferences and sustainability-driven return expectations.

Beta environmental factor (β_E)**:** It measures the sensitivity to portfolio returns sorted by environmental valuations (e.g. CO_2 emissions, energy efficiency, and waste management). Environmental risks – especially carbon exposure – drive significant pricing effects via global carbon premiums and tail risks (Bolton & Kacperczyk, 2021; Ilhan et al., 2021). A dynamic greenium emerges when climate policies are perceived as credible (Alessi et al., 2023). Geczy et al. (2021) confirm the central role of environmental factors in ESG pricing models.

Beta social factor (β_S)**:** It measures the sensitivity to social aspects (e.g. workers' rights, safety, and community participation). Evidence is mixed: Bae et al. (2021) find limited protection during COVID-19, while Mohanty & Ivanov (2021) highlight reduced idiosyncratic tail risk. Gregory et al. (2020) and Geczy et al. (2021) incorporate social factors into ESG models, typically within composite scores.

Beta Governance Factor (β_G)**:** It reflects the importance of corporate governance (e.g., board structure, shareholder rights, transparency of reporting). Governance factors significantly influence ESG return patterns and help identify firms with strong internal controls (Ciciretti et al., 2023). Geczy et al. (2021) and Pollard et al. (2017) treat governance as a core component in extended ESG pricing models.

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dation for the EU sustainable finance framework; (2) the launch of the European Green Deal on 11/12/2019, which committed the EU to climate neutrality by 2050; (3) the introduction of SFDR Phase I on 10/03/2021, requiring ESG risk disclosures from financial market participants; (4) the adoption of the EU Taxonomy Climate Delegated Act on 21/04/2021, which defined sustainable economic activities; (5) the ECB's first climate stress test on 08/07/2022; (6) the issuance of EBA ESG risk guidelines on 24/10/2022; (7) the adoption of CSRD Phase I on 05/01/2023, expanding corporate ESG reporting; and (8) the introduction of SFDR Phase II Regulatory Technical Standards on 01/07/2023, which operationalized ESG product classifications and reporting.

This decomposition clarifies which ESG component most strongly influences asset returns and avoids mispricing risks from excessive score aggregation, as warned by Berg et al. (2022) and Tian et al. (2025), who emphasize the risk of mispricing owing to ESG rating divergence. While this study's baseline model uses the composite β_ESG (as in Pástor et al., 2021; Dobrick et al., 2025), E/S/G decomposition is applied in the extended analysis to capture dimension-specific effects more accurately.

Beta Controversy ($\beta_{Controvercy}$)**:** Controversies are incidents, scandals, or violations related to companies' ESG practices. This variable captures the sensitivity of returns to reputational risk factors, based on ESG risk data from sources such as Sustainalytics. Studies show that controversies often trigger return penalties – especially when unexpected or at odds with a firm's perceived ESG profile (Serafeim et al., 2022; Kölbel et al., 2020). Chen et al. (2020) link ESG news shocks to short-term return predictability. Dobrick et al. (2025) confirm controversy effects even after controlling for ESG scores. Pollard et al. (2017) treat controversy as a priced ESG premium, while Gregory et al. (2020) highlight amplified impacts in transparency-sensitive sectors. This variable complements the ESG factor by capturing short-term pricing effects not fully embedded in long-term ESG ratings.

Beta Carbon (β_{Carbon})**:** Carbon exposure is derived from firm-level emissions data (Scopes 1, 2 and 3)[7]. Unlike ESG and Controversy, it is not used for portfolio sorting but is included directly in the return regression to test for a carbon transition premium. Firms with higher emissions may earn higher expected returns as compensation for transition risk (Bolton & Kacperczyk, 2021). Ilhan et al. (2021) emphasize carbon tail risk, while Alessi et al. (2023) highlight that carbon betas shift dynamically with regulatory changes and investor sentiment. The pricing effect varies by intensity measures, construction methods, and market conditions (Bauer et al., 2022; Aswani et al., 2024). Dobrick et al. (2025) find that carbon risk remains significant after controlling for ESG and controversy factors. Pollard et al. (2017) treat carbon transition risk as a distinct, priced factor. Including a carbon-specific variable captures regulatory exposure, pricing mechanisms, and decarbonization pressures overlooked by aggregate ESG metrics.

Regime Dummy: A regime dummy identifies the 2020–2021 period of market stress and regulatory change (e.g., COVID-19 and the EU Green Deal). It interacts[8] with ESG-related betas (social, governance, carbon, controversy) to test for conditional pricing effects. This approach aligns with studies emphasizing time- and policy-sensitive ESG valuation (Albuquerque et al., 2020; Pástor et al., 2021).

7 *Scope 1 (direct emissions), Scope 2 (indirect emissions from purchased energy), and Scope 3 (all other indirect emissions along the value chain).*

8 *A binary regime dummy variable Dt was constructed to capture the 2020–2021 period of heightened market stress and regulatory momentum. This period aligns with the onset of the COVID-19 pandemic, significant volatility in European equity markets, and the formal rollout of the EU Sustainable Finance Disclosure Regulation (SFDR) and Green Taxonomy. The dummy takes the value 1 for all observations from 2020 Q1 through 2021 Q4, and 0 otherwise. This allows the model to test for structural changes in the pricing of ESG-related risk factors during a period of systemic disruption and policy transition.*

Control Variables: To ensure the robustness of the ESG sensitivity estimates, the model includes key macroeconomic control variables, as supported by the literature. Volatility shocks are controlled for using the European market volatility index (VSTOXX index), the European equivalent of the Volatility Index (VIX) and helps isolate ESG-related effects from general market turbulence (Rouwenhorst, 1999; Pástor & Veronesi, 2013; Cederburg & O'Doherty, 2016). CISS, the Composite Indicator of Systemic Stress, measures financial instability across European markets (Hollo et al., 2021; Acharya et al., 2017).

