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# CLIMATE ACTION AND COST OF EQUITY: EXAMINING THE RELATIONSHIP BETWEEN ENVIRONMENTAL INITIATIVES AND EQUITY FINANCING OF EUROPEAN COUNTRIES

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**Abstract**

This thesis investigates the relationship between climate action and the cost of equity (CoE), analyzing data from 289 European firms (2018-2022). Climate action is represented by emission intensity, waste intensity, and renewable energy share. The adjusted Fama-French model identifies positive factor loadings for sustainable portfolios, indicating systematic sustainability risk premia and an associated CoE increase. In contrast, unsustainable portfolios exhibit negative factor loadings, resulting in lower CoE values. The finding for emission intensity is supported by the hybrid firm-level approach, developed in this thesis and employing panel data regression. These results suggest dual investor behavior and further research.

**Key words:** Climate Action, Cost of Equity, Systematic and Idiosyncratic Risk, Fama-French Factor Model, Panel Data Regression Model

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# 1. Introduction

Climate change poses a systemic risk to global economies and financial markets. Carbon-intensive companies face increasing regulatory measures, such as carbon pricing and emission caps, combined with growing market pressures that threaten future cash flows (Trinks et al. 2022; Ansar, Caldecot, and Tilbury 2013). Investors respond by reallocating capital from high-emission firms to sustainable alternatives, emphasizing the financial relevance of climate-related risks (Trinks et al. 2022). This dynamic underscores the financial market's role in supporting a low-carbon transition and highlights the interplay between climate risks and equity financing (Intergovernmental Panel on Climate Change 2018; United Nations Framework Convention on Climate Change 2015a).

While much of the existing literature focuses on the relationship between companies' equity costs and "carbon risk", broader environmental initiatives remain underexplored. Symbolic metrics, such as ESG ratings or disclosure indicators, dominate analyses but often fail to provide direct insights into actual environmental impacts (Chatterji, Levine, and Toffel 2009; Trinks et al. 2022). This thesis addresses this gap by focusing on three measurable and actionable climate variables: emission intensity, waste intensity, and the share of renewable energy consumption. These variables offer practical, quantifiable insights into firms' environmental practices, providing an alternative to abstract ESG metrics. The core objective of this thesis is twofold: to examine whether these climate variables reflect systematic or idiosyncratic risks and to assess their impact on equity financing through the CoE. By analyzing CoE, this thesis examines how investors balance the risks and opportunities associated with sustainability, reflecting their compensation demands for systematic risks and recognition of proactive environmental strategies (Bui, Moses, and Houqe 2019; Y.-B. Kim, An, and J. D. Kim 2015)

To achieve these objectives, the thesis employs two distinct methodologies on a dataset of 289 European firms spanning 2018–2022. First, the Fama-French approach, extended with SMUN factors (Sustainable Minus Unsustainable), using the climate variables mentioned above, which evaluate whether sustainability risks are systematically priced in financial markets. SMUN factors capture return differentials between sustainable (SU) and unsustainable (UN) portfolios, reflecting systematic sustainability risk premia. The approach also considers how investor perceptions of sustainability influence systematic risk pricing and the CoE. Second, a hybrid firm-level approach developed specifically for this thesis, which adapts Fama-French factors to the firm level, enabling granular analysis of idiosyncratic risks. By directly linking climate variables to CoE through dynamic and static panel regressions, this approach provides insights into how firm-specific environmental initiatives impact equity financing.

This thesis begins with a theoretical background on climate challenges and climate action, followed by a literature review on the impact of climate variables on the Cost of Equity (CoE). It then delves into the data and methodological approaches, outlines the hypotheses for both approaches, and presents the corresponding results. The thesis concludes with a discussion of the findings, methodological limitations, and potential directions for future research. Throughout this thesis, the terms *environmental initiatives* and *climate action* are used interchangeably to describe the overarching concept of environmental efforts undertaken by firms. These efforts are represented by the three aforementioned *climate variables*, which are also referred to as *climate action variables, environmental variables* or *sustainability variables.* The terms *share of renewable energy consumption, share of renewable energy,* and *renewable energy share* are also used synonymously.

## 2. Background and Context

### 2.1 Scientific Basis: Understanding Climate Challenges

Issues such as rising sea levels, extreme weather events, and ecosystem degradation driven by human-induced global warming, are affecting regions worldwide (OECD 2021a, 10; Wu and Lei Chen 2024, 21). Global warming refers to the sustained rise in Earth's average temperature due to the accumulation of greenhouse gases such as carbon dioxide ($CO_2$), methane ($CH_4$), and nitrous oxide ($N_2O$) (Wu and Lei Chen 2024, 22). Human activities – including the "burning [of] fossil fuels, unsustainable energy and land use, and untenable consumption and production patterns" (United Nations Department of Economic and Social Affairs 2023, 38) – are the primary drivers of global warming through their impact on greenhouse gas (GHG) emissions. Energy production alone contributes approximately 75% of global greenhouse gas emissions, primarily from coal, oil, and natural gas (International Energy Agency 2023). Deforestation exacerbates the problem by reducing the Earth's capacity to store carbon, while industrial activities release pollutants that further accelerate warming. Additionally, marine plastic waste disrupts ocean ecosystems, weakening their ability to sequester carbon and contributing to biodiversity loss. Methane, which is 25 times more potent than $CO_2$ and responsible for 0.5°C of current warming, originates from key sectors such as agriculture, fossil fuel extraction, transportation, and waste management. The waste sector accounts for 20% of methane emissions globally caused by human activities (Siegel 2022; International Energy Agency 2021, 2020). These examples underscore the diverse and interrelated ways human activities drive global warming and the necessity to change these patterns to avoid alarming consequences.

### 2.2 Frameworks and Definitions for Climate Action

Climate action refers to the measures and strategies implemented to mitigate climate change and adapt to its impacts (OECD 2024b). It encompasses a wide range of activities, including the reduction of GHG emissions, the transition to renewable energy sources, and the enhancement of resilience in communities and ecosystems (Winkelmann et al. 2022; OECD 2021a). Initiatives such as the Paris Agreement and the 2030 Agenda for Sustainable Development aim to address the goals of Climate Action (OECD 2021a, 13). The Paris Agreement underscores the need to limit "the increase in the global average temperature to well below 2°C" (United Nations Framework Convention on Climate Change 2015b, 3–4). Sustainable Development Goal (SDG) 13 emphasizes the urgency of combating climate change and its interconnectedness with global development and human well-being (United Nations Department of Economic and Social Affairs 2023). It calls for integrating climate resilience and mitigation efforts into both national policies and corporate strategies, fostering sustainability and human prosperity (Uitto, Puri, and van Berg 2017, 1–13). While SDG 13 and the Paris Agreement set broad global objectives, the Climate Action Index (CAI) provides actionable tools on a domestic level (OECD 2021b, 24). The CAI evaluates countries' climate efforts to support the Paris Agreement objectives. It tracks policy progress, enables cross-country comparisons, and facilitates statistical analysis to assess policy effectiveness (ibid.), while focusing on metrics such as emissions trends, energy efficiency and renewable energy adoption. For a comprehensive discussion on why emission intensity, waste intensity, and renewable energy share were chosen as climate action variables, and their alignment with the theoretical framework in this chapter, see **Appendix 01**. It further explains the derivation, relevance to CAI metrics, and corporate-level adaptation of these variables, providing essential context for their role in this thesis.

## 3. Literature Review – Impact of Climate Variables on CoE

The relationship between climate variables and CoE has been widely studied, emphasizing how environmental performance influences investor risk perceptions and required returns. This review examines the effects of emission intensity, waste intensity, and share of renewable energy consumption, categorizing findings into positive, negative, and no significant impacts, while highlighting key gaps in the literature.

### 3.1 Effects of Emission Intensity

A strong positive relationship between emission intensity and CoE is evident in many studies, with different methodologies employed to calculate CoE. Studies from Y.-B. Kim, An, and

J. D. Kim (2015), Bui, Moses, and Houqe (2019) and Li, Eddie, and Liu (2014) utilized PEG-based models, which focus on firm earnings and growth rates. Y.-B. Kim, An, and J. D. Kim analyzed 379 South Korean firms from 2007 to 2011, demonstrating that higher carbon intensity significantly increased CoE, particularly for energy-intensive industries. Li, Eddie, and Liu (2014) also identified a positive relationship between carbon emissions and CoE, highlighting investor penalties for environmentally harmful practices. Similarly, Bui, Moses, and Houqe (2019) investigated 34 countries and reported a statistically significant positive association between higher emission intensity and CoE, while controlling systematic risks using CAPM-based adjustments. Other studies relied on CAPM-based CoE approaches to assess CoE. Trinks et al. (2017) identified a 15-basis-point CoE increase per unit of GHG intensity among 1,920 global firms (2002-2016). A follow-up study in 2022 validated this result, analyzing 1,897 firms (2008-2016) with improved data and sector-adjusted metrics (Trinks et al. 2022). L. H. Chen and Silva Gao (2011) examined U.S. electric utilities and demonstrated that higher carbon emission rates significantly increase CoE and cost of debt (CoD), highlighting that markets price climate risks distinctly for equity and debt investors.

Instances of negative effects, where higher emissions correlate with lower CoE, are rare but have been observed in specific contexts. Trinks et al. (2017) reported anomalies where firms in low-emission industries faced reduced CoE despite high carbon intensity.

No significant effects of emission intensity on CoE are observed in the literature, reinforcing the consensus that high emissions are penalized by equity investors.

### 3.2 Effects of Waste Intensity

Direct research on waste intensity and CoE remains scarce. Ali et al. (2023) examined waste recycling and found that CoD decreased significantly for companies with effective waste management practices. Although the study did not explicitly examine CoE, the results suggest a potential indirect relationship where poor waste management could lead to a higher cost of equity as investors are more concerned.

No studies were found that reported negative or no relationship, highlighting a key gap in understanding this relationship.

**3.3 Effects of Renewable Energy**

The relationship between renewable energy adoption and CoE is underexplored, with no studies directly linking the two. Y.-B. Kim, An, and J. D. Kim (2015) suggested that renewable energy investments indirectly reduce CoE by lowering carbon intensity, but this relationship remains unexamined in isolation. Shin et al. (2018) evaluated renewable energy's broader financial benefits, finding improved firm performance but no direct impact on CoE. The absence of focused research underscores the need for further empirical investigations into renewable energy consumption as a determinant of equity financing costs.

**3.4 Limitations, Research Gaps, and Implications**

Although the reviewed studies provide important insights, they also exhibit several limitations. Regarding the influence of emissions, many studies rely on simplified models such as CAPM or PEG, which do not account for systematic risk factors such as firm size and value. Moreover, only a few studies consider moderating factors like industry-specific characteristics or regional legal frameworks, which can significantly influence the CoE relationship. To address these gaps, this thesis employs two relevant methodological frameworks: Fama-French models, which allow for a differentiated analysis by including size and value factors, and panel data regression, which captures both temporal dynamics and firm-level variations while accounting for industry-specific characteristics.

Additionally, direct empirical studies on waste intensity and the share of renewable energy adoption remain limited. This thesis extends the scope of analysis beyond emissions intensity to include these variables, ensuring a more comprehensive evaluation of environmental performance's impact on CoE.

# 4. Empirical Analysis: Data and Methodological Approaches

## 4.1 Introduction to Empirical Analysis

This chapter introduces the empirical analysis conducted to investigate the relationship between environmental initiatives and equity financing. It employs two complementary approaches: the adjusted portfolio-based Fama-French method and the hybrid firm-level method.

Portfolio-based approaches, such as the Fama-French framework, are well-established for capturing systematic market risks. By aggregating firm-level data into portfolios, these methods effectively capture broad market dynamics, making them valuable tools for financial analysis. In this thesis, the Fama-French approach is extended to include the SMUN factor. This factor incorporates three environmental dimensions – emission intensity, waste intensity, and renewable energy share – allowing an exploration of whether these dimensions contribute to systematic sustainability risk premia.

However, while portfolio-based methods, as noted by Fama and K. R. French (1993), effectively identify systematic market risks, Cederburg and O'Doherty (2015) highlight a key limitation: the inherent averaging effect of aggregation can obscure firm-specific risks and dynamics. To address this limitation, this thesis develops a hybrid approach at the firm level, which is an adapted method that is not found in existing literature and therefore needs to be carefully examined. In contrast to the classical approach, where the excess return is modeled, the hybrid method directly examines the CoE as the dependent variable. This method combines parts of the Fama-French multi-factor framework at firm level with panel regression models, which allows a direct examination of company-specific climate / environmental variables and their impact on CoE. By integrating company-specific data, the hybrid approach provides a more detailed assessment of idiosyncratic risks, particularly those associated with environmental initiatives, thereby closing gaps in traditional portfolio-based methods.

The subsequent sections build on this foundation: Chapter 4.2 outlines the data sources and provides a brief overview of the descriptive statistics, while Chapter 4.3 details the methodologies of the two approaches. These methodologies underpin the hypotheses formulated in Chapter 4.4 and the empirical results presented in Chapter 5.

**4.2 Data**

The primary database, Refinitiv, provided all firm-specific financial data and environmental performance metrics (London Stock Exchange Group). Firm-specific data included measures such as total returns and market capitalization, while environmental metrics included for example $CO_2$ equivalent emissions and share of renewable energy consumption. These datasets formed the basis for calculating excess returns, constructing Fama-French factors, and examining the relationship between climate action and CoE.

Benchmark Fama-French factors, downloaded from the Kenneth French Data Library, will validate the accuracy of portfolio-level factor calculations (K. French; Fama and K. R. French 2023). For the risk-free rate, both approaches in the thesis utilized the three-month EURIBOR from the European Central Bank, alongside ten-year German federal bonds and mid-term treasury notes from the Bundesbank, to calculate excess returns (Deutsche Bundesbank; European Central Bank). See **Appendix 02** for risk-free rate and market return developments.

Additionally, the COVID-19 Stringency Index, sourced from Our World in Data, was included in the hybrid approach to account for pandemic-related disruptions (Ritchie, Edouard, and Max 2023; Roser 2021).

Although detailed variable descriptions are provided in **Appendix 03**, the calculation of the climate variables central to this thesis follows the approach outlined by Trinks et al. (2017) and Bui, Moses, and Houqe (2019). Emission intensity ($CO_2$ equivalent emissions/revenue) and waste intensity (total waste/revenue) indicate lower sustainability at higher values, while renewable energy share (renewable energy consumption/total energy consumption) reflects greater sustainability at higher values. Normalizing these variables relative to operational performance ensures comparability across firms and facilitates the evaluation of environmental efficiency independent of firm size or scale (Bui, Moses, and Houqe 2019; Trinks et al. 2022). See boxplots of these three climate variables in **Appendix 04**.

The sample consists of 289 European companies in 17 countries observed consistently between 2018 and 2022, with 17,340 monthly observations for the adjusted Fama-French approach and 1,445 firm-year observations supporting the hybrid firm-level analysis. A detailed description of the sample, including exclusion criteria and preparation steps, is provided in **Appendix 05**

Methodologies

4.3.1 Adjusted Fama-French Approach

The Cost of Equity represents the return required by equity investors to compensate for the risks of holding a firm's shares. While the Capital Asset Pricing Model (CAPM) models CoE as a linear function of systematic risk (Sharpe 1964), the Fama-French Three-Factor Model (FF3F-Model) incorporates size (Small Minus Big = SMB) and value (High Minus Low = HML) factors to account for empirically observed size and value effects (Fama and K. R. French 1993, 1992). Although alternative methodologies, such as the Price/Earnings Growth (PEG) ratio and the Ohlson-Juettner model, provide practical tools for CoE estimation, they lack the theoretical rigor of multifactor models (Easton 2004; Ohlson and Juettner-Nauroth 2005). Multifactor frameworks such as Fama-French remain the gold standard for financial research, especially when analyzing complex variables like environmental risks (Easton 2004; Bui, Moses, and Houqe 2019; Fama and K. R. French 2015). While the Five-Factor (5F) model extends the FF3F-Model by adding profitability (RMW: Robust Minus Weak) and investment aggressiveness (CMA: Conservative Minus Aggressive), its application in this thesis was restricted due to the smaller sample size, which reduces statistical robustness when additional portfolios are constructed. Consequently, the 3F model as a more stable foundation for analyzing systematic risk premia will be employed.

To enhance the model's ability to capture sustainability-related attributes, this thesis incorporates the $SMUN_x$ factor, where $x$ represents one of three dimensions: emission intensity, waste intensity, or renewable energy share. Each sustainability dimension is treated independently due to the small sample size, capturing the unique characteristics of each dimension while ensuring statistical robustness. This approach allows for a more granular analysis of how specific environmental attributes influence systematic risk premia. The adjusted Fama-French regression equation used in this thesis is as follows:

$$R_{i,t} - R_{f,t} = a_i + b_i(R_{M,t} - R_{f,t}) + s_i SMB_t + h_i HML_t + \boldsymbol{sm_i SMUN_{x,t}} + \varepsilon_t \,, \quad (1)$$

where $R_{i,t}$ is the excess return of portfolio $i$ at time $t$, $R_{M,t}$ is the return of the market (Euro Stoxx 600 TR Index) at time *I,* and $R_{f,t}$ represents the risk-free rate. The intercept $a_i$ captures any abnormal return unexplained by the included factors, while the $b_i$, $s_i$, $h_i$, $sm_i$ measure the sensitivities of portfolio *i* to the respective factors market risk, size, value and the SMUN factor. The error term $\varepsilon_t$ accounts for idiosyncratic risk.

**Portfolio Rebalancing, Construction, and Factor Calculation**

Portfolios are rebalanced annually at the end of the year to align with the availability of climate data. Doing so ensures classifications are based on the most current information while maintaining temporal consistency. This timing contrasts with the classical Fama-French methodology, where rebalancing typically occurs mid-year in June (Fama and K. R. French 2015).

Portfolio construction is explained in detail in **Appendix 06**, limited by sample size to a 2x3x2 (size, value, sustainable) construction, resulting in 12 portfolios. The factors are derived in line with the classical Fama-French framework by utilizing the returns of the constructed portfolios.

Monthly portfolio returns are calculated using a cap-weight approach, reflecting institutional investment practices and serve as the baseline model for the main analysis. Larger companies, with higher market capitalizations, exert proportionally greater influence on portfolio returns. The formula used for calculating cap-weighted returns is provided in **Appendix 07**.

The SMB factor reflects the return difference between small-cap and large-cap portfolios, emphasizing size effects. It is calculated as

$$SMB = \frac{1}{3}[(SH - BH) + (SN - BN) + (SL - BL)] \tag{2}$$

The HML factor measures the return differential between high and low book-to-market portfolios, capturing value effects. It is computed as:

$$HML = \frac{1}{2}[(SH + BH) - (SL + BL)] \tag{3}$$

The SMUN factor functions analogously to SMB in the classical Fama-French framework. While SMB captures systematic size-based risk premia, SMUN reflects the systematic pricing effect of sustainability-related attributes. It does so by comparing the returns of portfolios classified as sustainable (SU) and unsustainable (UN), where the classification in the baseline regression is determined using the median split of sustainability variables. A significant SMUN suggests that sustainability contributes to systematic risk premia. This indicates that sustainability-related risks and opportunities are consistently priced across portfolios, reflecting their integration into investor decision-making and market valuation processes. The $SMUN_x$ factors where *x* stands for one of the dimensions *E* (emissions intensity), R (renewable energy) or $W$ (waste intensity) and SU and UN denote sustainable and unsustainable classifications are further calculated as:

$$SMUN_x = \frac{1}{2}[(SHSU_x + SNSU_x + SLSU_x + BHSU_x + BNSU_x + BLSU_x) - (SHUN_x + SNUN_x + SLUN_x + BHUN_x + BNUN_x + BLUN_x)] \tag{4}$$

In the formulas (2)-(4), $S$ and $B$ represent stocks sorted into size-based categories, whereas S for small, B for Big, while H, N, L refer to value-based categories (High, Neutral, and Low), (Fama and K. R. French 2015, 6). In the third equation (3), the sustainable variables $SMUN_x$ are integrated.

Following the construction of portfolios and the calculation of factors, time-series regression is employed to analyze the sensitivities of portfolio returns to these factors over time.

**Rolling Time-Series Regressions**

This thesis employs three different types of risk-free rates: EURIBOR, serving as the main reference for short-term rates and the primary benchmark for the thesis, reflecting eurozone-wide market conditions; 2-Year German Federal Treasury Notes, representing intermediate rates; and 10-Year German Federal Bonds, capturing long-term rates. The latter two rates were chosen due to Germany's benchmark status within the Eurozone, attributed to its high creditworthiness and market liquidity (Fitch Ratings 2023). Daily risk-free rate data are averaged to monthly to ensure consistency and alignment with the thesis's time-series regression framework, which is used to estimate the sensitivities of portfolio returns to the included factors.

The time-series regression method is applied within a rolling window framework to dynamically estimate time-varying factor sensitivities (Fama and K. R. French 2015). The general statistical model underlying this methodology is given by: $y_t = \alpha + \beta_{\chi_t} + \varepsilon_t$, where $y_t$ represents the dependent variable, $\alpha$ the intercept, $\beta$ the coefficient, and $\varepsilon_t$ the idiosyncratic error term (Hamilton 1994; Wooldridge 2010). As introduced earlier in paragraph 1, the relationship between portfolio excess returns and the factors is modeled using the Fama-French regression equation (1). The rolling framework adapts this structure by recalculating the sensitivities (e.g. $b_i$, $s_i$, $h_i$, $r_i$, $c_i$) over 12-month windows, allowing the model to capture evolving characteristics of portfolios and climate-related factors dynamically. By dynamically estimating these sensitivities, the rolling regression framework ensures robustness and flexibility in addressing the temporal variations in both financial and climate-related factors.

**Robustness of Methodology**

The robustness of the methodology is evaluated by assessing the stability of results across variations in portfolio segmentation and weighting schemes. This evaluation incorporates established robustness checks from classical Fama-French literature as well as additional tests designed specifically for this thesis.

In classical Fama-French literature, robustness is tested by employing alternative portfolio weighting methods, such as equally weighted portfolios, to ensure resilience against the disproportionate influence of large companies (Fama and K. R. French 2015). Equally weighted portfolios assign the same weight to all firms, providing an alternative to the size-weighted approach. The formula for equally weighted portfolio returns is provided in **Appendix 07**.

Additionally, alternative thresholds for portfolio segmentation, including 60:40 and 70:30 splits, are tested to confirm that results are not dependent on the median-based segmentation employed in the primary analysis. This ensures that the computation of the Sustainable Minus Unsustainable factor (SMUN) remains robust across varying segmentation strategies.

4.3.2 Hybrid Approach

The hybrid approach extends the traditional Fama-French methodology by adapting its factors to the firm level, addressing the limitations of portfolio-based aggregation highlighted in subchapter 4.1. Portfolio aggregation often obscures firm-specific risks by averaging data across portfolios. By focusing on firm-level data, the hybrid approach enables a more granular examination of how individual firms' environmental initiatives influence the CoE. Unlike the adjusted approach, which models excess returns as the dependent variable, the hybrid method directly examines CoE, offering a detailed assessment of idiosyncratic risks.

In addition, the hybrid approach allows the application of the Fama-French five-factor model (FF5), overcoming the limitation to the FF3 model in the adjusted approach, mentioned in the previous chapter. Instead of relying on portfolio construction, the factors are calculated for each company individually by comparing its data with the median of the sample to account for systematic risks at the company level. Detailed derivations of these firm-level factors, betas and firm-level CoE are provided in **Appendix 08**.

The CoE serves as the dependent variable in the hybrid model, which is specified as follows:

$$CoE_{i,t} = R_{f,t} + \beta_{M,i,t} * \left(R_{M,t} - R_{f,t}\right) + \beta_{SMB,i,t} * SMB_t + \beta_{HML,i,t} * HML_t + \beta_{RMW,i,t} * RMW_t + \beta_{CMA,i,t} * CMA_t \quad (5)$$

Where $\beta_{M,i,t}$, $\beta_{SMB,i,t}$, $\beta_{HML,i,t}$, $\beta_{RMW,i,t}$ represent firm-specific betas and $SMB_t$, $HML_t$, $RMW_t$, $CMA_t$ denote the corresponding premiums for market risk, size, value, profitability, and investment aggressiveness (Fama and K. R. French 2015).

**Panel data regressions**

Panel data regression is central to this approach, combining cross-sectional and time-series dimensions in a single econometric framework. This dual structure enables more efficient and precise estimation by increasing the data points available for analysis (Baltagi 2021; Hsiao 1985). These methods allow for the control of unobservable firm-specific factors and time-invariant characteristics, effectively addressing omitted variable bias and improving the reliability of results (Wooldridge 2010, 2020). Specifically, panel data techniques account for individual heterogeneity, such as industry-specific or managerial attributes, that might otherwise distort estimates. Detailed formulas and derivations are in **Appendix 09**.

**Dynamic Analysis: Capturing Short-Term Impacts**

The dynamic perspective focuses on short-term financial impacts by employing the First-Difference Model (FDM). This approach transforms the panel data regression by differencing consecutive observations (Baltagi 2021). By focusing on year-to-year variations, the FDM is particularly suited to investigating whether changes in climate variables – such as reductions in emissions intensity – lead to corresponding changes in CoE. This method enables the analysis of how annual environmental initiatives directly influence financial outcomes, linking incremental progress in sustainability metrics to shifts in the CoE. A full theoretical derivation of the FDM and its mathematical foundation is provided in **Appendix 09**.

The following formula for CoE estimation includes all variables, while the analysis evaluates them individually and tests both the FF3 and FF5 models.

$$\Delta CoE_{i,t} = \beta_{\mathrm{EI,i}} * \Delta EI_{i,t} + \beta_{RE,i} * \Delta RE_{i,t} + \beta_{WI,i} * \Delta WI_{i,t} + \beta_{MKT,i} * \Delta\left(R_m - R_f\right)_{i,t} + \beta_{SMB,i} * \Delta SMB_{i,t} + \beta_{HML,i} * \Delta HML_{i,t} + \beta_{RMW,i} * \Delta RMW_{i,t} + \beta_{CMA,i} * \Delta CMA_{i,t} + \varepsilon_{i,t} \quad (6)$$

In this formula, $\Delta EI_{i,t}$, $\Delta RE_{i,t}$, $\Delta WI_{i,t}$ represent annual changes in emission intensity, renewable energy share and waste intensity. The Fama-French factors $\Delta\left(R_m - R_f\right)_{i,t}$, $\Delta SMB_{i,t}$, $\Delta HML_{i,t}$, $\Delta RMW_{i,t}$, $\Delta CMA_{i,t}$ control for firm-level information while taking the market medians into account.

**Static Analysis: Assessing Long-Term Impacts**

The static analysis complements the dynamic perspective by examining long-term impacts of cumulative environmental changes on CoE. While both the FDM and static analyses are estimated using OLS (Baltagi 2021), the FDM focuses on year-to-year changes by applying a differencing transformation to eliminate time-invariant effects (Wooldridge 2010). Whereas the static analysis employs the classical OLS framework to evaluate the cumulative impact of sustained environmental initiatives on CoE over a longer time horizon (Greene 2019). The formula for static CoE estimation can be found in the **Appendix 10** with further information.

**Robustness Checks**

To ensure the stability of the results, robustness checks were performed based on established principles for dynamic panel data models as discussed by Wooldridge (2010) and Greene (2019). The dependent variable is lagged to determine whether shifts in climate variables or Fama-French factors affect CoE in the preceding year, while lagged independent variables were applied to test the persistence of past climate variables on current CoE. Additionally, alternative thresholds, such as the 75th and 90th percentiles, were employed for the calculation of Fama-

French factors to validate factor robustness. Detailed descriptions and mathematical derivations of these robustness tests are presented in **Appendix 11**.

### 4.4. Hypotheses Development

This chapter establishes the hypotheses for analyzing the relationship between sustainability factors, excess returns, and the CoE. The hypotheses are derived from the theoretical and empirical foundations outlined in chapters 3 and previous chapter 4.3, addressing both the adjusted Fama-French approach and the hybrid firm-level approach.

4.4.1 Hypotheses for the Adjusted Fama-French Approach

Building on Fama and K. R. French (2015), the first set of hypotheses evaluates whether the sustainability factor $SMUN_{x,t}$ introduced in the adjusted Fama-French framework, captures systematic risks reflected in excess returns. Specifically, the beta coefficients $sm_i$ for the $SMUN_{x,t}$ factor are tested to determine their significance. This directly aligns with the core objective of the Fama-French framework, which aims to expand factor models to fully capture systematic variations in returns. As Fama and K. R. French (2015, 2) state: "If the exposures to the five factors, $b_i, s_i, h_i, r_i$ and $c_i$, capture all variation in expected returns, the intercept $a_i$ in (1) is zero for all securities and portfolios *i*". Extending this to the sustainability factor, the thesis proposes:

$\boldsymbol{H_0}$: $sm_i = 0$ *($SMUN_{x,t}$ has no systematic impact on returns)*
$\boldsymbol{H_1}$: $sm_i \neq 0$ *($SMUN_{x,t}$ significantly impacts returns)*

The second hypothesis examines how $SMUN_{x,t}$ contributes to improving model completeness by reducing unexplained variations in portfolio returns $a_{SMUN}$. If the inclusion of $SMUN_{x,t}$ leads to a significant reduction in the intercept term ($\alpha$), it would indicate that the factor captures unique risks unaccounted for by size and value dimensions. Therefore, the second set of hypotheses is:

$\boldsymbol{H_0}$: $\alpha_{WithSMUN_{x,t}} = \alpha_{WithoutSMUN_{x,t}}$ ($SMUN_{x,t}$ does not improve model completeness)
$\boldsymbol{H_1}$: $\alpha_{WithSMUN_{x,t}} < \alpha_{WithoutSMUN_{x,t}}$ ($SMUN_{x,t}$ improves model completeness)

4.4.2 Hypotheses for the Hybrid Firm-Level Approach

The hybrid firm-level approach allows for a granular examination on how climate variables affect the CoE. The hypotheses for this approach are formulated based on the findings in Chapter 3, which reviewed empirical studies on the financial impacts of emission intensity, renewable energy share, and waste intensity.

Several studies, for example the ones by Y.-B. Kim, An, and J. D. Kim (2015) and Trinks et al. (2017, 2022), identify a positive relationship between emission intensity and CoE. Accordingly, it is hypothesized that firms with higher emission intensity face elevated equity financing costs. The null hypothesis is stated as:

*$H_0$: emission intensity has no significant impact on CoE*
*$H_1$: emission intensity significantly impacts CoE*

As previously mentioned, empirical literature does not provide direct evidence linking waste intensity or renewable energy share to the cost of equity. While some studies have explored these variables in relation to other financial metrics, such as the CoD or overall firm performance, no conclusive findings regarding CoE exist. Given this lack of evidence, the following hypotheses are proposed:

***$H_0$***: *Waste intensity has no significant impact on CoE.*
***$H_1$***: *Waste intensity significantly impacts CoE.*
and
***$H_0$***: *Renewable energy share has no significant impact on CoE.*
***$H_1$***: *Renewable energy share significantly impacts CoE.*

This empirical analysis combines insights from the adjusted Fama-French framework and firm-level approaches by testing the hypotheses in order to explore how environmental initiatives influence the CoE. The aim is to determine whether climate risks are reflected as systematic risks (see Fama-French framework) – or as idiosyncratic risks that are unique to individual firms and their sustainability strategies (see hybrid approach), or both. Therefore, both approaches directly address the broader question of how environmental initiatives impact equity financing and the perception of climate-related risks in financial markets.

# 5. Results

This chapter presents the results of the effects of climate variables – emission intensity, waste intensity, and renewable energy share – on excess returns (chapter 5.1) and the CoE (chapter 5.2). In chapter 4.1, these variables are classified as sustainability metrics under the SMUN framework, reflecting their systematic pricing effects as sustainable (SU) or unsustainable (UN). Conversely, in chapter 4.2, the hybrid model examines these variables as firm-specific measures (EI, WI, RE) to evaluate their direct impact on CoE.

## 5.1 Results Adjusted Fama-French Approach

This chapter presents the final results, while additional analyses, including descriptive statistics, percentile breakdowns, variable distribution with boxplots and the correlation matrix for the base case with market weighting and median splits, are detailed in Appendix 12. Furthermore, for all scenarios – including market weighting and robustness checks (with median and 70:30 splits) – various types of excess returns across all portfolios over the entire observation period are outlined in Appendix 13. These initial descriptive insights, particularly the portfolio excess returns and the correlation matrix, provide preliminary indications for the subsequent time-series regression results. However, only the table of the results for emission intensity is presented below as an example (Table 1) the other tables for waste intensity, renewable energy share are available in **Appendix 14** and all robustness checks in **Appendix 15**-**Appendix 17**.

The results derive from time-series regressions employing the classical three-factor Fama-French model (3F) and an extended four-factor model (4F) incorporating the $SMUN_x$ factor, which aims to test whether sustainability-related risks are systematically priced and where $x$ represents one of three climate/sustainability dimensions.

Table 1: Results of Market Weighting - Median split in $SMUN_E$

Table 1 compares the coefficients of the FF three-factor model (LHS) and the extended four-factor model (RHS). The fourth factor $SMUN_X$ (where x = E for emisson intensity) was constructed by splitting $SMUN_E$ variable at the median, classifying companies as SU (sustainable) below the median and UN (unsustainable) above the median. The results are based on market capitalization weighting, presenting the coefficients for both SU and UN classifications, with an emphasis on the statistical significance of the added factor. The coefficients are averaged for sustainable and unsustainable portfolios. The averages are represented as $\mu_{SU}$ (mean of sustainable portfolios) and $\mu_{UN}$ (mean of unsustainable portfolios).

| | $r_i = a_i + b_i(R_M - R_f) + s_iSMB + h_iHML$ | | | | | | $r_i = a_i + b_i(R_M - R_f) + s_iSMB + h_iHML + \boldsymbol{sm_iSMUN_x}$ | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Portfolio** | $\mathbf{a_i}$ | $\mathbf{b_i}$ | $\mathbf{s_i}$ | $\mathbf{h_i}$ | $\mathbf{R^2}$ | | $\mathbf{a_i}$ | $\mathbf{b_i}$ | $\mathbf{s_i}$ | $\mathbf{h_i}$ | $\mathbf{sm_i}$ | $\mathbf{R^2}$ |
| BHSU | 0.64 | 1.08*** | -0.13 | 0.15 | 0.79 | | 0.34 | 1.19*** | -0.59*** | 0.24*** | 0.39*** | 0.89 |
| BHUN | 0.71*** | 0.87*** | -0.58*** | 0.65*** | 0.96 | | 0.75*** | 0.85*** | -0.52*** | 0.64*** | -0.06 | 0.96 |
| BLSU | 1.00** | 0.72*** | -0.29* | -0.22*** | 0.61 | | 0.77** | 0.81*** | -0.64*** | -0.16** | 0.3*** | 0.76 |
| BLUN | 0.6*** | 0.99*** | -0.54*** | -0.58*** | 0.92 | | 0.61*** | 0.98*** | -0.52*** | -0.58*** | -0.02 | 0.92 |
| BNSU | 1.17*** | 0.74*** | -0.08 | -0.1 | 0.72 | | 0.97*** | 0.82*** | -0.38*** | -0.04 | 0.26*** | 0.83 |
| BNUN | 0.13 | 1.14*** | -1.43*** | 0.39*** | 0.82 | | 0.27 | 1.09*** | -1.22*** | 0.35*** | -0.18** | 0.84 |
| SHSU | 0.18 | 1.09*** | 0.37*** | 0.11* | 0.94 | | 0.14 | 1.11*** | 0.31*** | 0.12** | 0.05 | 0.94 |
| SHUN | 0.48 | 1.06*** | 0.01 | 0.52*** | 0.9 | | 0.50 | 1.05*** | 0.05 | 0.51*** | -0.04 | 0.9 |
| SLSU | 0.69 | 0.83*** | -0.08 | -0.01 | 0.63 | | 0.52 | 0.89*** | -0.34 | 0.05 | 0.22*** | 0.68 |
| SLUN | 0.71 | 1.01*** | 0.08 | -0.46*** | 0.66 | | 1.01** | 0.90*** | 0.54*** | -0.55*** | -0.39*** | 0.79 |
| SNSU | 0.7* | 0.99*** | 0.29*** | 0.04 | 0.94 | | 0.64*** | 1.01*** | 0.20** | 0.06 | 0.08** | 0.95 |
| SNUN | 0.2 | 0.97*** | 0.16 | -0.1 | 0.91 | | 0.26 | 0.95*** | 0.24** | -0.11** | -0.08* | 0.91 |
| $\mu$ | 0.60 | 0.96 | -0.19 | 0.03 | 0.82 | $\mu_{SU}$ | 0.56 | 0.97 | -0.24 | 0.05 | 0.22 | 0.84 |
| | | | | | | $\mu_{UN}$ | 0.57 | 0.97 | -0.24 | 0.04 | -0.13 | 0.89 |