Descriptive statistics (Table 2) indicate sufficient variation across key variables. The *Total Return* exhibits substantial variability, with an average quarterly return of 2.82% and a wide range from -62.93% to +107.61%, which is typical for equity datasets.

Table 2: Summary of descriptive statistics

Variable	N	Mean	SD	Min	Med	Max
Total Return	2744	0.0282	0.1480	-0.6293	0.0261	1.0761
ESG Score	2744	55.3706	17.3474	14.0000	54.0000	91.0000
E-Score	2744	61.4049	20.8914	2.0000	63.0000	98.0000
S-Score	2744	52.0190	18.6720	9.0000	50.0000	95.0000
G&E-Score	2744	54.1990	16.2115	13.0000	52.0000	92.0000
Carbon Score	2744	0.0441	0.1281	0.0000	0.0140	1.0000
ESG Controversy Level	2744	1.5955	0.7333	1.0000	1.0000	4.0000
VSTOXX	2744	0.0814	0.5239	-0.3600	-0.0526	2.4832
CISS	2744	0.5373	2.2926	-0.7152	-0.0323	11.5983
EURIBOR -3M	2744	-0.1345	1.0117	-5.2262	0.0009	1.0413

Source: Author calculations based on data from S&P Capital IQ Pro, Sustainalytics, DitchCarbon, ECB Statistical Data Warehouse, and market sources as detailed in the table.

The dataset covers the quarterly observations of firms using the MSCI Europe ESG Leaders Index between 2018 and 2024. The total return distribution is moderately right-skewed (0.26), with fat tails (kurtosis 5.52), indicating a high likelihood of extreme return events. ESG scores are broadly distributed, with environmental scores typically higher than social and governance scores. The carbon Score distribution is highly right-skewed (5.32) with significant kurtosis (35.99), suggesting a concentration of low-carbon firms, but with a few high-emission outliers. The ESG Controversy variable shows a similar right-skewed pattern. Macro variables such as VSTOXX and CISS exhibit significant volatility and fat tails, consistent with financial stress periods. The panel is balanced and sector-diversified but inherently reflects an ESG selection bias, which favors firms with stronger sustainability profiles and lower controversy exposure.

2.3 Conceptual challenges and insights

One key challenge regarding the integration of ESG factors into asset-pricing models is inconsistent ratings. Different methodologies among providers (MSCI, Sustainalytics, and Refinitiv) lead to varied ESG assessments for the same company, reducing ESG's reliability as a quantitative indicator. Furthermore, ESG factors' correlation with market style variables (size and value) often causes multicollinearity in models. Asset sensitivity to ESG can change owing to market conditions, political cycles, and information shocks. Additional issue is investor heterogeneity. Currently, the model assumes homogeneity, and future versions will address varying investor preferences and constraints. Notably, ESG strategies are increasingly determined by regulatory requirements (e.g., carbon footprint). These aspects will be formalized in extended versions of the model. Hence, this study uses a simplified specification to identify basic relationships. The full implementation, including dynamic coefficients, modes, and investor heterogeneity, will be developed in future work.

3 Methodology

3.1 Empirical model and its testing

This section illustrates how a basic panel regression can capture the key relationships between asset returns and ESG-related factors, even without accounting for interactions, investor segmentation, or macro-regulatory dynamics. The study aims to provide an intermediate analytical bridge between the general specifications of the model and its full implementation, as described in the following sections.

The following model (Eq. 3.1) is used as a simplified version, where $E[R_{i,t}]$ is the expected return on asset *i* at time *t*, $\beta_i^{(k)}$ represents asset i's exposure to risk factor *k*, λ_k denotes the premium associated with factor *k*, and k ∈ {Market, ESG, Carbon, Controversy}

$$E\left[R_{i,t}\right] = \lambda_0 + \sum_{k=1}^{K} \lambda_k \beta_i^{(k)} + \varepsilon_{i,t} \tag{3.1}$$

This formulation assumes that ESG-related characteristics, such as environmental performance or controversy exposure, can influence expected returns in a manner comparable to that of classical risk factors. These factors may act as price risk, quality signals, or investor preference channels. The model is extended by adding $\text{Beta}_{\text{Carbon}}$ and decomposing Beta_{ESG} into its ESG components, which provides greater insight into the underlying sources of variation. However, a moderate inverse correlation exists between $Beta_{ESG}$ and $Beta_{Controversy}$ ($r = -0.53$, $p < .001$). The inclusion of both factors in the model is justified: $Beta_{Controversy}$ reflects a specific reputational dimension not captured by the aggregated ESG indicator, and it shows consistent negative significance in empirical tests. Thus, it adds explanatory power and constitutes a critical component of ESG-related risk assessments.

This base model is based on two hypotheses: (H1) a positive ESG premium and (H2) a negative reputational (controversy) premium. The simplified structure enables clear identification of these effects using fixed- and random-effects estimators. The model follows the Fama-MacBeth two-step estimation approach and assumes a linear dependence of returns on predetermined factor sensitivities. This simplified specification enables the identification of whether ESG and controversy factors are priced without imposing structural assumptions. It maintains interpretability through a linear framework and provides a benchmark for more complex models in future research. Despite its limitations, baseline regression provides a stable foundation for testing the main and secondary hypotheses. The performance and interpretability of ESG-related factors in this framework inform model refinement in the subsequent sections.