* p<0.1, ** p<0.05, *** p<0.01

The corresponding null hypothesis ($H_0: sm_i = 0$) posits that sustainability does not impact returns, while the alternative ($H_1: sm_i \neq 0$) suggests a significant sustainability effect. The following evidence strongly supports rejecting $H_0$ in favor of $H_1$. Under the main configuration (e.g., median splits and market-cap weighting), at least 8 to 10 of the 12 portfolios show $sm_i$-coefficients significantly different from zero at the 10% level. SU portfolios consistently exhibit positive $sm_i$-values, for example around 0.22 for emissions, 0.18 for waste, and 0.15 for renewables under market-cap weighting (**Appendix 14**) – values that can increase by approximately 0.3 when switching to equal weighting (**Appendix 16**). These positive loadings suggest that integrating sustainability attributes correlates statistically significantly with higher excess returns, translating into an increased CoE as investors demand compensation for perceived sustainability risks. This reflects systematic risk pricing, where higher expected returns for sustainable exposures increase equity financing costs. However, concerns around resource allocation – such as diverting focus from profitability to long-term sustainability initiatives – may also contribute to this perception of heightened risk. In contrast, UN portfolios present neutral or negative $sm_i$-values (e.g., -0.13 for emissions), indicating a relative disadvantage. This clear and consistent pattern across all three sustainability measures (climate variables) reinforces the conclusion that environmental characteristics are systematically priced, confirming $H_1$. The second hypothesis regarding model completeness examined whether adding $SMUN_x$ would reduce the intercept α ($H_1$), which represents the unexplained return variations not accounted for by the included factors. While data supports $H_0$, no conclusive evidence favors $H_1$. Although in some instances, such as emission intensity, α decreases slightly (e.g., from about 0.60 to 0.56), these changes are neither substantial nor consistent across sustainability dimensions. Consequently, there is no clear indication that $SMUN_x$ improves model completeness beyond what size and value already explain.

Robustness checks reinforce these conclusions (**Appendix 15**). Varying weighting schemes (market-cap vs. equal weighting) and for both, threshold splits (e.g., 70:30 vs. median splits) do not alter the fundamental direction or significance of the $sm_i$-coefficients. Equal weighting often yields slightly higher $R^2$ values, somewhat lower α-values, and more pronounced $sm_i$-loadings, further highlighting the economic importance of sustainability factors without undermining the main results. In all scenarios, SU portfolios retain positive $sm_i$-values and UN portfolios maintain neutral-to-negative ones, demonstrating that environmental risk premia are not artifacts of a particular methodological choice.

For established factors, size and value loadings align with classical expectations, and the market factor remains stable and significant. Differences in SMB or HML exposures between SU and UN portfolios appear less pronounced than those observed for $sm_i$.

### 5.2 Results Hybrid Approach

This section focuses on the panel data regression results testing the hypotheses from Chapter 4.4.2, with regression output tables clearly linked for reference (**Appendix 19**). Supporting statistics, including descriptive summaries, percentile breakdowns, boxplots for distribution overview and a correlation matrix, are provided in **Appendix 18**, alongside robustness checks such as analyses with lagged variables.

The first hypothesis addresses the impact of emission intensity (EI) on CoE. The null hypothesis ($H_0$) posits that emission intensity has no significant effect on CoE. The results clearly support rejecting H0 in favor of $H_1$, as a statistically significant negative relationship between EI and CoE is observed. In the dynamic regressions (see **Appendix 19a**), EI demonstrates a negative coefficient ($\beta = -0.1240$, $p < 0.01$), indicating that firms with higher emission intensity experience lower subsequent equity financing costs. This relationship remains robust across all tests, including specifications with lagged CoE and lagged climate variables. The static regressions (see **Appendix 19b)** confirm this pattern, with cumulative changes in EI over the observation period showing a consistent and statistically significant negative effect on CoE in 2022. These findings highlight the importance of emission intensity as a determinant of CoE.

In contrast, the second hypothesis examines the effects of waste intensity (WI) and the renewable energy share (RE) on CoE. The null hypothesis ($H_0$) for this analysis states that neither WI nor RE significantly influence CoE, while the alternative hypothesis ($H_1$) suggests a meaningful impact. However, the results provide no evidence to reject $H_0$. Across both dynamic and static regressions (**Appendix 19**), coefficients for WI and RE are statistically insignificant, indicating that these variables do not exert measurable effects on CoE. This outcome holds consistently, even under robustness checks employing lagged variables and alternative factor thresholds (**Appendix 20** and **Appendix 21**). The insignificance of WI and RE suggests either limited relevance to equity investors or potential measurement constraints in capturing their financial impact.

## 6. Discussion

This thesis examined the relationship between climate variables and the CoE using two distinct methodologies: the adjusted Fama-French framework, extended with sustainability factors

(SMUN), and a hybrid firm-level approach. Both methods offer complementary insights, and their varying degrees of robustness and scope highlight different aspects of climate-related risk. Under the adjusted Fama-French model, sustainable portfolios (SU) consistently show higher excess returns (positive $sm_i$-values), whereas firms with weaker sustainability performance appear less risky in both the adjusted Fama-French model (negative excess returns, lower CoE) and the hybrid model (higher emissions, lower CoE).

These findings deviate sharply – particularly with respect to emissions – from prior studies often showing a positive correlation between higher emissions and a higher CoE (Y.-B. Kim, An, and J. D. Kim 2015; Li, Eddie, and Liu 2014; Trinks et al. 2017; L. H. Chen and Silva Gao 2011). Commonly, that correlation is ascribed to regulatory pressures, reputational risks, or uncertainties linked to climate policy. Several factors may explain discrepancy. One possibility is that European investors view sustainability as riskier, demanding higher returns and thus elevating CoE for "sustainable" firms. Another possibility is that the thesis's timeframe (2018-2022), marked by the COVID-19 pandemic, the Ukraine war, and subsequent energy crises, influenced results in ways not captured by a more conventional market environment.

It is hypothesized that two dominant investor perspectives coexist. On the one hand, pro-sustainability investors channel capital into "sustainable" firms, driving higher valuations and thus, excess returns for sustainable portfolios. This is consistent with record inflows into sustainable funds and policy moves such as the EU Green Deal. On the other hand, conservative or risk-averse investors may perceive sustainability projects – particularly those involving lengthy horizons, like a transition to renewable energy – as riskier. During uncertain times, these investors could gravitate toward companies perceived as financially robust, often emissions-intensive or value-oriented. This dichotomy is likely amplified by Europe's inherently risk-averse investor base, reinforcing a dual pattern of investment behavior.

Additionally, pivotal global events during the study period likely magnified the effect. In the COVID-19 era, investors favored conservative positions in financially stable firms, while the Ukraine war and energy crisis deepened market uncertainty, prompting a "flight to quality". Large-cap and value-oriented companies less exposed to rising energy costs or gas dependency became relatively attractive, reflected by the notably high $h_i$-values (beta of HML) for BHUN portfolios in the relevant table (see e.g **Appendix 14** and **Appendix 15**). As a result, investors may have prioritized near-term financial stability (lower CoE) over longer-range sustainability objectives, assigning a risk premium to firms perceived as more "sustainable".

Despite these insights, several methodological and data-related constraints persist. The adjusted Fama-French approach relies on a relatively short 60-month window that may not capture full market cycles and is restricted to only 12 portfolios due to the limited sample size. Moreover, it does not explicitly account for extraordinary events such as COVID-19. In contrast, the hybrid approach includes pandemic-related variables to capture disruptions caused by nationwide lockdowns, yet it remains hindered by the complexities of firm-level factor calculations and beta reassignment. Furthermore, results for waste intensity and renewable energy share remain statistically insignificant – potentially reflecting measurement gaps or limited investor interest in these specific metrics – further complicating interpretability.

Overall, the adjusted Fama-French model appears robust for capturing systematic sustainability risk premia, even with data constraints. The hybrid model provides valuable firm-level insights, particularly for emissions, but remains limited by methodological constraints and a lack of significance for the other two variables. Future research might refine firm-specific factor calculations, extend the observation period, and broaden the sample to determine whether a unified approach can reconcile systematic and idiosyncratic climate-related risks in equity financing. Examining investor behaviors during crises, as well as regional and sector-specific differences, could also yield deeper insights into how climate risks shape CoE.

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# Appendix

## List of Abbreviations

### Fundamentals / General Information



### Fundamentals / Adjusted Fama-French Approach



### Fundamentals / Hybrid Approach:



### Results / Adjusted Fama-French Approach

**Figures:**



**Tables**

## List of Abbreviations

| | |
|---|---|
| AIC | Akaike Information Criterion |
| AMKT | Adjusted Market Return |
| ARE | Adjusted Renewable Energy |
| AWI | Adjusted Waste Intensity |
| BAI | Bayesian Information Criterion |
| CA | Climate Action |
| CAI | Climate Action Index |
| CAPM | Capital Asset Pricing Model |
| CoE | Cost of Equity |
| COVID | Coronavirus Disease |
| EI | Emission Intensity |
| ESG | Environmental, Social, and Governance |
| EU | European Union |
| EURIBOR | Euro Interbank Offered Rate |
| FF | Fama-French |
| FF3 | Fama-French Three-Factor Model |
| FF5 | Fama-French Five-Factor Model |
| FDM | First-Difference Model |
| GHG | Greenhouse Gas |
| HML | High Minus Low |
| IPCC | Intergovernmental Panel on Climate Change |
| IQR | Interquartile Range |
| OECD | Organisation for Economic Co-operation and Development |
| OLS | Ordinary Least Squares |
| PEG | Price Earnings Growth (Model) |
| RE | Renewable Energy Share |
| RMW | Robust Minus Weak |
| SDG | Sustainable Development Goal |
| SMB | Small Minus Big |
| SMUN | Sustainable Minus Unsustainable |
| SU | Sustainable |
| UN | Unsustainable |
| WI | Waste Intensity |

## Appendix 01: Why Emission Intensity, Waste Intensity and Share of Renewable Energy Are Used as Climate Action Variables

This appendix elaborates on the rationale behind selecting emission intensity, waste intensity, and renewable energy share as climate action variables. It provides a detailed explanation of their relevance as measurable indicators of corporate climate efforts and their alignment with the broader theoretical framework in Chapter 2. The appendix also discusses the derivation of these variables and their adaptation for corporate-level analysis, ensuring consistency with global climate action metrics.

As previously mentioned in Chapter 2.2, the Climate Action Index is used to track countries' progress toward achieving climate targets. Various indicators, such as GHG emissions or material use, are utilized for this purpose. As outlined in Chapter 2, in addition to greenhouse gases, energy production and waste – particularly in their connection to greenhouse gas emissions – are key drivers of global warming. For this reason, these factors serve as climate variables in this thesis and are adapted to the corporate level and now will be elaborated upon.

### Appendix 01a: Climate Variable One

Emissions, particularly GHG, are a primary driver of global warming (Wu and Lei Chen 2024, 22). Monitoring their trends is essential for measuring and managing climate action (OECD 2021b, 7). Data on emission intensity (per capita or GDP) highlights how efficiently nations decouple their output from economic growth (OECD 2024a). The corporate sector is particularly critical in light of its contribution to global GHG emissions, with 100 companies accounting for 70% of emissions since 1988 (Griffin 2017, 4). Therefore, the first variable emission intensity in this thesis serves as a key indicator for cross-company comparisons (OECD 2024a).

Appendix 01b: Climate Variable Two

According to the OECD Climate Action Dashboard (OECD 2024a), the energy industry is one of the primary sources of GHG emissions. To achieve climate action goals, such as meeting the 1.5°C target set by the Paris Agreement, alternatives to high-emission energy systems must be developed (OECD 2021b, 13). The CAI measures progress in these developments using indicators such as "energy use: production, supply, and consumption" (OECD 2024a). The significance of renewable energy continues to grow as it increasingly represents "the cheapest and most sustainable option for energy production" (OECD 2021b, 14) and occupies a larger share of the global energy mix. On firm-level and in light of this thesis, renewable energy therefore serves as the second variable, enabling the development of sustainable energy consumption to be both measurable and comparable.

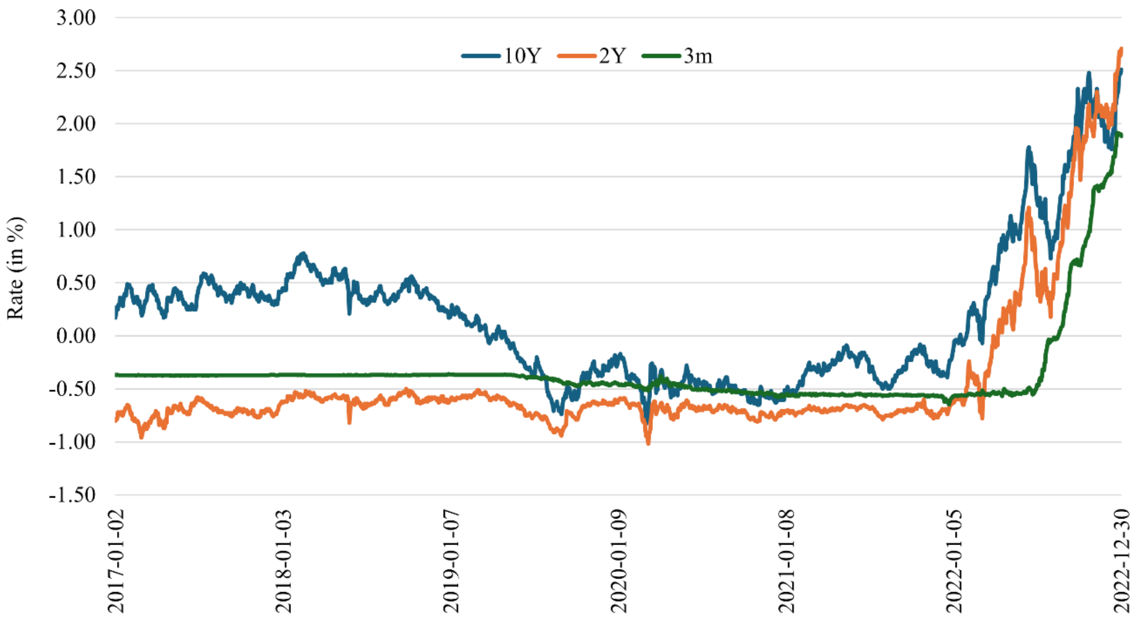
Appendix 01c: Climate Variable Three

Rising temperatures impact marine plastic waste by altering its decomposition, distribution, and biological interactions, threatening ecosystems (Wu and Lei Chen 2024, 26). To protect marine environments, reducing GHG emissions and improving plastic, waste management is crucial, as mismanaged waste exacerbates pollution, harms biodiversity, and reduces the ocean's carbon sequestration capacity (ibid.). Reduction, Recycling and circular economy initiatives mitigate these effects, significantly offsetting emissions associated with raw material extraction and processing (Alsheyab 2022, 2133; Siegel 2022). Reflecting the CAI’s material use metric, waste intensity is introduced as the third climate variable, emphasizing its role in promoting resource efficiency and sustainability in corporate practices

## Appendix 02: Overview of Interest Rate and Market Return ($R_M$) Developments

**Figure 01:** Overview of Interest Rate Developments

Figure 01 provides an overview of short-term, intermediate, and long-term interest rate trends in the Eurozone, which are crucial as inputs for the time-series regression in Section 4.3.1 (Adjusted Fama-French Approach), the CoE calculation in Section 4.3.2 (Hybrid Approach), and the factor calculation of MKT in both approaches.

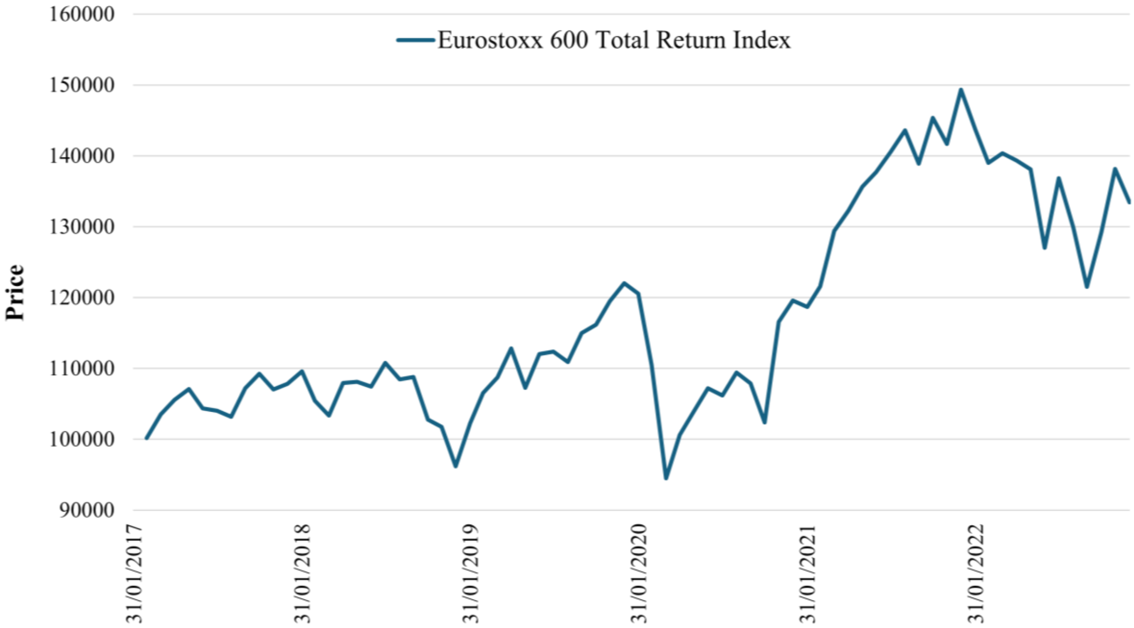



Note: The EURIBOR 3-month (3m) rate reflects short-term market conditions and remained negative until 2022, while the 2Y (2-Year German Federal Treasury Notes) and 10Y (10-Year German Federal Bonds) rates represent intermediate and long-term benchmarks, respectively. All rates experienced a sharp increase in 2022 due to inflationary pressures and policy shifts. Despite variations in interest rate trends, particularly until 2019, the robustness of results was maintained, with consistent findings observed irrespective of whether EURIBOR or 10-Year German rates were used as benchmarks.

Source: own creation, data received from ECB and Deutsche Bundesbank

**Figure 02**: Overview of Market Return ($R_M$)

Figure 02 illustrates the development of the market return (R$R_M$), proxied by EURO STOXX 600, over the period 2017 to 2022.




Note: The market return shows significant fluctuations, with pronounced drops during early 2020, coinciding with the COVID-19-induced market crash, and a subsequent recovery through 2021 and 2022.

Source: own creation, data received from refinitiv

**Appendix 03: Overview of variables used in this thesis**

**Table 01:** Variables Overview

| Variables | Additional Information | Source |
|---|---|---|
| **Climate Action Variables** | | |
| Emission Intensity | *Calculation:* estimated co2 equivalents emission total / total revenue | Refinitiv |
| Waste Intensity | *Calculation:* waste total / total revenue | Refinitiv |
| Share of Renewable Energy Consumption | *Calculation:* total renewable energy / energy use total | Refinitiv |

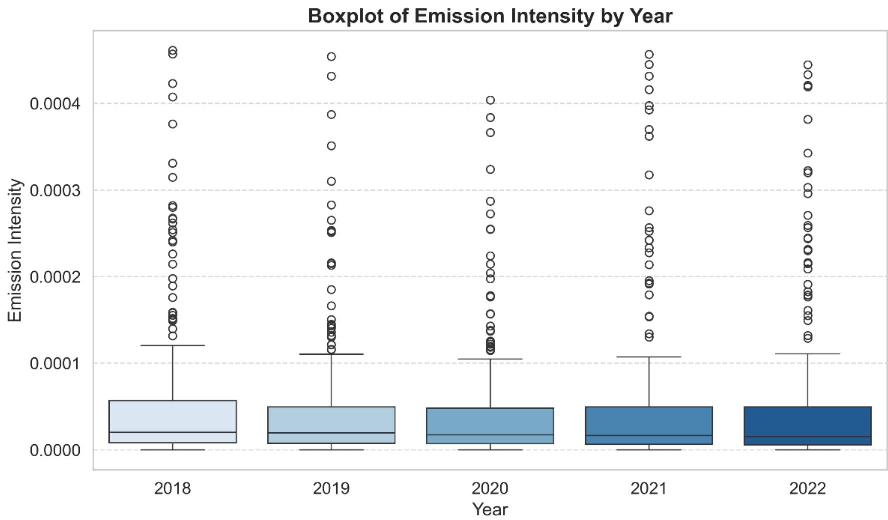
| | | |
|---|---|---|
| **Equity Financing Variables** | | |
| Cost of Equity | see **Appendix 08** | Own |
| **Firm Variables** | | Refinitiv |
| Ticker | | Refinitiv |
| Country of Exchange | | Refinitiv |
| Total Return | | Refinitiv |
| Total Revenue | | Refinitiv |
| Market Cap | | Refinitiv |
| Shareholders Equity | | Refinitiv |
| Book-to-Market-Ratio | *Calculation:* Market Cap / Shareholders Equity | own |
| Gross Profit | For Financials the net return had been used instead of Gross Profit | Refinitiv |
| Total Assets | | Refinitiv |
| **Others** | | |
| Market Return | Euro Stoxx 600 Total Index | Refinitiv |
| Euribor 3-Months | Risk-Free Rate (short-term) | ECB |
| 10-Year German Federal Bond | Risk-Free Rate (intermediate) | Deutsche Bundesbank |
| 2-Year German Federal Treasury Notes | Risk-Free Rate (long-term) | Deutsche Bundesbank |
| Covid Stringency Index | | Our World in Data |
| Benchmark Fama-French Factors | | Kenneth French Data Library |

## Appendix 04: Boxplots of the Climate Variables Emission Intensity, Waste Intensity, and Renewable Energy Share

This appendix presents boxplots for the three key climate variables — emission intensity, waste intensity, and renewable energy share — over the years 2018 to 2022. These visualizations offer insights into the distributions of these variables, highlight the extent of outliers, and provide a basis for understanding the variability and trends within the dataset. They also demonstrate the results of the percentile-based filtering and provide a foundation and necessity for the z-score standardization applied later in the analysis.

**Figure 03:** Boxplot Emission Intensity

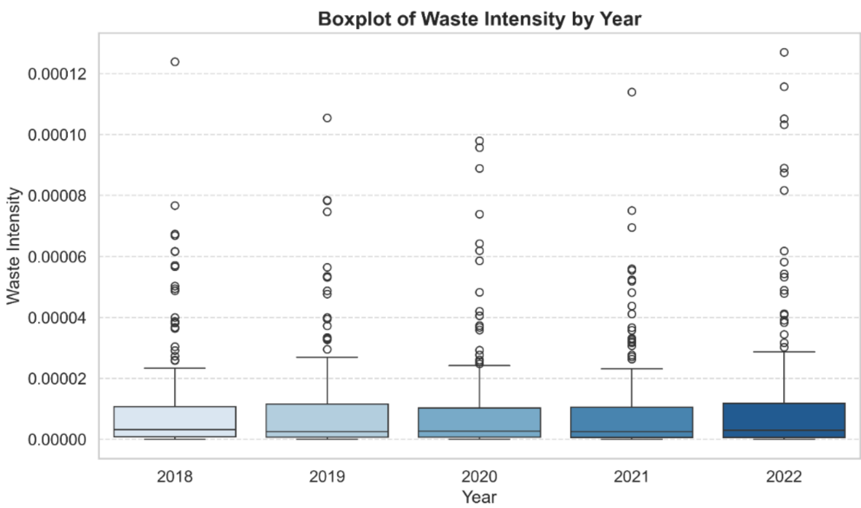
Figure 03 illustrates the annual distribution of emission intensity values from 2018 to 2022. The figure highlights the overall variability of the data, as well as the presence of outliers that remain after applying the 99th percentile filter.




Note: Emission intensity shows a positively skewed distribution with a consistent median across the observed years. While extreme outliers have been reduced through filtering, some high residual values persist. To address this, a z-score standardization will be implemented to normalize the dataset for further regression analysis.

**Figure 04**: Boxplot Waste Intensity

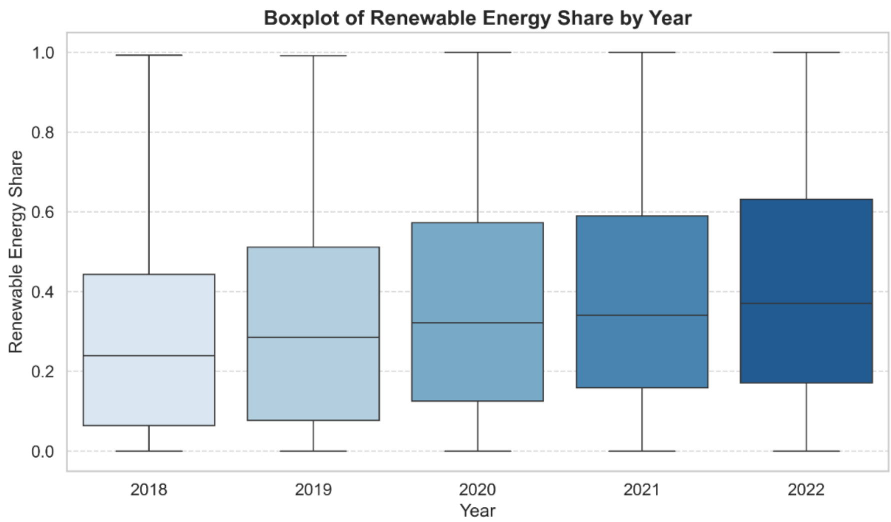
Figure 04 demonstrates how waste intensity values are distributed yearly, capturing the range, median, and outliers for the period 2018-2022.



Note: Waste intensity exhibits similar characteristics to emission intensity, with a right-skewed distribution and visible outliers, even after filtering above the 99th percentile. These remaining extreme values are inherent to the variability of this variable. Again, the later on applied z-score standardization will mitigate the potential influence of outliers and ensure comparability.

**Figure 05**: Boxplot Renewable Energy Share

Figure 05 showcases the yearly distribution of the renewable energy share, focusing on changes in the median and interquartile range (IQR) over time.




Note: The renewable energy share demonstrates an increasing trend in the median over the years, suggesting a gradual shift towards higher adoption of renewable energy among firms. The interquartile range remains relatively stable, indicating consistent variability across the dataset.

**Appendix 05: The Sample**

The sample was drawn from European companies listed in Refinitiv, initially spanning the years 2017-2023. While 2017 and 2023 included just over 1,000 firms, the period 2018-2022 consistently featured between 1,900 and 2,220 firms. This broader coverage and greater data availability for key variables made 2018-2022 the most suitable timeframe for analysis.

After merging financial and climate-related datasets, companies missing data for any year within the selected period were excluded, reducing the sample to 310 firms. Outliers in critical variables, including e.g. total assets, shareholders' equity, and estimated CO2 emissions, were identified and removed based on the 99$^{th}$ percentile (Hoaglin, Iglewicz, and Tukey 1986; Hyndman and Fan 1996; Misra, Osogba, and Powers 2020). Firms lacking specific data for 2017 – necessary to initialize rolling time-series regressions in the adjusted approach – were also excluded.

The final sample consisted of 289 companies consistently observed across all five years (2018-2022). Sixty monthly data for total return and risk-free rates were used to calculate excess returns and Fama-French factors in the adjusted approach but did not alter the sample size. For the hybrid approach, the final dataset provided 1,445 firm-year observations, supporting robust panel regression analyses that integrated climate-related variables.

**Appendix 06: Portfolio Construction Process**

The construction of portfolios follows a hierarchical sorting process, displayed in the paper of Fama and K. R. French (2015, 6) incorporating size, value, and sustainability dimensions.

Companies are initially divided into two size categories based on the median market capitalization as a threshold: Big (B) for firms above the median and Small (S) for those below. Within each size group, firms are further classified by their book-to-market ratio (B/M) into three categories: Low (L) for values below the 30th percentile, Neutral (N) for values between the 30th and 70th percentiles, and High (H) for values above the 70th percentile (Fama and K. R. French 2015, 5). The cross-product of these classifications produces six primary portfolios:

| | High | Medium | Low |
|---|---|---|---|
| Big | BH | BN | BL |
| Small | SH | SN | SL |

To incorporate sustainability dimensions, firms are classified into Sustainable (SU) and Unsustainable (UN) groups using the median as a threshold. This classification is applied separately for each sustainability metric, including emissions intensity, renewable energy share, and waste intensity. This generates twelve distinct portfolios, such as Small-High-Sustainable (SHSU) and Big-Low-Unsustainable (BLUN), capturing the intersection of size, value, and sustainability attributes.

| | BH | BL | BN | SH | SL | SN |
|---|---|---|---|---|---|---|
| SU | BHSU | BLSU | BNSU | SHSU | SLSU | SNSU |
| UN | BHUN | BLUN | BNUN | SHUN | SLUN | SNUN |

To maintain robust portfolio sizes and ensure adequate representation, each sustainability metric is treated as a distinct factor, resulting in three independent $SHUN_x$ factors: $SHUN_E$ (emissions intensity), $SHUN_R$ (renewable energy share), and $SHUN_W$ (waste intensity). This approach ensures that each metric is evaluated independently, with sufficient data points for reliable analysis.

**Appendix 07: Theoretical Foundation of Portfolio Weighting**

*Market-Capitalization Weighting Scheme: Main Analysis*

Capital-weighted portfolios are used in the main analysis as they reflect the investment reality of institutional investors more realistically. The weighting of individual companies is based on their market capitalization; therefore, larger companies have a greater influence on the calculated returns. The cap-weighted portfolio return is calculated as follows:

$$R_{Portfolio} = \sum_{i=1}^{n} \omega_i \mathrm{R}_i \ , \qquad \omega_i = \frac{MarketCap_i}{\sum_{j=1}^{n} \mathrm{MarketCap}_i}$$

$R_{Portfolio}$ represents the overall portfolio return represents, $\omega_i$ is the weight assigned to firm $i$ based on its market cap, and $\mathrm{R}_i$ denotes the return of firm $i$.

*Equal Weighting Scheme: Robustness check*

Equal weighted portfolios are used to find out whether the outcomes of the main analysis are reliant on the cap-weighting, or if the outcome is resistant to different weighting schemes.

The return for an equally weighted portfolio is calculated as follows:

$$R_{Portfolio} = \frac{1}{N}\sum_{i=1}^{N} \mathrm{R}_i,$$

where $\mathrm{R}_i$ represents the return of company $i$, and $N$ is the total number of companies in the portfolio. The SMB, HML, and SMUN factors are recalculated on the basis of equally weighted portfolios and are compared with the capital-weighted results.

**Appendix 08: Deriving CoE on Firm-Level**

*Step 1: Firm-Level Fama-French Factor Calculations*

This appendix outlines the firm-level calculations of Fama-French factors (MKT, SMB, HML, RMW, CMA) applied in the hybrid approach. The sample median is used as a threshold for all factor calculations to create a consistent and robust benchmark for classifying firms. Compared to the mean, the median is less sensitive to outliers, making it better suited for financial datasets with skewed distributions (seen in **Appendix 12**) (Wooldridge 2010, 2020). Moreover, using the median introduces an implicit market comparison into the calculations, as firms are evaluated relative to a central benchmark within the dataset. This ensures that size, value, and profitability classifications remain conceptually aligned with the market-relative structure of the traditional Fama-French methodology.

The following formulas define the firm-level Fama-French factors:

1. MKT (Market Risk Premium): The market risk premium is set as the difference between the market return ($R_m$) and the risk-free rate $R_f$ for all companies:

   $$MKT_i = R_m - R_f$$

   Where $R_{m,i}$ is the market return for firm I, and $R_f$ is the risk-free rate.

2. SMB (Small Minus Big):

$$SMB_i = \frac{Market\ Capitalization_i}{Median\ of\ Market\ Capitalizations}$$

3. HML (High Minus Low):

$$HML_i = \frac{Book\ Value_i\ (Shareholders'\ equity)_i}{Median\ Market\ Capitalization}$$

4. RMW (Robust Minus Weak): For Financial Institutions the net profit has been used instead of the gross profit.

$$RMW_i = \frac{Gross\ Profit_i}{Median\ Gross\ Profit}$$

5. CMA (Conservative Minus Aggressive): The variable Total Assets needed to be acquired for the years 2017 in order to assure CMA results in 2018:

$$CMA_i = \frac{Total\ Assets_{i,t} - Total\ Assets_{i,t-1}}{Total\ Assets_{t-1}} / \frac{Median\ Total\ Assets_{i,t} - Median\ Total\ Assets_{i,t-1}}{Median\ Total\ Assets_{t-1}}$$

*Step 2: Determining Sensitivities*

The Fama-French factors calculated in Step 1 are applied in a multiple regression framework to estimate the sensitivities of firm-level excess returns. Specifically, the annual excess return of the firm serves as the dependent variable. This is defined as the difference between the firm's total return and the risk-free rate, where the risk-free rate is calculated as the annual average of EURIBOR and the average yield to maturity (YTM) on 10-year German federal bonds.

The regression model can be expressed as:

$$ER_{i,t} = \alpha + \beta_{MKT,i}(MKT_t) + \beta_{SMB,i} * SMB_t + \beta_{HML,i} * HML_t + \beta_{RMW,i} * RMW_t + \beta_{CMA,i} * CMA_t + \varepsilon_{i,t},$$

where $ER_{i,t}$ is the excess return of firm *i* in time period *t*, the time-varying Fama-French factors are $MKT_t$, $SMB_t$, $HML_t$, $RMW_t$, $CMA_t$, and the $\beta$ coefficients represent the firm's sensitivity to each respective factor and $\varepsilon_{i,t}$, is the time-varying error term.

*Step 3: Portfolio-Averaged Betas and Final CoE Calculation*

To ensure stability in the estimation of $\beta$ coefficients, the calculated firm-level betas are averaged across portfolios. Each firm is then assigned the average beta of its respective portfolio. This step accounts for potential noise estimation and provides more reliable beta values.

The CoE for each firm is then calculated using the following formula:

$CoE_{i,t} = R_{f,t} + \beta_{MKT,i} * (MKT_t) + \beta_{SMB,i} * SMB_t + \beta_{HML,i} * HML_t + \beta_{RMW,i} * RMW_t + \beta_{CMA,i} * CMA_t$,

where $CoE_{i,t}$ is the Cost of Equity for firm I in time period t, $R_{f,t}$ is the risk-free rate in time period *t*, and ß$_{X,i}$ represents the firm *i*'s sensitivities to each Fama-French factor.

**Appendix 09: Theoretical Framework Panel Data Regressions**

*Panel Data Regression Framework*

Panel data regression integrates cross-sectional and time-series dimensions, enabling efficient and precise econometric estimation. The general model is expressed as:

$$y_{it} = a_i + \beta x_{it} + c_i + u_{it}$$

Where $y_{it}$ serves as the dependent variable, $x_{it}$ as the explanatory variables, $a_i$ the individual-specific intercept, $c_i$ as the unobservable firm-specific effects, $u_{it}$ as the idiosyncratic error term.