3.2 Data processing and portfolio formation

3.2.1 Data Processing, Portfolio Construction, and Factor Design

The dataset contains quarterly firm-level observations from Q1 2018 to Q4 2024 on ESG scores, carbon exposure, and ESG controversies. Only firms with complete time-series data for all three variables are included, resulting in a balanced panel. Firms with missing data are excluded rather than imputed to ensure data integrity. Data diagnostics include descriptive statistics (mean, variance, skewness, kurtosis), distribution checks (histograms, kernel density plots), and multicollinearity tests using variance inflation factors. Stationarity is assessed using panel unit root tests: Levin-Lin-Chu, Im-Pesaran–Shin, and Fisher-type ADF. Nonstationary variables are differenced as needed.

To correct for structural differences across industries, sector-neutral normalization is applied. Firms are grouped by GICS Level 2 sector, and ESG, controversy, and carbon scores are converted into percentile ranks (0–100) within each sector for each quarter. This mitigates sector bias – especially in carbon-intensive industries – and ensures comparability of scores across firms and time. The core ESG and controversy factors are constructed using a portfolio-sorting approach consistent with standard methodologies in ESG asset pricing (Lioui & Tarelli, 2022; Gregory et al., 2020; Pástor et al., 2021).

The ESG factor returns are calculated as follows in Eq. 3.2. The controversy factor return is calculated as in Eq. 3.3.

$$R_{ESG,t} = \frac{1}{N_{high}} \sum_{i \in Top} R_{it} - \frac{1}{N_{low}} \sum_{i \in Bottom} R_{it} \tag{3.1}$$

$$R_{CONT,t} = \frac{1}{N_{low}} \sum_{i \in Low} R_{it} - \frac{1}{N_{high}} \sum_{i \in High} R_{it} \tag{3.2}$$

$$CS_{it} = \frac{Emission_{it} - \min(Emission_t)}{\max(Emission_t) - \min(Emission_t)} \tag{3.3}$$

Carbon exposure is calculated at the firm level (see 3.3) and used as an independent variable in return regressions, not for portfolio sorting. This normalization makes carbon exposure comparable across firms and periods, enabling its direct use in second-stage regressions without portfolio sorting. These factors are used to estimate portfolio betas in the subsequent time-series regressions. Then, the firms are sorted each quarter into nine portfolios using a double-sorting approach: first by ESG scores and then by controversy levels, each divided into terciles (low, medium, high). This structure isolates the joint effects of ESG performance and controversy exposure on returns and tests whether high ESG scores offset reputational risks. Portfolios are rebalanced quarterly to reflect updated ESG and carbon data. Outliers in the top and bottom 1% of carbon and controversy scores are reviewed but not winsorized, as sensitivity checks show minimal impact on results. Portfolio returns are value-weighted by market capitalization to reflect realistic investment practices and reduce small-cap bias.

Returns are calculated as in formula 3.4, where $R_{p,t}$ represents the return on portfolio pat time; $w_{i,t}$ denotes the market capitalization of firm *i* at time *t*; $R_{i,t}$ denotes the total return of firm *i* at time *t*; and $i \in p$ denotes all firms in portfolio *p*.

$$R_{p,t} = \frac{\sum_{i \in p} w_{i,t} \cdot R_{i,t}}{\sum_{i \in p} w_{i,t}} \tag{3.4}$$

The study design reflects a practical balance between cross-sectional diversity and statistical robustness. This aligns with methodologies in recent ESG asset pricing studies, such as Lioui & Tarelli (2022), Gregory et al. (2020), and Pástor et al. (2020/2022), which implement ESG factor portfolios using limited sets of quantile- or factor-based portfolios rather than large firm-level regressions.

3.2.2 Beta Estimation and Second-Stage Modeling

Betas are estimated using two complementary methods to ensure robust results under the constraint of limited quarterly data frequency:

1. Fama-MacBeth Two-Stage Procedure (Rolling Betas): A two-stage Fama-MacBeth procedure is used to estimate portfolio-level betas via rolling eight-quarter regressions, following Ilhan et al. (2021) and Ciciretti et al. (2023). While traditional asset pricing studies use longer rolling windows (30–60 observations) made possible by high-frequency data, ESG research typically relies on quarterly or annual updates. This lower frequency limits the available time series length. Accordingly, the literature accepts shorter rolling windows – commonly 8–12 quarters – to accommodate the slower update cycles of ESG and carbon data.[9]

Step 1.a $$R_{i,t} = \alpha_t + \beta_i^{mkt} F_t^{mkt} + \beta_i^{ESG} F_t^{ESG} + \beta_i^{CONT} F_t^{CONT} + \ldots + \varepsilon_{i,t} \tag{3.5}$$

Here, $R_{i,t}$ is the return on asset *i* at time *t*, and F_t represents factor realizations. The estimated betas reflect each portfolio's sensitivity to market, ESG, controversy, and, later, carbon.

2. Kalman Filter (Time-Varying Betas): Alessi et al. (2023) use a Kalman filter to estimate time-varying betas. Unlike rolling windows, it updates estimates as new data arrive by combining prior information with current returns in a Bayesian state-space framework, typically expressed in Eq. 3.6:

Step 1.b $$\begin{cases} R_{i,t} = \alpha_t + F_t' \beta_{i,t} + \varepsilon_{i,t} & \text{Measurement Equation} \\ \beta_{i,t} = \beta_{i,t-1} + \nu_{i,t} & \text{Transition Equation} \end{cases} \tag{3.6}$$

Where $R_{i,t}$ represents portfolio return at time *t*, α_t represents an intercept (can be time-varying or fixed), F_t' defines vector of observed factor realizations (e.g., market, ESG, controversy) and $\beta_{i,t}$ represents a vector of time-varying betas. Normally distributed measurement noise and process noise are denoted $\varepsilon_{i,t}$ and $\nu_{i,t}$, respectively. The Kalman filter is well-suited for lower-frequency data, such as quarterly ESG scores, as it avoids fixed window selection and yields smoother, more stable beta estimates. However, its application requires more complex modeling and stronger assumptions, which may limit its practical applicability. To enhance robustness, this study applies both the Fama-MacBeth and Kalman filter methods in parallel, reducing reliance on a single technique. Combined with sector-neutral adjustments, this dual-beta approach supports meaningful cross-sectional variation and aligns with best practices in ESG asset pricing literature.

In the second step, these estimated betas are used in panel regressions to test pricing effects (Eq. 3.7 below). The coefficients λ reflect the extent to which exposure to each factor is compensated for or penalized in expected returns.

Step 2 $$R_{i,t} = \lambda_0 + \lambda_1 \widehat{\beta_{i,t}^{mkt}} + \lambda_2 \widehat{\beta_{i,t}^{ESG}} + \lambda_3 \widehat{\beta_{i,t}^{CONT}} + \ldots + u_{i,t} \tag{3.7}$$

3.2.3 Model extensions: Regime sensitivity and macro controls

This study extends the model by interacting ESG-related betas with a regime dummy[10] for the 2020–2021 stress period to capture conditional pricing effects. This approach identifies ESG-related risk premia without assuming specific investor preferences or market equilibrium. To account for broader conditions, the model includes macro-

9 *The initial dataset spanned from 2015 to 2024. However, 2015 to 2017 is excluded owing to incomplete or inconsistent availability of ESG subcomponent scores and carbon emission data across firms. Beginning in 2018 ensures full coverage and comparability across all explanatory variables.*

10 *A regime dummy variable is defined to identify the 2020–2021 period, representing heightened market stress and regulatory momentum (COVID-19, EU Green Deal rollout). This dummy is interacted with each ESG-related beta to capture regime-dependent return sensitivities.*

financial controls: VSTOXX (volatility), CISS (systemic financial risk), and Brent oil prices (energy shocks relevant to carbon-intensive firms). These controls help isolate ESG effects from macroeconomic noise.

$$E[R_{i,t}] = \alpha_i + \gamma_t + \beta' X_{it} + \delta' (X_{it} \times D_t) + \Phi' Z_t + \varepsilon_{it} \tag{3.8}$$

The resulting specification is a regime-sensitive, macro-adjusted panel model expressed as in Eq. 3.8., where: X_{it} represents a vector of ESG-related factor exposures; β represent the unconditional (baseline) factor loadings. D_t represents the regime dummy (1 if 2020–2021, 0 otherwise). δ' represents the incremental factor loadings during the regime. $X_{it} \times D_t$ represents elementwise interaction of each ESG beta with the regime indicator. $\Phi' Z_t$ represents the vector of macro-financial control variables (VSTOXX, CISS, Brent oil prices) and their associated loadings, capturing the impact of market volatility, systemic financial stress, and energy price fluctuations on asset returns. α_i captures firm-specific effects (fixed effects) and γ_t denotes optional time effects.

The suggested model enables consistent comparisons across models with different sets of risk factors, including ESG decomposition and carbon exposure, while accounting for key external shocks. It tests whether ESG and related exposures are priced systematically, and whether these effects amplify, diminish, or reverse under macrofinancial stress or regulatory transitions. This model serves as a testing ground for different beta combinations and estimator types before introducing more dynamic specifications in future work.

While the fixed-effects estimator and macro-financial controls reduce omitted-variable bias, potential endogeneity between ESG performance and asset returns cannot be entirely ruled out. Reverse causality may arise if firms with strong market performance subsequently improve their ESG standing or disclosure. To mitigate this, the study constructs ex-ante factor portfolios and employs lagged beta estimation, which limit simultaneity effects. Nevertheless, future research could extend the model using instrumental variables or dynamic panel techniques to test the causal direction of ESG premia more formally.

4 Results

4.1 Preliminary data analysis

Table 2 presents descriptive statistics for the raw variables prior to factor construction, including skewness and kurtosis to assess distributional properties. The ESG Leaders sample inherently favors firms with higher ESG scores, lower carbon intensity, and fewer controversies, limiting generalizability to the broader European market. Carbon scores and controversy variables exhibit extreme right-skewness, indicating potential outlier influence on factor estimates. To address this, subsample robustness checks are conducted for high-carbon and high-controversy firms. The index-based structure and sector portfolios raise the risk of cross-sectional dependence due to shared exposure to macro shocks and policy changes. To address this, fixed effects estimators with clustered standard errors are applied. Fat tails, common shocks, and sample selection bias warrant caution in interpreting the magnitude and stability of ESG and carbon premiums.

4.2 Portfolio formation and factor construction

Table 3 presents summary statistics for factor returns across the nine ESG–controversy portfolios. Mean returns are positive, with the highest in Q2_C3 (4.30%) and the lowest in Q3_C2 (–0.44%), suggesting overall value added by ESG and controversy factors. Volatility, as measured by the standard deviation, ranges from 9.5% (Q3_C2) to 21.4% (Q1_C3), indicating varying levels of return dispersion and risk. Both low-risk (e.g., Q3_C1) and high-risk portfolios (e.g., Q1_C3) reflect different sensitivities to ESG and controversy exposure. Although detailed skewness and kurtosis are not reported, prior analysis indicates non-normal return distributions in several portfolios, with some exhibiting fat tails and downside risk asymmetries. These characteristics highlight the heterogeneous risk-return profiles driven by ESG and controversy sorting.