*First-Difference Model*

First-Difference Model eliminates time-invariant unobservable effects by differencing consecutive observations:

$\Delta y_{it} = y_{it} - y_{i,t-1}$, $\qquad \Delta x_{it} = x_{it} - x_{i,t-1}$

The differenced equation becomes:

$$\Delta y_{it} = \beta \Delta x_{it} + \Delta u_{it},$$

where $\Delta u_{it} = u_{it} - u_{i,t-1}$ is the differenced error term. Derived from Wooldridge (2010) and Baltagi (2021), the FDM captures year-to-year dynamics while ensuring consistent estimates under strict exogeneity: $E\left(\frac{\Delta \mathrm{u}_{it}}{\Delta \mathrm{x}_{it}}\right) = 0$

**Appendix 10: Static Analysis**

This appendix provides an explanation of the static analysis methodology, which complements the dynamic analysis discussed in the main text. While the dynamic approach captures year-to-year variations in environmental factors and their immediate effects on CoE, the static analysis focuses on cumulative, long-term impacts, offering a broader perspective on the financial outcomes of sustainability initiatives.

The formula used for the static analysis of CoE is as follows:

$$\boldsymbol{CoE_{i,2022}} = (\boldsymbol{\beta_{\mathrm{EI,i}}} * \Delta \boldsymbol{EI_{i,2018-2022}}) + (\boldsymbol{\beta_{RE,i}} * \Delta \boldsymbol{RE_{i,2018-2022}}) + (\boldsymbol{\beta_{W,i}} * \Delta \boldsymbol{W_{i,2018-2022}}) + \boldsymbol{\beta_{MKT,i}} * \left(\boldsymbol{R_m} - \boldsymbol{R_f}\right)_{\boldsymbol{i,2018-2022}} + (\boldsymbol{\beta_{SMB,i}} * \boldsymbol{SMB_{i,2018-2022}}) + (\boldsymbol{\beta_{HML,i}} * \boldsymbol{HML_{i,2018-2022}}) + (\boldsymbol{\beta_{RMW,i}} * \boldsymbol{RMW_{i,2018-2022}}) + (\boldsymbol{\beta_{CMA,i}} * \boldsymbol{CMA_{i,2018-2022}}) + \boldsymbol{\varepsilon_i}$$

The static analysis evaluates the cumulative changes in environmental factors – over the period 2018-2022. The CoE values from 2022 are used as the dependent variable to determine whether these long-term developments in climate and Fama-French variables have improved firms' equity financing conditions.

By aggregating changes over the observation period, the static analysis captures the sustained efforts of firms to improve environmental performance, offering insights into their long-term financial implications. The final year's CoE reflects the impact of accumulated changes throughout the period. This choice ensures that the results align with market expectations and financing conditions as of the most recent data point.

**Appendix 11: Robustness Checks – Methodological Details**

The robustness checks conducted in this thesis aim to assess the temporal dynamics between climate variables, Fama-French factors, and the CoE. Specifically, lagged variables are employed to test twofold: (1) whether investors incorporate future changes in climate and Fama-French factors into present equity costs (lagged dependent variable approach), and (2) whether past changes in these variables influence CoE with a delay (lagged independent variable approach). Both methods build on panel data econometric principles outlined by Wooldridge (2010) and Hsiao (1985).

*1) Lagged Variables*

*1a) Lagged Dependent Variables*

Firstly, the dependent variable is shifted backward in time (Lagged_YoY_Change_CoE) to examine whether changes in climate variables or Fama-French factors impact CoE in the prior year. The rationale stems from investor behavior: markets may preemptively price in expected changes in climate strategies or financial metrics based on firm publications, sustainability disclosures, or general market trends.

The regression model is expressed as:

$$CoE_{i,t-1} = \beta_1 * ClimateVar_{i,t+1} + \beta_2 * FFfactors_{i,t+1} + \epsilon_{i,t}$$

This setup tests whether forward-looking investor expectations, based on anticipated environmental initiatives, influence equity costs.

*1b) Lagged Independent Variables*

Secondly, the explanatory variables (climate variables and Fama-French factors) are shifted backward in time (Lagged_YoY_Change) to assess their delayed influence on current CoE. This tests whether investors react late to changes, possibly due to slower dissemination or interpretation of environmental and financial data. The regression model is given by:

$$CoE_{i,t} = \beta_1 * ClimateVar_{i,t-1} + \beta_2 * FFfactors_{i,t-1} + \epsilon_{i,t}$$

This model evaluates the persistence of prior-year changes in climate and FF variables on CoE.

Both approaches collectively examine how investor expectations and delayed market reactions shape the relationship between sustainability efforts and financial performance.

*2) Alternative Thresholds for Fama-French Factors*

Robustness checks also included recalculating the individual Fama-French factors using alternative thresholds instead of the sample median. Specifically, the 75th and 90th percentiles (only 75th percentiles are shown in the result sections) were used to classify size, book-to-market, and the additional factors CMA and RMW, to see the effect on CoE and respectively on the regression models. This approach ensures the robustness of the factor computation process against arbitrary threshold selection.

**Appendix 12: Descriptive Statistics, Percentile Breakdown and Boxplots and Correlation Matrix**

Appendix 12a: Descriptive Statistics of Key Fama-French Factor Variables (2018–2022)

**Table 02**: Descriptive Statistics Adjusted Fama-French Approach

Table 02 provides descriptive statistics (mean, standard deviation, minimum, and maximum) for the main factors analyzed in this thesis.

| Variables | Obs | Mean | Std. dev. | Min | Max |
|---|---|---|---|---|---|
| SMUN_E | 60 | 0.022 | 6.254 | -17.456 | 9.770 |
| SMUN_R | 60 | 0.803 | 5.586 | -14.511 | 18.625 |
| SMUN_W | 60 | 1.250 | 5.786 | -11.022 | 22.598 |
| SMB | 60 | -0.908 | 2.811 | -11.706 | 5.861 |
| HML | 60 | -1.513 | 5.036 | -17.525 | 15.330 |
| MKT_Euribor | 60 | 0.644 | 5.375 | -16.810 | 20.859 |

Note: This table reports basic descriptive statistics for the primary factor variables used in the analysis. SMUN_E, SMUN_R, and SMUN_W capture sustainability-related excess returns tied to emission intensity, renewable energy share, and waste intensity, respectively. For example, SMUN_E has a mean near zero (0.022) but a relatively high standard deviation (6.254), suggesting considerable variability in emission-based excess returns across the observed periods.

Appendix 12b: Percentile Breakdown of Key Variables (2018-2022)

**Table 03**: Percentile Breakdown Adjusted Fama-French Approach

Table 03 presents the percentile breakdown of each variable, highlighting how returns and factor exposures are distributed within the sample period.

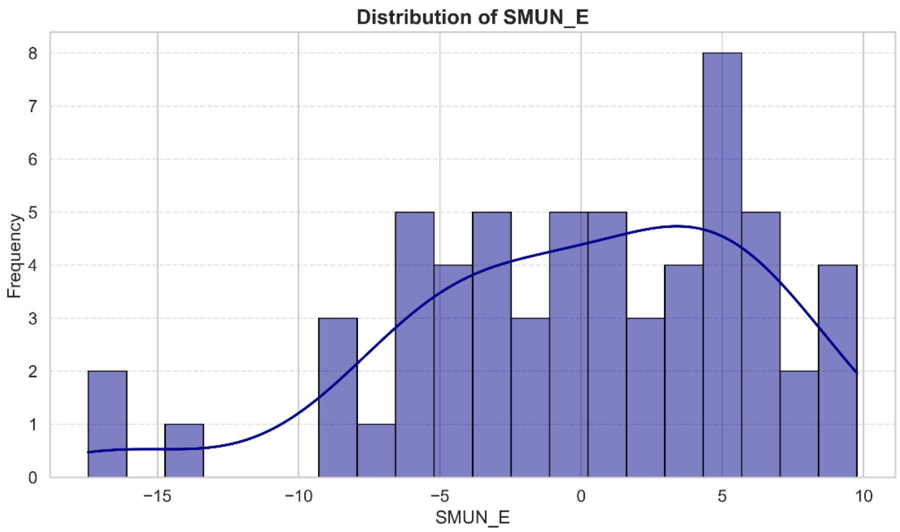
| Variables | 25th Percentile | 50th Percentile (Median) | 75th Percentile | 95th Percentile |
|---|---|---|---|---|
| SMUN_E | -3.975 | 0.768 | 4.806 | 9.121 |
| SMUN_R | -2.177 | 0.569 | 4.597 | 7.616 |
| SMUN_W | -2.610 | 1.456 | 5.286 | 8.034 |
| SMB | -2.405 | -1.210 | 0.528 | 3.616 |
| HML | -3.410 | -1.401 | 0.760 | 5.919 |
| MKT_Euribor | -2.142 | 0.444 | 3.753 | 6.174 |

Note: This percentile breakdown highlights how each factor distributes within the sample period. SMUN_R's 95th percentile (7.616) indicates that renewable-related excess returns can reach relatively high levels, while SMUN_E's median (0.768) remains comparatively moderate.

Appendix 12c. Distributions of Climate Variables and Fama-French Factors (2018-2022)

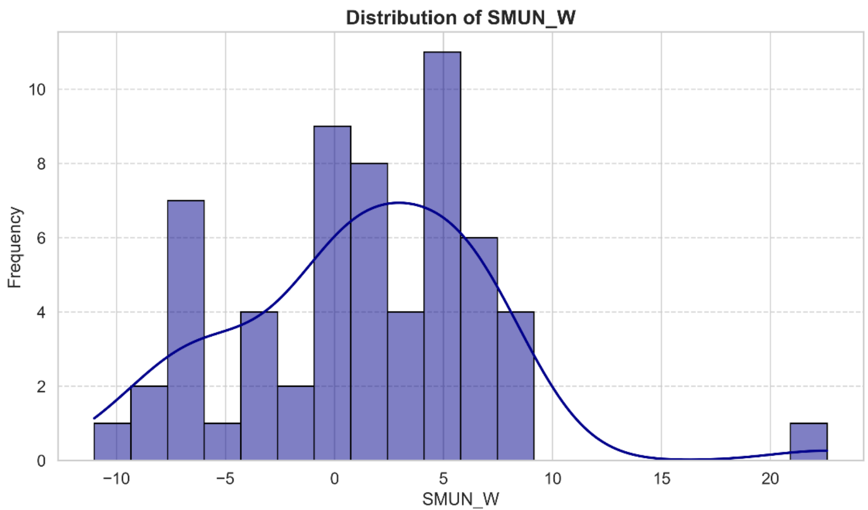
This appendix presents the monthly distributions of the primary factor returns from 2018 to 2022, providing a clearer view of their frequency, spread, and potential skewness or outliers. Each histogram includes a smoothed density curve to show the approximate shape of the distribution. A total of 60 monthly observations are used for each factor.

**Figure 06:** Distribution of SMUN_E



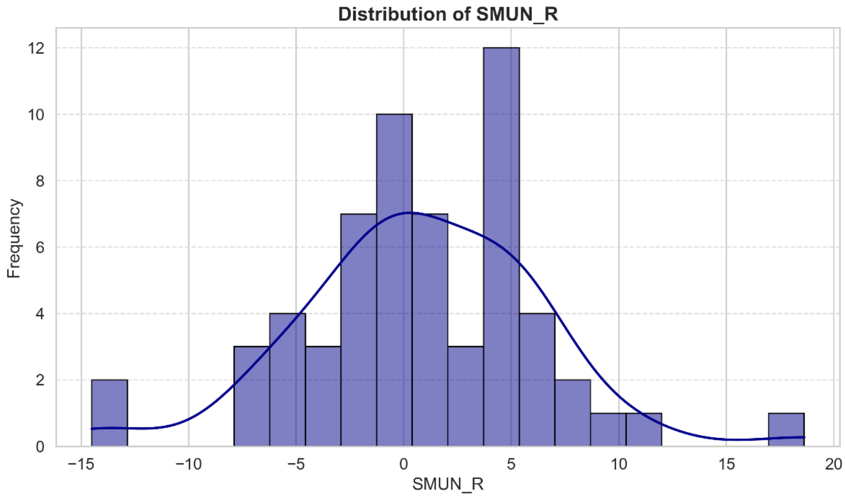

Note: SMUN_E (emission-intensity) factor appears roughly centered near zero but has a noticeable tail on both sides. Negative values from -15 to -10 are not uncommon, while a single cluster around +5 indicates that emission-related returns can be substantially positive in certain months.

**Figure 07:** Distribution of SMUN_W



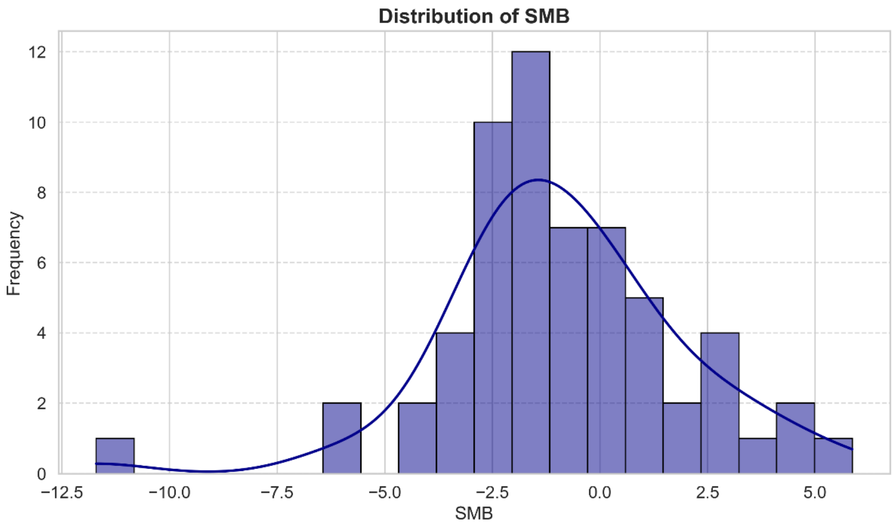

Note: This histogram depicts the SMUN_W (waste-intensity) factor. Most values cluster between -10 and +10, but an extreme right-tail observation exceeds +20. The slightly right-skewed shape suggests that, while typical monthly SMUN_W values center near zero or the low single digits, occasional positive outliers can occur.

**Figure 08**: Distribution of SMUN_R



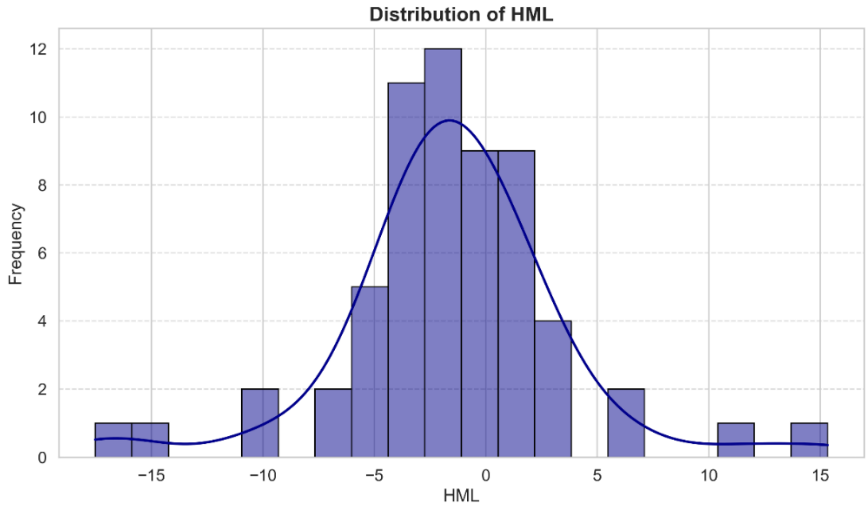

Note: SMUN_R (renewable energy share) factor displays a mild left skew, with a few observations falling below -10. The bulk of the distribution lies around -5 to +5, implying moderate variability in renewables-based excess returns. Rare peaks above +15 underscore the possibility of sudden, large positive returns in certain months.

**Figure 09**: Distribution of SMB



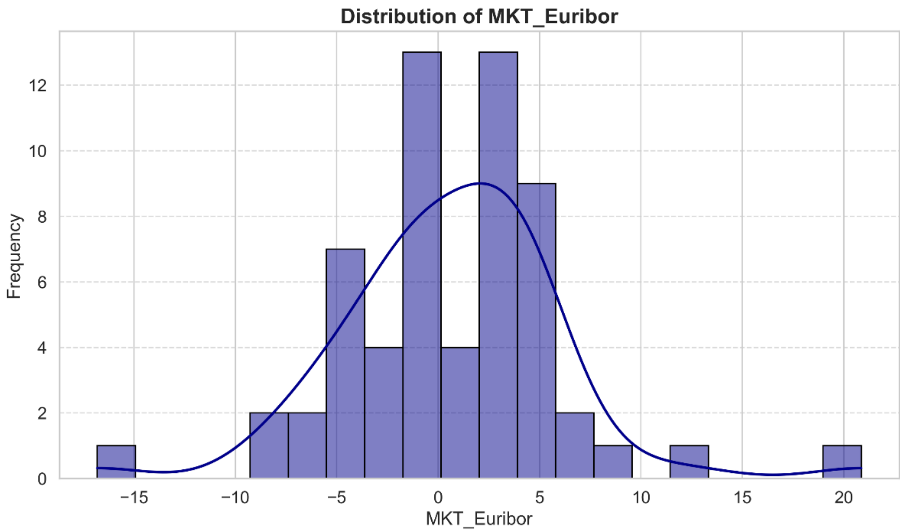

Note: The SMB factor is centered around -2 to -3, implying that large-cap portfolios outperformed small-cap portfolios on average during the observed period. However, the right tail extends beyond +5, indicating episodes where small-cap stocks significantly outpaced large-cap peers in certain months.

**Figure 10:** Distribution of HML




Note: HML shows a relatively symmetric shape around zero, though with some observations near ±15. The distribution's center near -2 to 0 suggests that growth-oriented (low B/M) stocks often performed marginally better than value-oriented (high B/M) stocks, but again, occasional negative and positive outliers of ±15 indicate value stocks had strong fluctuations in some months.

**Figure 11:** Distribution of MKT_Euribor




Note: The MKT_Euribor factor, representing the market's excess return over Euribor, peaks around -1 to +3, with a cluster of observations near zero. Negative outliers below -10 and a rare spike above +20 highlight that some months witnessed extreme market performance (positive or negative), underscoring the broader volatility during the 2018-2022 period.

Appendix 12d: Pearson's Correlation Matrix for Fama-French Factors (2018–2022)

**Table 04**: Pearson's Correlation Matrix Adjusted Fama-French Approach

Table 04 shows the correlation coefficients among the primary variables and factors, illustrating their pairwise relationships.

| Variables | SMUN_E | SMUN_R | SMUN_W | SMB | HML | MKT_Euribor |
|---|---|---|---|---|---|---|
| SMUN_E | 1 | | | | | |
| SMUN_R | -0.035 | 1 | | | | |
| SMUN_W | 0.422*** | 0.200 | 1 | | | |
| SMB | -0.331*** | -0.327** | -0.767*** | 1 | | |
| HML | 0.062 | -0.634*** | -0.084 | 0.431*** | 1 | |
| MKT_Euribor | 0.043 | -0.502*** | -0.355*** | 0.505*** | 0.438*** | 1 |

Note: This percentile breakdown highlights how each factor distributes within the sample period. SMUN_R's 95th percentile (7.616) indicates that renewable-related excess returns can reach relatively high levels, while SMUN_E's median (0.768) remains comparatively moderate. These distributions help contextualize the range of performance across different sustainability factors.

**Appendix 13: Cumulative and Average Monthly Excess Returns for the 12 Constructed Portfolios (Market-Cap Weighted and Equal Weighted)**

**Table 05** displays the cumulative excess returns for the 12 constructed portfolios under market-cap weighting, comparing sustainable (SU) and unsustainable (UN) segments.

| | Excess Return E | | Excess Return W | | Excess Return R | |
|---|---|---|---|---|---|---|
| Portfolio | SU | UN | SU | UN | SU | UN |
| BH | 51.01 | 109.15 | 74.38 | 31.26 | 82.29 | 49.17 |
| BL | 360.00 | 286.48 | 387.98 | 158.25 | 381.15 | 265.72 |
| BN | 167.72 | 249.15 | 197.83 | 174.40 | 206.47 | 161.18 |
| SH | -41.02 | -41.32 | -12.09 | -80.32 | -24.18 | -70.57 |
| SL | 251.02 | 142.53 | 248.42 | 137.64 | 197.92 | 221.90 |
| SN | 45.88 | 80.33 | 48.10 | 73.07 | 99.76 | 27.48 |

Note: BLSU (Big-Low-Sustainable) displays the highest cumulative return in several columns, sometimes exceeding 370 %. Differences such as SL (Small-Low) also show a wide gap between SU and UN configurations (e.g., ~65 % difference). These numbers suggest that certain size-value-sustainability mixes outperform others over the sample period.

**Table 06** lists the cumulative excess returns for the 12 constructed portfolios under equal weighting, illustrating how weighting choices may affect observed performance

| | Excess Return E | | Excess Return W | | Excess Return R | |
|---|---|---|---|---|---|---|
| Portfolio | SU | UN | SU | UN | SU | UN |
| BH | 47.66 | 33.76 | 53.89 | 5.38 | 41.70 | 31.52 |
| BL | 273.34 | 174.03 | 262.73 | 192.09 | 273.90 | 200.34 |
| BN | 162.58 | 166.76 | 172.17 | 153.18 | 182.59 | 142.61 |
| SH | -187.54 | -59.71 | -78.21 | -102.09 | -83.45 | -99.89 |
| SL | 203.62 | 50.23 | 207.00 | 36.14 | 171.84 | 99.63 |
| SN | 81.36 | 48.46 | 62.15 | 58.08 | 83.22 | 30.48 |

Note: Under equal weighting, certain portfolios (e.g., BL and SL) show even higher cumulative returns for sustainable (SU) segments compared to market-cap weighting. BN, however, features closer returns between SU and UN, indicating that not all low- vs. high-sustainability splits lead to substantial performance spreads.

**Table 07** displays the average excess returns for the 12 constructed portfolios under market-cap weighting, comparing sustainable (SU) and unsustainable (UN) segments.

| | Excess Return E | | Excess Return W | | Excess Return R | |
|---|---|---|---|---|---|---|
| Portfolio | SU | UN | SU | UN | SU | UN |
| BH | 4.25 | 9.10 | 6.20 | 2.60 | 6.86 | 4.10 |
| BL | 30.00 | 23.87 | 32.33 | 13.19 | 31.76 | 22.14 |
| BN | 13.98 | 20.76 | 16.49 | 14.53 | 17.21 | 13.43 |
| SH | -3.42 | -3.44 | -1.01 | -6.69 | -2.01 | -5.88 |
| SL | 20.92 | 11.88 | 20.70 | 11.47 | 16.49 | 18.49 |
| SN | 3.82 | 6.69 | 4.01 | 6.09 | 8.31 | 2.29 |

Note: Under market-cap weighting, these average monthly excess returns suggest that some sustainable (SU) portfolios significantly outperform their unsustainable (UN) counterparts. For instance, BL-SU exceeds BL-UN by nearly 8 percentage points in the waste (W) column (32.33 vs. 13.19). By contrast, BN exhibits a smaller difference between SU and UN, highlighting that not all size-value-sustainability combinations yield pronounced return gaps. Overall, these figures reinforce the idea that climate-related attributes can influence portfolio performance under market-cap weighting.

**Table 08** lists the average excess returns for the 12 constructed portfolios under equal weighting, illustrating how weighting choices may affect observed performance

| | Excess Return E | | Excess Return W | | Excess Return R | |
|---|---|---|---|---|---|---|
| Portfolio | SU | UN | SU | UN | SU | UN |
| BH | 3.97 | 2.81 | 2.63 | 3.47 | 10.78 | 1.08 |
| BL | 22.78 | 14.50 | 16.70 | 22.82 | 52.55 | 38.42 |
| BN | 13.55 | 13.90 | 11.88 | 15.22 | 34.43 | 30.64 |
| SH | -15.63 | -4.98 | -8.32 | -6.95 | -15.64 | -20.42 |
| SL | 16.97 | 4.19 | 8.30 | 14.32 | 41.41 | 7.23 |
| SN | 6.78 | 4.04 | 2.54 | 6.93 | 12.43 | 11.62 |

Note: This table illustrates average monthly excess returns, highlighting that some SU portfolios (like BL-SU or SL-SU) outperform their UN counterparts by wide margins (e.g., BL SU vs. UN: 52.55 vs. 38.42 in the R column). At the same time, other portfolios (e.g., BN) show smaller differences. Overall, these figures support the notion that sustainability splits can significantly affect average monthly performance.

### Appendix 14: Results of Market Weighting – Median Split in $SMUN_x$

Appendix 14a-4c show the results for $SMUN_E$, $SMUN_W$, and $SMUN_R$

### Appendix 15: Results (Robustness) of Market Weighting – 70:30 Split in $SMUN_x$

Appendix 15a-15c show the results for $SMUN_E$, $SMUN_W$, and $SMUN_R$

### Appendix 16: Results (Robustness) of Equal Weighting – Median Split in $SMUN_x$

Appendix 16a-16c show the results for $SMUN_E$, $SMUN_W$, and $SMUN_R$

### Appendix 17: Results (Robustness) of Equal Weighting – 70:30 Split in $SMUN_x$

Appendix 17a-17c show the results for $SMUN_E$, $SMUN_W$, and $SMUN_R$

Appendix 14a: Results of Market Weighting – Median Split in $SMUN_E$

**Table 09** compares the coefficients of the FF three-factor model (LHS) and the extended four-factor model (RHS). The fourth factor $SMUN_X$ (where x = E for emisson intensity) was constructed by splitting $SMUN_E$ variable at the median, classifying companies as SU (sustainable) below the median and UN (unsustainable) above the median. The results are based on market capitalization weighting, presenting the coefficients for both SU and UN classifications, with an emphasis on the statistical significance of the added factor. The coefficients are averaged for sustainable (SU) and unsustainable (UN) portfolios. The averages are represented as $\mu_{SU}$ (mean of sustainable portfolios) and $\mu_{UN}$ (mean of unsustainable portfolios).

| | $r_i = a_i + b_i(R_M - R_f) + s_iSMB + h_iHML$ | | | | | | $r_i = a_i + b_i(R_M - R_f) + s_iSMB + h_iHML + \boldsymbol{sm_iSMUN_x}$ | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Portfolio** | $\mathbf{a_i}$ | $\mathbf{b_i}$ | $\mathbf{s_i}$ | $\mathbf{h_i}$ | $\mathbf{R^2}$ | | $\mathbf{a_i}$ | $\mathbf{b_i}$ | $\mathbf{s_i}$ | $\mathbf{h_i}$ | $\mathbf{sm_i}$ | $\mathbf{R^2}$ |
| BHSU | 0.64 | 1.08*** | -0.13 | 0.15 | 0.79 | | 0.34 | 1.19*** | -0.59*** | 0.24*** | 0.39*** | 0.89 |
| BHUN | 0.71*** | 0.87*** | -0.58*** | 0.65*** | 0.96 | | 0.75*** | 0.85*** | -0.52*** | 0.64*** | -0.06 | 0.96 |
| BLSU | 1.00** | 0.72*** | -0.29* | -0.22*** | 0.61 | | 0.77** | 0.81*** | -0.64*** | -0.16** | 0.3*** | 0.76 |
| BLUN | 0.6*** | 0.99*** | -0.54*** | -0.58*** | 0.92 | | 0.61*** | 0.98*** | -0.52*** | -0.58*** | -0.02 | 0.92 |
| BNSU | 1.17*** | 0.74*** | -0.08 | -0.1 | 0.72 | | 0.97*** | 0.82*** | -0.38*** | -0.04 | 0.26*** | 0.83 |
| BNUN | 0.13 | 1.14*** | -1.43*** | 0.39*** | 0.82 | | 0.27 | 1.09*** | -1.22*** | 0.35*** | -0.18** | 0.84 |
| SHSU | 0.18 | 1.09*** | 0.37*** | 0.11* | 0.94 | | 0.14 | 1.11*** | 0.31*** | 0.12** | 0.05 | 0.94 |
| SHUN | 0.48 | 1.06*** | 0.01 | 0.52*** | 0.9 | | 0.50 | 1.05*** | 0.05 | 0.51*** | -0.04 | 0.9 |
| SLSU | 0.69 | 0.83*** | -0.08 | -0.01 | 0.63 | | 0.52 | 0.89*** | -0.34 | 0.05 | 0.22*** | 0.68 |
| SLUN | 0.71 | 1.01*** | 0.08 | -0.46*** | 0.66 | | 1.01** | 0.90*** | 0.54*** | -0.55*** | -0.39*** | 0.79 |
| SNSU | 0.7* | 0.99*** | 0.29*** | 0.04 | 0.94 | | 0.64*** | 1.01*** | 0.20** | 0.06 | 0.08** | 0.95 |
| SNUN | 0.2 | 0.97*** | 0.16 | -0.1 | 0.91 | | 0.26 | 0.95*** | 0.24** | -0.11** | -0.08* | 0.91 |
| $\mu$ | 0.60 | 0.96 | -0.19 | 0.03 | 0.82 | $\mu_{SU}$ | 0.56 | 0.97 | -0.24 | 0.05 | 0.22 | 0.84 |
| | | | | | | $\mu_{UN}$ | 0.57 | 0.97 | -0.24 | 0.04 | -0.13 | 0.89 |

* p<0.1, ** p<0.05, *** p<0.01

Appendix 14b: Results of Market Weighting – Median Split in $SMUN_W$

**Table 10** compares the coefficients of the FF three-factor model (LHS) and the extended four-factor model (RHS). The fourth factor $SMUN_X$ (where x = W for waste intensity) was constructed by splitting $SMUN_W$ variable at the median, classifying companies as SU (sustainable) below the median and UN (unsustainable) above the median. The results are based on market capitalization weighting, presenting the coefficients for both SU and UN classifications, with an emphasis on the statistical significance of the added factor. The coefficients are averaged for sustainable (SU) and unsustainable (UN) portfolios. The averages are represented as $\mu_{UN}$ (mean of sustainable portfolios) and $\mu_{SU}$ (mean of unsustainable portfolios).

| | $r_i = a_i + b_i(R_M - R_f) + s_iSMB + h_iHML$ | | | | | | $r_i = a_i + b_i(R_M - R_f) + s_iSMB + h_iHML + \boldsymbol{sm_iSMUN_x}$ | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Portfolio** | **$a_i$** | **$b_i$** | **$s_i$** | **$h_i$** | **$R^2$** | | **$a_i$** | **$b_i$** | **$s_i$** | **$h_i$** | **$sm_i$** | **$R^2$** |
| BHSU | 0.7 | 1.1*** | 0.3* | 0.23** | 0.86 | | 0.77** | 1.08*** | -0.5** | 0.38*** | 0.44*** | 0.9 |
| BHUN | 0.67*** | 0.88*** | -0.64*** | 0.58*** | 0.94 | | 0.64*** | 0.89*** | -0.31** | 0.52*** | -0.19*** | 0.95 |
| BLSU | -0.24 | 0.95*** | -0.48*** | -0.42*** | 0.87 | | -0.23 | 0.94*** | -0.69*** | -0.38*** | 0.12* | 0.88 |
| BLUN | 0.89*** | 0.92*** | -0.5*** | -0.52*** | 0.9 | | 0.87*** | 0.93*** | -0.27* | -0.56*** | -0.13** | 0.9 |
| BNSU | 0.68*** | 0.83*** | -0.04 | -0.16*** | 0.87 | | 0.7*** | 0.83*** | -0.19 | -0.13** | 0.09 | 0.87 |
| BNUN | 0.33 | 1.11*** | -1.46*** | 0.42*** | 0.83 | | 0.33 | 1.11*** | -1.41*** | 0.41*** | -0.03 | 0.83 |
| SHSU | 0.02 | 1.15*** | 0.49*** | 0.08 | 0.94 | | 0.06 | 1.14*** | 0.05 | 0.17*** | 0.25*** | 0.95 |
| SHUN | 0.58* | 1.00*** | -0.04 | 0.49*** | 0.92 | | 0.59* | 1.00** | -0.1 | 0.5*** | 0.04 | 0.92 |
| SLSU | 1.14** | 0.85*** | 0.27 | 0.11 | 0.66 | | 1.18** | 0.84*** | -0.17 | 0.20 | 0.24 | 0.68 |
| SLUN | 0.52 | 0.96*** | -0.11 | -0.48*** | 0.68 | | 0.45 | 0.98*** | 0.71*** | -0.64*** | -0.45*** | 0.75 |
| SNSU | 0.63*** | 1.03*** | 0.36*** | -0.02 | 0.96 | | 0.63 | 1.03*** | 0.42*** | -0.04 | -0.04* | 0.96 |
| SNUN | 0.26 | 0.93*** | -0.04 | 0.05 | 0.84 | | 0.23 | 0.94*** | 0.28 | -0.02 | -0.18* | 0.85 |
| $\mu$ | 0.52 | 0.98 | -0.16 | 0.03 | 0.86 | $\mu_{SU}$ | 0.52 | 0.98 | -0.18 | 0.03 | 0.18 | 0.87 |
| | | | | | | $\mu_{UN}$ | 0.52 | 0.98 | -0.18 | 0.04 | -0.16 | 0.87 |

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Appendix 14c: Results of Market Weighting – Median Split in $SMUN_R$

**Table 11** compares the coefficients of the FF three-factor model (LHS) and the extended four-factor model (RHS). The fourth factor $SMUN_X$ (where x = R for share of renewable energy consumption) was constructed by splitting $SMUN_R$ variable at the median, classifying companies as SU (sustainable) above the median and UN (unsustainable) below the median. The results are based on market capitalization weighting, presenting the coefficients for both SU and UN classifications, with an emphasis on the statistical significance of the added factor. The coefficients are averaged for sustainable (SU) and unsustainable (UN) portfolios. The averages are represented as $\mu_{SU}$ (mean of sustainable portfolios) and $\mu_{UN}$ (mean of unsustainable portfolios).

| | $r_i = a_i + b_i(R_M - R_f) + s_i SMB + h_i HML$ | | | | | | $r_i = a_i + b_i(R_M - R_f) + s_i SMB + h_i HML + \boldsymbol{sm_i SMUN_x}$ | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Portfolio** | **$a_i$** | **$b_i$** | **$s_i$** | **$h_i$** | **$R^2$** | | **$a_i$** | **$b_i$** | **$s_i$** | **$h_i$** | **$sm_i$** | **$R^2$** |
| BHSU | 0.57** | 0.92*** | -0.46*** | 0.38*** | 0.9 | | 0.54** | 1.00*** | -0.49*** | 0.54*** | 0.27*** | 0.94 |
| BHUN | 0.98*** | 0.95*** | -0.25* | 0.65*** | 0.89 | | 0.99*** | 0.89*** | -0.23* | 0.56*** | -0.16** | 0.9 |
| BLSU | 0.56** | 0.97*** | -0.64*** | -0.62*** | 0.89 | | 0.55** | 1.02*** | -0.66*** | -0.52*** | 0.18*** | 0.91 |
| BLUN | 1*** | 0.81*** | -0.17 | -0.21*** | 0.77 | | 1.00*** | 0.81*** | -0.17 | -0.21** | 0.01 | 0.77 |
| BNSU | 1.01*** | 0.8*** | -0.11 | -0.02 | 0.84 | | 1.00*** | 0.83*** | -0.12 | 0.05 | 0.11* | 0.84 |
| BNUN | -0.08 | 1.24*** | -1.72*** | 0.47*** | 0.77 | | -0.04 | 1.13*** | -1.69*** | 0.27** | -0.35*** | 0.81 |
| SHSU | 0.47 | 0.93*** | 0.16 | 0.34*** | 0.91 | | 0.47 | 0.95*** | 0.15 | 0.37*** | 0.05 | 0.91 |
| SHUN | 0.09 | 1.23*** | 0.32** | 0.2*** | 0.93 | | 0.11 | 1.15*** | 0.34*** | 0.06 | -0.26*** | 0.95 |
| SLSU | 0.56 | 0.96*** | -0.06 | -0.3*** | 0.72 | | 0.54* | 1.02*** | -0.08 | -0.19* | 0.19** | 0.74 |
| SLUN | 0.88** | 0.9*** | 0.09 | -0.26** | 0.67 | | 0.9** | 0.81*** | 0.12 | -0.43*** | -0.3*** | 0.72 |
| SNSU | 0.41 | 0.93*** | 0.01 | -0.07 | 0.87 | | 0.4 | 0.97*** | -0.02 | 0.01 | 0.13* | 0.88 |
| SNUN | 0.53** | 1.01*** | 0.44*** | 0.04 | 0.96 | | 0.54** | 1.00*** | 0.44*** | 0.01 | -0.05 | 0.96 |
| $\mu$ | 0.58 | 0.97 | -0.20 | 0.05 | 0.84 | $\mu_{SU}$ | 0.58 | 0.96 | -0.20 | 0.04 | 0.15 | 0.87 |
| | | | | | | $\mu_{UN}$ | 0.58 | 0.96 | -0.20 | 0.04 | -0.18 | 0.84 |