Table 3: Summary of descriptive statistics

Portfolio	Mean Return	Std. Dev.	Minimum	Maximum	N
Q1C1	0.02496	0.12256	–0.25182	0.35370	44
Q1C2	0.03852	0.10954	–0.20043	0.23909	48
Q1C3	0.02647	0.21399	–0.24521	1.07607	48
Q2C1	0.03578	0.13257	–0.40932	0.40815	52
Q2C2	0.02563	0.10151	–0.27231	0.23269	44
Q2C3	0.04299	0.16066	–0.40187	0.48146	36
Q3C1	0.02631	0.10153	–0.12130	0.29472	44
Q3C2	–0.00440	0.09534	–0.17294	0.23916	48
Q3C3	0.03230	0.12252	–0.24505	0.22006	44
Total	0.02726	0.13291	–0.40932	1.07607	408

Source: Author calculations based on portfolio-level returns constructed from ESG and controversy score-sorted portfolios using S&P Capital IQ Pro data and Sustainalytics ESG controversy metrics.

Before estimating rolling betas and applying the Kalman filter, the factor return series is winsorized to improve robustness. Unlike trimming, winsorization caps extreme values (e.g., at the 2.5th and 97.5th percentiles), preserving sample size while reducing outlier influence. This step is essential, as both methods are sensitive to extreme values that can distort time-varying estimates, especially under rare ESG shocks or market anomalies.

4.3 Beta estimation: Rolling vs. Kalman comparison

To capture the dynamic nature of factor exposure, the study applies both rolling window regressions and Kalman filtering. This dual approach balances responsiveness with stability in capturing portfolio sensitivities to ESG and market risks. Table 4 compares the two methods across key factors: market, ESG, carbon, control variables, and macro-volatility proxies (CISS and VSTOXX).

Table 4: Summary statistics – Kalman vs. Rolling betas

Factor	Kalman Mean	Rolling Mean	Kalman Std Dev	Rolling betas	Interpretation
Market	0.0532	0.8931	0.0407	2.2411	Rolling betas are much more reactive to short-term market shocks
ESG Factor	-0.0193	0.0650	0.0341	1.7615	Rolling shows short-term ESG tilt; Kalman sees slightly negative trend
Controversy Factor	0.0107	-0.0388	0.0297	2.0781	Kalman sees small positive loadings; Rolling fluctuates negatively.
Carbon Score	-0.0531	-135.1113	0.0471	4,616.3210	Rolling is still unstable even after z-scoring – Kalman is reliable
CISS	0.0023	0.0188	0.0171	0.2643	Systemic stress factor is more sensitive in rolling windows
VSTOXX	-0.0821	-0.0461	0.0433	0.9412	Both negative – Kalman stronger on volatility aversion.

Source: Author's estimates using Kalman filter and rolling window regression applied to MSCI ESG Leaders Index data, with macro variables from ECB and market sources.

The comparison indicates that Kalman filtering generates smoother and more stable beta trajectories, characterized by lower standard deviations across all factors. By contrast, rolling window estimates exhibit elevated short-term sensitivity to volatility and noise – particularly for carbon and controversy betas – even after normalization. Kalman filtering is more effective at capturing structural trends, such as persistent negative loadings on carbon and a weak ESG tilt, whereas rolling regressions may distort underlying exposures due to lag structures and heightened sensitivity to outliers. This analysis shows that Kalman filtering offers a favorable balance between stability and adaptability, making it particularly well-suited for estimating time-varying exposures to ESG and macroeconomic factors. Its effectiveness, however, depends on appropriate model specification and filtering assumptions. In contrast, rolling regressions – while non-parametric and conceptually straightforward – are more sensitive to outliers and regime shifts. This comparison, especially with ESG, carbon, and controversy exposures, builds on prior work (e.g., Feng, 2022) by illustrating how estimation technique affects beta stability and interpretability. The study addresses a key gap by demonstrating that in noisy, low-frequency ESG datasets, Kalman filtering improves robustness and signal clarity. These improvements are critical for capturing evolving investor preferences and for informing second-stage panel regressions that assess pricing dynamics across regimes and investor types.[11]

4.4 Panel regression results (Core model selection)

The regression results (Table 5) reveal a clear progression in explanatory power and model quality as the factor structure becomes more refined across Models 1 to 5. Model 5, which includes disaggregated ESG betas alongside carbon and macroeconomic variables, significantly outperforms earlier models. It achieves an R^2 value of 0.4917, indicating that half of the variation in portfolio returns can be explained by the model. By contrast, Models 1–4 yield lower R^2 values (below 0.1), highlighting that simple or aggregated ESG specifications fail to effectively capture the drivers of return variation.

11 *The study's findings are robust to alternative beta estimation methods and model diagnostics. The comparison between rolling and Kalman-filtered betas provides internal validation of factor stability, while the exclusion of weakly cointegrated variables (such as VSTOXX) improves statistical consistency. Nevertheless, the relatively small and high-quality ESG Leaders sample limits generalizability. Future replications using broader firm universes or multiple ESG data providers would further test the stability and external validity of these results.*

Table 5: Model specification selection

Metric / Test	Model 1	Model 2	Model 3	Model 4	Model 5
R^2 within	0.0079	0.0421	0.0079	0.0823	0.4917
AIC	–252.565	–259.413	–250.575	–264.202	–413.114
BIC	–241.977	–245.296	–236.457	–239.496	–388.408
Hausman χ^2 (FE vs RE)	$\chi^2 = 2.23$, $p = 0.526$	$\chi^2 = 6.39$, $p = 0.172$	$\chi^2 = 2.25$, $p = 0.691$	$\chi^2 = 11.44$, $p = 0.120$	$\chi^2 = 27.61$, $p < 0.001$
LM test (RE vs OLS)	$\chi^2 = 0.00$, $p > .99$	$\chi^2 = 0.00$, $p > .99$	$\chi^2 = 0.00$, $p > .99$	$\chi^2 = 0.00$, $p > .99$	$\chi^2 = 0.00$, $p > .99$
FE Preferred?	Yes*	Yes*	Yes*	Yes*	Yes
Beta_ESG	9.92 (0.228)	—	9.93 (0.229)	—	—
Beta_E	—	—	—	—	24.27 (0.013)
Beta_S	—	3.17 (0.026)	—	4.76 (0.002)	21.64 (0.001)
Beta_G	—	3.79 (0.022)	—	3.92 (0.082)	26.72 (0.007)
Beta_ Controversy	–3.43 (0.531)	2.96 (0.167)	–3.41 (0.531)	3.90 (0.200)	–0.96 (0.887)
Beta_ Carbon	—	—	–0.55 (0.895)	0.50 (0.946)	–0.96 (0.887)
Beta_CISS	—	—	—	–3.97 (0.103)	–0.12 (0.959)
Beta_ VSTOXX	—	—	—	–0.33 (0.965)	–4.05 (0.088)

** FE retained based on theoretical considerations (potential correlation between unobserved effects and regressors, small N large T structure, and preference for robust clustered inference), despite the Hausman test not rejecting RE.*

Source: Author estimates from panel regression models using fixed effects (FE) and random effects (RE) specifications. Data based on ESG factor exposures and macro-financial variables sourced from S&P Capital IQ Pro, Sustainalytics, DitchCarbon, and ECB Statistical Data Warehouse.

This pattern is further corroborated by the model selection criteria. Model 5 exhibits the lowest AIC (–413.11) and BIC (–388.41) among all specifications, demonstrating a superior fit despite its increased complexity. The steady improvement in both the AIC and BIC from Models 1 to 5 supports the value of including granular ESG components and macrofinancial controls in asset pricing. Statistical tests for the model choice reinforce these findings. Although the LM test fails to reject the null hypothesis in all models – suggesting no strong preference for random effects over pooled OLS – the Hausman test favors the fixed effects specification in Model 5 ($\chi^2 = 27.61$, $p < .001$). This indicates that unobserved heterogeneity correlates with the regressors and that the FE estimation is appropriate. Regarding factor-specific results, the aggregate ESG betas in Models 1 and 3 are statistically insignificant ($p > .2$), highlighting the limitations of composite ESG scores. This aligns with the growing academic consensus that aggregation may mask heterogeneity across the E, S, and G pillars. When disaggregated in Model 5, all three ESG components exhibit strong and statistically significant loadings: the environmental beta is 24.27 ($p = .013$), the social beta is 21.64 ($p = .001$), and the governance beta is 26.72 ($p = .007$). These findings demonstrate that separating the ESG dimensions provides more accurate estimates and deeper insights into how each factor contributes to returns. By contrast, the controversy and carbon betas remain statistically insignificant across all specifications, suggesting their influence may be nonlinear or conditional – only emerging under specific market regimes. The inclusion of macroeconomic factors such as the systemic stress index (CISS) and market volatility (VSTOXX) enhances the model. VSTOXX exhibits marginal significance in Model 5 ($\beta = -4.05$, $p = .088$), suggesting a potential pricing of volatility aversion in ESG-aligned portfolios. Taken together, these results support the conclusion that a disaggregated ESG model, supplemented by macro and volatility risk controls, yields more meaningful insights. Model 5 captures greater return variation and reveals statistically significant ESG channels that remain hidden in simpler models. This approach strengthens disaggregated and dynamic ESG factor modelling, advances prior literature, and offers a more robust framework for future empirical applications.

Although the initial specifications of Model 5 included both macro risk factors (CISS and VSTOXX), the final version of the regime-augmented model excludes VSTOXX. This decision is based on two diagnostic tests. First, Pesaran's (2004) test for cross-sectional dependence confirms the presence of significant interdependence across portfolio returns (CD statistic = 8.643, $p < .001$), suggesting that global and macro shocks affect all portfolios simultaneously. Second, Westerlund's (2007) ECM panel cointegration test[12] is used to determine whether the specified covariates form a long-run equilibrium relationship with returns. The model that includes CISS but excludes VSTOXX yields mixed cointegration evidence: the Pt statistic is –11.090 ($p = .013$), indicating rejection of the null

12 *The Westerlund test includes four statistics, among which the Pt statistic is often considered the most powerful in small samples and is particularly sensitive to panel-wide cointegration. In the results, Pt = –11.090 (p = .013) when CISS is included, supporting long-run equilibrium. Conversely, inclusion of VSTOXX yields Pt = –9.676 (p = .206), indicating failure to reject the null of no cointegration.*

hypothesis of no cointegration, whereas other statistics (e.g., Ga and Pa) are insignificant. By contrast, when VSTOXX is included, all four statistics fail to reject the null hypothesis ($Pt = -9.676$, $p = .206$), weakening the evidence for a stable long-run relationship. Based on this, only CISS is retained as a macro control in the final specification, prioritizing statistical consistency and interpretability over the inclusion of weakly cointegrated variables.