* p<0.1, ** p<0.05, *** p<0.01

Appendix 15a: Results (Robustness) of Market Weighting – 70:30 Split in $SMUN_E$

**Table 12** compares the coefficients of the FF three-factor model (LHS) and the extended four-factor model (RHS). The fourth factor $SMUN_X$ (where x = E for emisson intensity) was constructed by splitting $SMUN_E$ variable with 70:30, classifying companies as SU (sustainable) below the 30th percentile and UN (unsustainable) above the 70th percentile. The results are based on market capitalization weighting, presenting the coefficients for both SU and UN classifications, with an emphasis on the statistical significance of the added factor. The coefficients are averaged for sustainable (SU) and unsustainable (UN) portfolios. The averages are represented as $\mu_{SU}$ (mean of sustainable portfolios) and $\mu_{UN}$ (mean of unsustainable portfolios).

| | $r_i = a_i + b_i(R_M - R_f) + s_iSMB + h_iHML$ | | | | | | $r_i = a_i + b_i(R_M - R_f) + s_iSMB + h_iHML + \boldsymbol{sm_iSMUN_x}$ | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Portfolio** | $\mathbf{a_i}$ | $\mathbf{b_i}$ | $\mathbf{s_i}$ | $\mathbf{h_i}$ | $\mathbf{R^2}$ | | $\mathbf{a_i}$ | $\mathbf{b_i}$ | $\mathbf{s_i}$ | $\mathbf{h_i}$ | $\mathbf{sm_i}$ | $\mathbf{R^2}$ |
| BHSU | 0.04 | 1.27*** | -0.94*** | 0.59*** | 0.86 | | 0.07 | 1.27*** | -1.00*** | 0.4*** | 1.12*** | 0.91 |
| BHUN | 0.89*** | 1.05*** | -0.51*** | 0.69*** | 0.94 | | 0.88*** | 1.05*** | -0.48*** | 0.77*** | -0.47*** | 0.95 |
| BLSU | 0.52 | 0.99*** | 0.01 | -0.21 | 0.75 | | 0.53 | 0.99*** | -0.01 | -0.24 | 0.23 | 0.75 |
| BLUN | 0.32 | 1.21*** | -0.47*** | -0.65*** | 0.94 | | 0.31 | 1.21*** | -0.45*** | -0.61*** | -0.21 | 0.94 |
| BNSU | 0.4 | 1.09*** | -0.94*** | 0.04 | 0.81 | | 0.41 | 1.09*** | -0.98*** | -0.08 | 0.66*** | 0.84 |
| BNUN | 0.57** | 0.9*** | -0.83*** | 0.16* | 0.89 | | 0.56** | 0.89*** | -0.81*** | 0.21** | -0.28* | 0.89 |
| SHSU | 0.2 | 1.08*** | 0.51*** | 0.18** | 0.95 | | 0.21 | 1.08*** | 0.49*** | 0.13 | 0.30* | 0.96 |
| SHUN | 0.77* | 0.96*** | 0.22 | 0.61*** | 0.87 | | 0.74* | 0.95*** | 0.28 | 0.79*** | -1.06*** | 0.91 |
| SLSU | 1.03** | 1.08*** | 0.72** | -0.02 | 0.82 | | 1.05** | 1.09*** | 0.69** | -0.11 | 0.54* | 0.83 |
| SLUN | 0.1 | 1.13*** | 0.87*** | -1.07*** | 0.8 | | 0.08 | 1.13*** | 0.91*** | -0.94*** | -0.77*** | 0.83 |
| SNSU | 0.61*** | 1.11*** | 0.51*** | -0.09 | 0.95 | | 0.62*** | 1.11*** | 0.49*** | -0.14* | 0.31** | 0.96 |
| SNUN | 0.21 | 1.23*** | 0.28 | -0.18 | 0.85 | | 0.19 | 1.22*** | 0.32 | -0.07 | -0.62*** | 0.87 |
| $\mu$ | 0.47 | 1.09 | -0.05 | 0.00 | 0.87 | $\mu_{SU}$ | 0.48 | 1.11 | -0.05 | -0.01 | 0.53 | 0.88 |
| | | | | | | $\mu_{UN}$ | 0.46 | 1.08 | -0.04 | 0.03 | -0.57 | 0.90 |

* p<0.1, ** p<0.05, *** p<0.01

Appendix 15b: Results (Robustness) of Market Weighting – 70:30 Split in $SMUN_W$

**Table 13** compares the coefficients of the FF three-factor model (LHS) and the extended four-factor model (RHS). The fourth factor $SMUN_X$ (where x = W for waste intensity) was constructed by splitting $SMUN_W$ variable with 70:30, classifying companies as SU (sustainable) below the the 30$^{th}$ percentile and UN (unsustainable) above the 70$^{th}$ percentile. The results are based on market capitalization weighting, presenting the coefficients for both SU and UN classifications, with an emphasis on the statistical significance of the added factor. The coefficients are averaged for sustainable (SU) and unsustainable (UN) portfolios. The averages are represented as $\mu_{SU}$ (mean of sustainable portfolios) and $\mu_{UN}$ (mean of unsustainable portfolios).

| | $r_i = a_i + b_i(R_M - R_f) + s_iSMB + h_iHML$ | | | | | | $r_i = a_i + b_i(R_M - R_f) + s_iSMB + h_iHML + \boldsymbol{sm_iSMUN_x}$ | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Portfolio** | **$a_i$** | **$b_i$** | **$s_i$** | **$h_i$** | **$R^2$** | | **$a_i$** | **$b_i$** | **$s_i$** | **$h_i$** | **$sm_i$** | **$R^2$** |
| BHSU | 0.95** | 1.12*** | 0.18 | 0.40*** | 0.85 | | 0.77** | 1.08*** | -0.5** | 0.38*** | 0.44*** | 0.9 |
| BHUN | 0.74*** | 0.87*** | -0.58*** | 0.67*** | 0.95 | | 0.64*** | 0.89*** | -0.31** | 0.52*** | -0.19*** | 0.95 |
| BLSU | 0.09 | 0.73*** | -0.23* | -0.50*** | 0.69 | | -0.23 | 0.94*** | -0.69*** | -0.38*** | 0.12* | 0.88 |
| BLUN | 0.15 | 0.97*** | -0.49*** | -0.55*** | 0.86 | | 0.87*** | 0.93*** | -0.27* | -0.56*** | -0.13** | 0.9 |
| BNSU | 0.55 | 0.93*** | -0.13 | -0.06 | 0.8 | | 0.7*** | 0.83*** | -0.19 | -0.13** | 0.09 | 0.87 |
| BNUN | 0.32* | 1.15*** | -1.58*** | 0.48*** | 0.82 | | 0.33 | 1.11*** | -1.41*** | 0.41*** | -0.03 | 0.83 |
| SHSU | 0.07 | 1.03*** | 0.55*** | 0.04 | 0.86 | | 0.06 | 1.14*** | 0.05 | 0.17*** | 0.25*** | 0.95 |
| SHUN | 0.54 | 0.88*** | -0.11 | 0.53*** | 0.86 | | 0.59* | 1.00** | -0.1 | 0.5*** | 0.04 | 0.92 |
| SLSU | 0.86* | 0.94*** | 0.11 | -0.07 | 0.69 | | 1.18** | 0.84*** | -0.17 | 0.20 | 0.24 | 0.68 |
| SLUN | 0.85 | 1.15*** | -0.18 | -0.44*** | 0.67 | | 0.45 | 0.98*** | 0.71*** | -0.64*** | -0.45*** | 0.75 |
| SNSU | 0.86*** | 1.08*** | 0.29** | -0.06 | 0.92 | | 0.63 | 1.03*** | 0.42*** | -0.04 | -0.04* | 0.96 |
| SNUN | 0.69 | 0.87*** | -0.07 | 0.02 | 0.7 | | 0.23 | 0.94*** | 0.28 | -0.02 | -0.18* | 0.85 |
| $\mu$ | 0.55 | 0.97 | -0.19 | 0.04 | 0.80 | $\mu_{SU}$ | 0.58 | 0.97 | -0.19 | 0.04 | 0.17 | 0.82 |
| | | | | | | $\mu_{UN}$ | 0.55 | 0.97 | -0.19 | 0.04 | -0.17 | 0.83 |

* p<0.1, ** p<0.05, *** p<0.01

Appendix 15c: Results (Robustness) of Market Weighting – 70:30 Split in $SMUN_R$

**Table 14** compares the coefficients of the FF three-factor model (LHS) and the extended four-factor model (RHS). The fourth factor $SMUN_X$ (where x = R for share of renewable energy consumption) was constructed by splitting $SMUN_R$ variable with 70:30, classifying companies as SU (sustainable) above the 70$^{th}$ percentile and UN (unsustainable) below the 30$^{th}$ percentil. The results are based on market capitalization weighting, presenting the coefficients for both SU and UN classifications, with an emphasis on the statistical significance of the added factor. The coefficients are averaged for sustainable (SU) and unsustainable (UN) portfolios. The averages are represented as $\mu_{SU}$ (mean of sustainable portfolios) and $\mu_{UN}$ (mean of unsustainable portfolios).

| | $r_i = a_i + b_i(R_M - R_f) + s_i SMB + h_i HML$ | | | | | | $r_i = a_i + b_i(R_M - R_f) + s_i SMB + h_i HML + \boldsymbol{sm_i SMUN_x}$ | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Portfolio** | **$a_i$** | **$b_i$** | **$s_i$** | **$h_i$** | **$R^2$** | | **$a_i$** | **$b_i$** | **$s_i$** | **$h_i$** | **$sm_i$** | **$R^2$** |
| BHSU | 0.25 | 0.82*** | -0.49*** | 0.32*** | 0.80 | | 0.54** | 1.00*** | -0.49*** | 0.54*** | 0.27*** | 0.94 |
| BHUN | 0.71 | 0.90*** | -0.39* | 0.52*** | 0.72 | | 0.99*** | 0.89*** | -0.23* | 0.56*** | -0.16** | 0.9 |
| BLSU | 0.64** | 0.88*** | -0.67*** | -0.64*** | 0.80 | | 0.55** | 1.02*** | -0.66*** | -0.52*** | 0.18*** | 0.91 |
| BLUN | 1.43*** | 0.88*** | -0.16 | -0.09 | 0.61 | | 1.00*** | 0.81*** | -0.17 | -0.21** | 0.01 | 0.77 |
| BNSU | 0.77** | 0.87*** | -0.25* | -0.03 | 0.79 | | 1.00*** | 0.83*** | -0.12 | 0.05 | 0.11* | 0.84 |
| BNUN | 0.11** | 1.30*** | -1.92*** | 0.54*** | 0.74 | | -0.04 | 1.13*** | -1.69*** | 0.27** | -0.35*** | 0.81 |
| SHSU | 0.37 | 0.86*** | 0.13 | 0.31*** | 0.86 | | 0.47 | 0.95*** | 0.15 | 0.37*** | 0.05 | 0.91 |
| SHUN | 0.12* | 1.23*** | 0.21 | 0.10 | 0.90 | | 0.11 | 1.15*** | 0.34*** | 0.06 | -0.26*** | 0.95 |
| SLSU | 0.48 | 0.92*** | -0.07 | -0.37*** | 0.57 | | 0.54* | 1.02*** | -0.08 | -0.19* | 0.19** | 0.74 |
| SLUN | 0.82 | 0.74*** | 0.01 | -0.19 | 0.43 | | 0.9** | 0.81*** | 0.12 | -0.43*** | -0.3*** | 0.72 |
| SNSU | 0.16 | 0.93*** | -0.19 | -0.09 | 0.79 | | 0.4 | 0.97*** | -0.02 | 0.01 | 0.13* | 0.88 |
| SNUN | 0.52*** | 1.00*** | 0.33*** | 0.09 | 0.92 | | 0.54** | 1.00*** | 0.44*** | 0.01 | -0.05 | 0.96 |
| $\mu$ | 0.50 | 0.94 | -0.29 | 0.04 | 0.74 | $\mu_{SU}$ | 0.49 | 0.94 | -0.29 | 0.03 | 0.16 | 0.80 |
| | | | | | | $\mu_{UN}$ | 0.49 | 0.94 | -0.28 | 0.03 | -0.18 | 0.75 |

* p<0.1, ** p<0.05, *** p<0.01

Appendix 16a: Results (Robustness) of Equal Weighting – Median Split in $SMUN_E$

**Table 15** compares the coefficients of the FF three-factor model (LHS) and the extended four-factor model (RHS). The fourth factor $SMUN_X$ (where x = E for emission intensity) was constructed by splitting $SMUN_E$ variable at the median, classifying companies as SU (sustainable) below the median and UN (unsustainable) above the median. The results are based on equal weighting, presenting the coefficients for both SU and UN classifications, with an emphasis on the statistical significance of the added factor. The coefficients are averaged for sustainable (SU) and unsustainable (UN) portfolios. The averages are represented as $\mu_{SU}$ (mean of sustainable portfolios) and $\mu_{UN}$ (mean of unsustainable portfolios).

| | $r_i = a_i + b_i(R_M - R_f) + s_iSMB + h_iHML$ | | | | | | $r_i = a_i + b_i(R_M - R_f) + s_iSMB + h_iHML + \boldsymbol{sm_iSMUN_x}$ | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Portfolio** | $\mathbf{a_i}$ | $\mathbf{b_i}$ | $\mathbf{s_i}$ | $\mathbf{h_i}$ | $\mathbf{R^2}$ | | $\mathbf{a_i}$ | $\mathbf{b_i}$ | $\mathbf{s_i}$ | $\mathbf{h_i}$ | $\mathbf{sm_i}$ | $\mathbf{R^2}$ |
| BHSU | 0.33 | 1.08*** | -0.55** | 0.50*** | 0.91 | | 0.39 | 1.12*** | -0.6*** | 0.47*** | 0.68*** | 0.93 |
| BHUN | 0.84*** | 1.03*** | -0.49** | 0.77*** | 0.94 | | 0.81*** | 1.02*** | -0.47*** | 0.81*** | -0.49** | 0.96 |
| BLSU | 0.23 | 0.9*** | -0.21 | -0.38*** | 0.87 | | 0.25 | 0.91*** | -0.23 | -0.39*** | 0.12 | 0.89 |
| BLUN | 0.33** | 1.12*** | -0.46*** | -0.53*** | 0.95 | | 0.33** | 1.12*** | -0.47*** | -0.54*** | -0.08 | 0.96 |
| BNSU | 0.38* | 0.96*** | -0.71*** | 0.06 | 0.9 | | 0.45** | 1.00*** | -0.77*** | 0.03 | 0.74*** | 0.94 |
| BNUN | 0.52*** | 0.88*** | -0.56*** | 0.08 | 0.93 | | 0.51*** | 0.88*** | -0.56*** | 0.09 | -0.14 | 0.94 |
| SHSU | 0.22 | 1.03*** | 0.43*** | 0.2*** | 0.96 | | 0.26 | 1.06*** | 0.42*** | 0.19*** | 0.36** | 0.97 |
| SHUN | 0.37 | 0.84*** | 0.42 | 0.82*** | 0.9 | | 0.29 | 0.80*** | 0.50*** | 0.88*** | -1.04*** | 0.93 |
| SLSU | 0.71** | 0.86*** | 1.00*** | -0.24* | 0.82 | | 0.8** | 0.91*** | 0.95** | -0.31** | 1.00*** | 0.86 |
| SLUN | 0.69** | 1.00*** | 0.85*** | -0.78*** | 0.81 | | 0.63* | 0.97*** | 0.92*** | -0.74*** | -0.96*** | 0.85 |
| SNSU | 0.53*** | 1.00*** | 0.46*** | -0.03 | 0.95 | | 0.58*** | 1.03*** | 0.44*** | -0.06 | 0.46*** | 0.97 |
| SNUN | 0.27 | 1.1*** | 0.17*** | -0.17 | 0.91 | | 0.24 | 1.09*** | 0.21*** | -0.16 | -0.46** | 0.93 |
| $\mu$ | 0.45 | 0.98 | 0.03 | 0.03 | 0.90 | $\mu_{SU}$ | 0.45 | 1.00 | 0.03 | -0.01 | 0.57 | 0.92 |
| | | | | | | $\mu_{UN}$ | 0.46 | 0.98 | 0.02 | 0.06 | -0.53 | 0.92 |

* p<0.1, ** p<0.05, *** p<0.01

Appendix 16b: Results (Robustness) of Equal Weighting – Median Split in $SMUN_W$

**Table 16** compares the coefficients of the FF three-factor model (LHS) and the extended four-factor model (RHS). The fourth factor $SMUN_X$ (where x = W for waste intensity) was constructed by splitting $SMUN_W$ variable at the median, classifying companies as SU (sustainable) below the median and UN (unsustainable) above the median. The results are based on equal weighting, presenting the coefficients for both SU and UN classifications, with an emphasis on the statistical significance of the added factor. The coefficients are averaged for sustainable (SU) and unsustainable (UN) portfolios. The averages are represented as μ$\mu_{SU}$ (mean of sustainable portfolios) and $\mu_{UN}$ (mean of unsustainable portfolios).