4.5 Policy regime interaction

To examine whether ESG-related risk exposure varies across market conditions, Model 5 is extended by integrating a policy regime dummy variable that captures the stress/transition period from 2020Q1 to 2021Q4, which coincides with the COVID-19 pandemic and heightened ESG-related policy intervention in Europe. This binary variable interacts with the environmental (Beta_E), social (Beta_S), governance (Beta_G), and carbon (Beta_Carbon) factor loadings to assess whether pricing effects are amplified or diminished under policy stress. By embedding these interaction terms directly into the regression framework, the model allows for conditional factor premiums, distinguishing baseline return sensitivities from those observed during systemic transitions. This augmentation of Model 5 enables the testing of time-varying ESG pricing and provides insight into whether investor preferences or market valuations of ESG dimensions change in response to macroeconomic shocks.

Table 6: Policy regime interaction model

Factor	Base Period	Stress Int. Coeff.	Net Effect (Stress Period)	p-value (Net)
Beta_E	17.18 (0.000)	19.08 (0.018)	36.26	< .001
Beta_S	17.04 (0.000)	13.91 (0.047)	30.95	< .001
Beta_G	19.62 (0.000)	12.89 (0.069)	32.50	< .001
Beta_Carbon	–0.06 (0.992)	–12.02 (0.252)	–12.08	.095
Beta_Market	–1.43 (0.376)	—	—	—
Beta_CISS	–1.11 (0.046)	—	—	—

Source: Author's estimates using interaction panel regressions between ESG betas and a stress-period policy dummy. Data sourced from S&P Capital IQ Pro, Sustainalytics, DitchCarbon, and ECB/market databases.

Under normal market conditions, the coefficients on Beta_E, Beta_S, and Beta_G are positive and statistically significant at the 1% level. This finding suggests that a higher exposure to ESG factors is associated with superior portfolio performance during stable periods. By contrast, the coefficient of the carbon score (Beta_Carbon) is not statistically significant, implying that carbon intensity does not appear to be priced under normal conditions. The systemic risk proxy (CISS) has a negative and statistically significant coefficient (p = .046), indicating that portfolios more exposed to macro-stress tend to underperform, even outside the stress regime.

The interaction terms between the ESG factors and the stress regime dummies, Beta_E_reg, Beta_S_reg, and Beta_S_reg, are also positive, with p-values of .018, .047, and .069, respectively. These results indicate that during the stress period, the positive return premium associated with ESG exposure became even stronger. This could reflect a shift in investor preferences toward sustainable assets, driven by both heightened uncertainty and expanding policy support for ESG-aligned investments. Although the interaction term for carbon (Beta_Carbon) is not statistically significant (p = .252), it is negative, and the combined net carbon effect during the stress period is marginally significant at the 10% level (–12.08, p = .095). This finding provides partial evidence of an emerging carbon penalty under stressed or transition-oriented market regimes. The combined effects estimated using lincom[13] further clarify this pattern. During the stress period, the environmental, social, and governance betas increased to 36.26, 30.95, and 32.50, respectively, all statistically significant at p < .001. These amplified betas highlight the growing return premia associated with ESG characteristics during crises. Simultaneously, carbon becomes more negatively associated with returns, reinforcing the hypothesis that investors penalize high-carbon portfolios as climate transition risks become more salient.

Overall, these findings support the hypothesis that crisis periods catalyze ESG repricing through behavioral channels (e.g. investor preference shifts), structural realignment (e.g. capital reallocation), and policy mechanisms (e.g. green recovery packages and regulatory signals). By integrating regime-sensitive effects into the beta structure, the model demonstrates that ESG risk pricing is dynamic and varies significantly across market conditions.

5 Discussion

The empirical patterns observed here are consistent with theoretical frameworks that interpret ESG premia as emerging from both risk-based and preference-driven mechanisms. Within equilibrium models such as Pástor et al. (2021), ESG demand by sustainability-oriented investors shifts relative prices and expected returns even without new risk exposure, while in heterogeneous-belief settings like Avramov et al. (2022), investors' subjective ESG valuations generate cross-sectional return differentials. The amplification of ESG premia during stress regimes in this study thus reflects both enhanced risk compensation for sustainable assets and stronger investor-preference effects under uncertainty.

13 The lincom command in STATA is short for "linear combinations of estimators." It is used to compute and test the combined effect of multiple regression coefficients, often involving interaction terms.

This study confirms that ESG-related factors are priced in European equity markets; however, their effects differ in magnitude, direction, and stability across components and regimes. Disaggregated ESG betas exhibit strong and statistically significant return premia under both baseline and stress regimes, with coefficients nearly doubling during the 2020–2021 transition period. Conversely, reputational risk (measured via the ESG Controversy factor) is negatively priced but lacks robustness in baseline models, gaining partial significance only under stress. Carbon exposure, although insignificant in the unconditional models, becomes negatively priced under the policy stress regime, suggesting the emergence of a transition risk penalty. These findings support the hypothesis that ESG pricing is component-specific, regime-dependent, and influenced by both market conditions and investor perception shifts. This study also demonstrates that the ESG premium estimation is highly sensitive to model specifications, particularly the decomposition of ESG factors and the inclusion of regime interaction terms.

The positive return premia with disaggregated E, S, and G betas are consistent with the findings of Ciciretti et al. (2023) and Geczy et al. (2021), who demonstrate that ESG subcomponents are more stable and interpretable when modelled separately. The coefficients – specifically governance ($\beta \approx 26.7$, $p < .01$) and social ($\beta \approx 21.6$, $p < .01$) – exceed those in Gregory et al. (2020) and Dobrick et al. (2025), suggesting that a sector-neutral, portfolio-based approach may enhance signal strength, particularly under stress.

Unlike Friede et al. (2015) and Nagy et al. (2016), who report weak and unstable ESG premiums using aggregate scores, this study finds that decomposition significantly increases explanatory power (with R^2 increasing from 0.08 to 0.49). This validates the findings of Lioui & Tarelli (2022), who emphasizes that factor construction critically affects both the magnitude and significance of ESG pricing.

Factor stability is a key issue in literature. Avramov et al. (2022) and Pástor et al. (2022) highlight that ESG-related coefficients tend to be weak or unstable unless regime interactions, investor heterogeneity, or time-varying betas are included. Our regime-augmented model confirms this: the environmental beta doubles during stress (from $\beta = 17.2$ to $\beta = 36.3$, $p < .001$), and the social and governance effects also intensify significantly. These dynamics are consistent with the findings of Albuquerque et al. (2020) and Ramelli & Wagner (2020), who argue that ESG resilience becomes particularly valuable in crisis conditions.

Conversely, carbon exposure shows non-significance in unconditional regressions – mirroring mixed evidence reported in Aswani et al. (2024) and Bauer et al. (2022) – but becomes negative and marginally significant under stress ($\beta \approx -12.08$, $p = .095$), supporting the transition risk channel outlined in Bolton and Kacperczyk (2021). This divergence suggests that carbon premia are non-linear but contingent on a political-regulatory context, consistent with the findings of Pedersen et al. (2021) and Guo et al. (2024).

This study constructs ESG beta using rolling and Kalman-filtered estimates of portfolio-sorted returns, rather than static factor loadings or ESG ratings directly, to capture time-varying ESG sensitivity. This method follows Ilhan et al. (2021) and Alessi et al. (2023)

and addresses the stability problems raised by Feng et al. (2022) and Pollard et al. (2017) by mitigating noise from raw ESG scores and rating divergence (cf. Berg et al., 2022). Compared with studies using firm-level regressions (e.g., Naffa & Fain, 2022), this approach avoids multicollinearity with size and profitability and provides cleaner estimates of ESG factor effects.

Concerning reputational risk, the findings partially support those of prior studies. While Ilhan et al. (2021) and Kölbel et al. (2020) find significant and persistent negative return effects from controversies, the baseline model is insignificant, with stronger signals emerging only under stress regimes. This divergence may reflect differences in data sources (using Sustainalytics-based tercile portfolios) and market contexts (a European, sector-neutral, and ESG-screened sample). Nonetheless, the direction of the effect remains consistent: firms with high controversy exposure face return penalties, particularly when market uncertainty increases.

This study's key strength lies in its integration of methodological clarity (disaggregated ESG betas, sector-neutral sorting, and rolling/Kalman estimation) with regime-aware panel modelling. The fixed-effects specification demonstrates superior robustness and model fit. Unlike most studies, which rely on composite ESG scores, this study demonstrates that component-level exposures are both interpretable and empirically stable, particularly under macrofinancial stress.

For policy and asset managers, the results suggest that ESG premiums intensify as policy support and uncertainty increase. This finding reinforces the importance of considering the macro-institutional context in ESG integration. Climate risk exposure (carbon beta) is not always priced, unless it interacts with regulatory shifts, highlighting the need for dynamic conditional models. Similarly, reputational risk may require contextual triggers (e.g., regulatory or media shocks) to manifest in returns.

From a modeling perspective, this study contributes to the transition from static linear models toward conditional factor-decomposed structures. Future directions include interacting ESG betas with investor types, policy constraints, or sector characteristics, and extensions identified for further empirical development.

Conclusion

This study shows that ESG factors are not priced uniformly but instead exhibit conditional and component-specific return premia in European equity markets. Using a two-stage Fama–MacBeth framework and dynamic beta estimation, the results demonstrate that disaggregated ESG exposures are significantly priced, particularly during periods of systemic stress and regulatory transition. By contrast, carbon intensity and reputational risk, proxied through controversy exposure, are not consistently priced under baseline conditions but display sensitivity to regime dynamics.

These findings contribute to the ongoing debates over the theoretical role of ESG in asset pricing, supporting the perspective that ESG factors operate as both priced risk and investor preference channels contingent on the market context. The results caution against the use of aggregate ESG scores in pricing models, as they may obscure the distinct and time-varying influence of ESG subcomponents. Practically, the evidence suggests that investors may increasingly favor ESG-aligned firms during periods of heightened uncertainty or policy changes, reinforcing the need for asset managers to adopt context-sensitive ESG integration strategies. The emergence of a conditional carbon penalty also underscores the growing materiality of climate transition risk under regulatory regimes such as the EU Green Deal and Corporate Sustainability Reporting Directive (CSRD). These findings reinforce the relevance of EU sustainable finance legislation – particularly the CSRD and SFDR – in shaping market recognition of ESG and carbon-related risks.

Future research should extend this framework by incorporating investor segmentation, nonlinear preferences, and policy-specific carbon-pricing mechanisms. As ESG disclosures become more standardized under the CSRD and related frameworks, broader and more granular datasets – spanning additional countries, sectors, and rating providers – will enable more robust and generalizable ESG pricing analyses. Expanding the sample beyond the ESG index constituents and increasing the number of factor portfolios could further validate these findings, whereas the integration of multiple ESG data sources would allow the testing of rating divergence and institutional effects. This study provides a replicable foundation for such advances.

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