| | $r_i = a_i + b_i(R_M - R_f) + s_iSMB + h_iHML$ | | | | | | $r_i = a_i + b_i(R_M - R_f) + s_iSMB + h_iHML + \boldsymbol{sm_iSMUN_x}$ | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Portfolio** | $\mathbf{a_i}$ | $\mathbf{b_i}$ | $\mathbf{s_i}$ | $\mathbf{h_i}$ | $\mathbf{R^2}$ | | $\mathbf{a_i}$ | $\mathbf{b_i}$ | $\mathbf{s_i}$ | $\mathbf{h_i}$ | $\mathbf{sm_i}$ | $\mathbf{R^2}$ |
| BHSU | 0.7 | 1.1*** | 0.3* | 0.23** | 0.86 | | 0.45 | 1.18*** | -0.58*** | 0.59*** | 0.79*** | 0.94 |
| BHUN | 0.67*** | 0.88*** | -0.64*** | 0.58*** | 0.94 | | 0.70*** | 1.03*** | -0.39** | 0.69*** | -0.60*** | 0.96 |
| BLSU | -0.24 | 0.95*** | -0.48*** | -0.42*** | 0.87 | | 0.20 | 0.93*** | -0.43*** | -0.43*** | 0.41** | 0.9 |
| BLUN | 0.89*** | 0.92*** | -0.5*** | -0.52*** | 0.9 | | 0.38** | 1.11*** | -0.41*** | -0.49*** | -0.07 | 0.95 |
| BNSU | 0.68*** | 0.83*** | -0.04 | -0.16*** | 0.87 | | 0.44** | 0.96*** | -0.77*** | 0.07 | 0.67*** | 0.95 |
| BNUN | 0.33 | 1.11*** | -1.46*** | 0.42*** | 0.83 | | 0.5*** | 0.88*** | -0.57*** | 0.10** | -0.37** | 0.94 |
| SHSU | 0.02 | 1.15*** | 0.49*** | 0.08 | 0.94 | | 0.25 | 1.01*** | 0.38** | 0.29*** | 0.82*** | 0.97 |
| SHUN | 0.58* | 1.00*** | -0.04 | 0.49*** | 0.92 | | 0.36 | 0.94*** | 0.35* | 0.61*** | -0.95*** | 0.95 |
| SLSU | 1.14** | 0.85*** | 0.27 | 0.11 | 0.66 | | 0.9* | 0.82*** | 1.41*** | -0.34** | 0.21 | 0.77 |
| SLUN | 0.52 | 0.96*** | -0.11 | -0.48*** | 0.68 | | 0.44 | 1.05*** | 0.63*** | -0.76*** | -0.51* | 0.85 |
| SNSU | 0.63*** | 1.03*** | 0.36*** | -0.02 | 0.96 | | 0.53*** | 1.08*** | 0.49*** | -0.1** | 0.15 | 0.98 |
| SNUN | 0.26 | 0.93*** | -0.04 | 0.05 | 0.84 | | 0.19 | 0.99*** | 0.23 | -0.1 | -0.61*** | 0.92 |
| $\mu$ | 0.45 | 0.99 | 0.03 | 0.01 | 0.91 | $\mu_{SU}$ | 0.47 | 0.99 | 0.08 | 0.02 | 0.50 | 0.91 |
| | | | | | | $\mu_{UN}$ | 0.43 | 0.99 | -0.02 | 0.01 | -0.51 | 0.92 |

* p<0.1, ** p<0.05, *** p<0.01

Appendix 16c: Results (Robustness) of Equal Weighting – Median Split in $SMUN_R$

**Table 17** compares the coefficients of the FF three-factor model (LHS) and the extended four-factor model (RHS). The fourth factor $SMUN_X$ (where x = R for share of renewable energy consumption) was constructed by splitting $SMUN_R$ variable at the median, classifying companies as SU (sustainable) above the median and UN (unsustainable) below the median. The results are based on equal weighting, presenting the coefficients for both SU and UN classifications, with an emphasis on the statistical significance of the added factor. The coefficients are averaged for sustainable (SU) and unsustainable (UN) portfolios. The averages are represented as $\mu_{SU}$ (mean of sustainable portfolios) and $\mu_{UN}$ (mean of unsustainable portfolios).

| | $r_i = a_i + b_i(R_M - R_f) + s_iSMB + h_iHML$ | | | | | | $r_i = a_i + b_i(R_M - R_f) + s_iSMB + h_iHML + \boldsymbol{sm_i SMUN_x}$ | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Portfolio** | **$a_i$** | **$b_i$** | **$s_i$** | **$h_i$** | **$R^2$** | | **$a_i$** | **$b_i$** | **$s_i$** | **$h_i$** | **$sm_i$** | **$R^2$** |
| BHSU | 0.54** | 1.14*** | -0.51*** | 0.61*** | 0.95 | | 0.49** | 1.13*** | -0.32* | 0.56*** | 0.72*** | 0.96 |
| BHUN | 0.83*** | 0.86*** | -0.44** | 0.78*** | 0.93 | | 0.87*** | 0.88*** | -0.56*** | 0.82*** | -0.48* | 0.94 |
| BLSU | 0.29** | 1.11*** | -0.53*** | -0.54*** | 0.96 | | 0.26*** | 1.10*** | -0.44*** | -0.57*** | 0.36** | 0.97 |
| BLUN | 0.32** | 0.98*** | -0.23** | -0.42*** | 0.94 | | 0.33** | 0.99*** | -0.28** | -0.4*** | -0.20 | 0.94 |
| BNSU | 0.61*** | 0.86*** | -0.63*** | 0.11* | 0.93 | | 0.61*** | 0.86*** | -0.62*** | 0.11 | 0.04 | 0.93 |
| BNUN | 0.29* | 0.99*** | -0.63*** | 0.05 | 0.95 | | 0.30*** | 0.99*** | -0.67*** | 0.06 | -0.17 | 0.95 |
| SHSU | 0.41 | 0.92*** | 0.29** | 0.53*** | 0.95 | | 0.35*** | 0.90*** | 0.51*** | 0.46*** | 0.85*** | 0.96 |
| SHUN | 0.12 | 1.07*** | 0.54*** | 0.25*** | 0.95 | | 0.19* | 1.09*** | 0.31* | 0.32*** | -0.91*** | 0.97 |
| SLSU | 0.58* | 1.04*** | 0.53** | -0.54*** | 0.87 | | 0.54*** | 1.03*** | 0.66*** | -0.58*** | 0.5* | 0.88 |
| SLUN | 0.76** | 0.87*** | 1.3*** | -0.59*** | 0.86 | | 0.80*** | 0.88*** | 1.15*** | -0.55*** | -0.57** | 0.87 |
| SNSU | 0.52** | 1.01*** | 0.19 | -0.02 | 0.92 | | 0.44*** | 0.98*** | 0.45*** | -0.1 | 1.01*** | 0.95 |
| SNUN | 0.34** | 1.06*** | 0.52*** | -0.13** | 0.98 | | 0.35*** | 1.06*** | 0.50*** | -0.12*** | -0.10* | 0.98 |
| $\mu$ | 0.47 | 0.99 | 0.03 | 0.01 | 0.93 | $\mu_{SU}$ | 0.45 | 0.99 | 0.04 | -0.02 | 0.57 | 0.94 |
| | | | | | | $\mu_{UN}$ | 0.48 | 0.98 | 0.07 | 0.02 | -0.40 | 0.93 |

* p<0.1, ** p<0.05, *** p<0.01

Appendix 17a: Results (Robustness) of Equal Weighting – 70:30 Split in $SMUN_E$

**Table 18** compares the coefficients of the FF three-factor model (LHS) and the extended four-factor model (RHS). The fourth factor $SMUN_X$ (where x = E for emission intensity) was constructed by splitting $SMUN_E$ variable with 70:30, classifying companies as SU (sustainable) below the 30th percentile and UN (unsustainable) above the 70th percentile. The results are based on equal weighting, presenting the coefficients for both SU and UN classifications, with an emphasis on the statistical significance of the added factor. The coefficients are averaged for sustainable (SU) and unsustainable (UN) portfolios. The averages are represented as $\mu_{SU}$ (mean of sustainable portfolios) and $\mu_{UN}$ (mean of unsustainable portfolios).

| | $r_i = a_i + b_i(R_M - R_f) + s_iSMB + h_iHML$ | | | | | | $r_i = a_i + b_i(R_M - R_f) + s_iSMB + h_iHML + \boldsymbol{sm_iSMUN_x}$ | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Portfolio** | $\mathbf{a_i}$ | $\mathbf{b_i}$ | $\mathbf{s_i}$ | $\mathbf{h_i}$ | $\mathbf{R^2}$ | | $\mathbf{a_i}$ | $\mathbf{b_i}$ | $\mathbf{s_i}$ | $\mathbf{h_i}$ | $\mathbf{sm_i}$ | $\mathbf{R^2}$ |
| BHSU | 0.04 | 1.27*** | -0.94*** | 0.59*** | 0.86 | | 0.07 | 1.27*** | -1.00*** | 0.4*** | 1.12*** | 0.91 |
| BHUN | 0.89*** | 1.05*** | -0.51*** | 0.69*** | 0.94 | | 0.88*** | 1.05*** | -0.48*** | 0.77*** | -0.47*** | 0.95 |
| BLSU | 0.52 | 0.99*** | 0.01 | -0.21 | 0.75 | | 0.53 | 0.99*** | -0.01 | -0.24 | 0.23 | 0.75 |
| BLUN | 0.32 | 1.21*** | -0.47*** | -0.65*** | 0.94 | | 0.31 | 1.21*** | -0.45*** | -0.61*** | -0.21 | 0.94 |
| BNSU | 0.4 | 1.09*** | -0.94*** | 0.04 | 0.81 | | 0.41 | 1.09*** | -0.98*** | -0.08 | 0.66*** | 0.84 |
| BNUN | 0.57** | 0.9*** | -0.83*** | 0.16* | 0.89 | | 0.56** | 0.89*** | -0.81*** | 0.21** | -0.28* | 0.89 |
| SHSU | 0.2 | 1.08*** | 0.51*** | 0.18** | 0.95 | | 0.21 | 1.08*** | 0.49*** | 0.13 | 0.30* | 0.96 |
| SHUN | 0.77* | 0.96*** | 0.22 | 0.61*** | 0.87 | | 0.74* | 0.95*** | 0.28 | 0.79*** | -1.06*** | 0.91 |
| SLSU | 1.03** | 1.08*** | 0.72** | -0.02 | 0.82 | | 1.05** | 1.09*** | 0.69** | -0.11 | 0.54* | 0.83 |
| SLUN | 0.1 | 1.13*** | 0.87*** | -1.07*** | 0.8 | | 0.08 | 1.13*** | 0.91*** | -0.94*** | -0.77*** | 0.83 |
| SNSU | 0.61*** | 1.11*** | 0.51*** | -0.09 | 0.95 | | 0.62*** | 1.11*** | 0.49*** | -0.14* | 0.31** | 0.96 |
| SNUN | 0.21 | 1.23*** | 0.28 | -0.18 | 0.85 | | 0.19 | 1.22*** | 0.32 | -0.07 | -0.62*** | 0.87 |
| $\mu$ | 0.47 | 1.09 | -0.05 | 0.00 | 0.87 | $\mu_{SU}$ | 0.48 | 1.11 | -0.05 | -0.01 | 0.53 | 0.88 |
| | | | | | | $\mu_{UN}$ | 0.46 | 1.08 | -0.04 | 0.03 | -0.57 | 0.90 |

* p<0.1, ** p<0.05, *** p<0.01

Appendix 17b: Results (Robustness) of Equal Weighting – 70:30 Split in $SMUN_W$

**Table 19** This table compares the coefficients of the FF three-factor model (LHS) and the extended four-factor model (RHS). The fourth factor $SMUN_X$ (where x = W for waste intensity) was constructed by splitting $SMUN_W$ variable with 70:30, classifying companies as SU (sustainable) below the 30th percentile and UN (unsustainable) above the 70th percentile. The results are based on equal weighting, presenting the coefficients for both SU and UN classifications, with an emphasis on the statistical significance of the added factor. The coefficients are averaged for sustainable (SU) and unsustainable (UN) portfolios. The averages are represented as $\mu_{SU}$ (mean of sustainable portfolios) and $\mu_{UN}$ (mean of unsustainable portfolios).

| | $r_i = a_i + b_i(R_M - R_f) + s_iSMB + h_iHML$ | | | | | | $r_i = a_i + b_i(R_M - R_f) + s_iSMB + h_iHML + \boldsymbol{sm_iSMUN_x}$ | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Portfolio** | **$a_i$** | **$b_i$** | **$s_i$** | **$h_i$** | **$R^2$** | | **$a_i$** | **$b_i$** | **$s_i$** | **$h_i$** | **$sm_i$** | **$R^2$** |
| BHSU | 0.95** | 1.12*** | 0.18 | 0.40*** | 0.85 | | 0.97*** | 1.13*** | -0.65*** | 0.6*** | 0.44*** | 0.92 |
| BHUN | 0.74*** | 0.87*** | -0.58*** | 0.67*** | 0.95 | | 0.74*** | 0.87*** | -0.49*** | 0.64*** | -0.05 | 0.95 |
| BLSU | 0.09 | 0.73*** | -0.23* | -0.50*** | 0.69 | | 0.09 | 0.74*** | -0.39** | -0.46*** | 0.09 | 0.7 |
| BLUN | 0.15 | 0.97*** | -0.49*** | -0.55*** | 0.86 | | 0.15 | 0.97*** | -0.44*** | -0.56*** | -0.03 | 0.86 |
| BNSU | 0.55 | 0.93*** | -0.13 | -0.06 | 0.8 | | 0.56* | 0.93*** | -0.51*** | 0.04 | 0.21*** | 0.83 |
| BNUN | 0.32* | 1.15*** | -1.58*** | 0.48*** | 0.82 | | 0.31 | 1.15*** | -1.2 | 0.39*** | -0.21*** | 0.84 |
| SHSU | 0.07 | 1.03*** | 0.55*** | 0.04 | 0.86 | | 0.09 | 1.04*** | 0.02 | 0.17** | 0.29** | 0.9 |
| SHUN | 0.54 | 0.88*** | -0.11 | 0.53*** | 0.86 | | 0.54 | 0.88*** | 0.19 | 0.45*** | -0.16 | 0.87 |
| SLSU | 0.86* | 0.94*** | 0.11 | -0.07 | 0.69 | | 0.87* | 0.95*** | -0.12 | -0.02 | 0.12 | 0.7 |
| SLUN | 0.85 | 1.15*** | -0.18 | -0.44*** | 0.67 | | 0.83* | 1.14*** | 0.58** | -0.63*** | -0.41*** | 0.75 |
| SNSU | 0.86*** | 1.08*** | 0.29** | -0.06 | 0.92 | | 0.86*** | 1.08*** | 0.5*** | -0.12* | -0.12** | 0.93 |
| SNUN | 0.69 | 0.87*** | -0.07 | 0.02 | 0.7 | | 0.69 | 0.86*** | 0.22 | -0.06 | -0.16* | 0.72 |
| $\mu$ | 0.55 | 0.97 | -0.19 | 0.04 | 0.80 | $\mu_{SU}$ | 0.58 | 0.97 | -0.19 | 0.04 | 0.17 | 0.82 |
| | | | | | | $\mu_{UN}$ | 0.55 | 0.97 | -0.19 | 0.04 | -0.17 | 0.83 |

* p<0.1, ** p<0.05, *** p<0.01

Appendix 17c: Results (Robustness) of Equal Weighting – 70:30 Split in $SMUN_R$

**Table 20** compares the coefficients of the FF three-factor model (LHS) and the extended four-factor model (RHS). The fourth factor $SMUN_X$ (where x = R for share of renewable energy consumption) was constructed by splitting $SMUN_R$ variable with 70:30, classifying companies as SU (sustainable) above the 70th percentile and UN (unsustainable) below the 30th percentile. The results are based on equal weighting, presenting the coefficients for both SU and UN classifications, with an emphasis on the statistical significance of the added factor. The coefficients are averaged for sustainable (SU) and unsustainable (UN) portfolios. The averages are represented as $\mu_{SU}$ (mean of sustainable portfolios) and $\mu_{UN}$ (mean of unsustainable portfolios).

| | $r_i = a_i + b_i(R_M - R_f) + s_iSMB + h_iHML$ | | | | | | $r_i = a_i + b_i(R_M - R_f) + s_iSMB + h_iHML + \boldsymbol{sm_iSMUN_x}$ | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Portfolio** | $\mathbf{a_i}$ | $\mathbf{b_i}$ | $\mathbf{s_i}$ | $\mathbf{h_i}$ | $\mathbf{R^2}$ | | $\mathbf{a_i}$ | $\mathbf{b_i}$ | $\mathbf{s_i}$ | $\mathbf{h_i}$ | $\mathbf{sm_i}$ | $\mathbf{R^2}$ |
| BHSU | 0.25 | 0.82*** | -0.49*** | 0.32*** | 0.80 | | 0.49** | 1.13*** | -0.32* | 0.56*** | 0.72*** | 0.96 |
| BHUN | 0.71 | 0.90*** | -0.39* | 0.52*** | 0.72 | | 0.87*** | 0.88*** | -0.56*** | 0.82*** | -0.48* | 0.94 |
| BLSU | 0.64** | 0.88*** | -0.67*** | -0.64*** | 0.80 | | 0.26*** | 1.10*** | -0.44*** | -0.57*** | 0.36** | 0.97 |
| BLUN | 1.43*** | 0.88*** | -0.16 | -0.09 | 0.61 | | 0.33** | 0.99*** | -0.28** | -0.4*** | -0.20 | 0.94 |
| BNSU | 0.77** | 0.87*** | -0.25* | -0.03 | 0.79 | | 0.61*** | 0.86*** | -0.62*** | 0.11 | 0.04 | 0.93 |
| BNUN | 0.11** | 1.30*** | -1.92*** | 0.54*** | 0.74 | | 0.30*** | 0.99*** | -0.67*** | 0.06 | -0.17 | 0.95 |
| SHSU | 0.37 | 0.86*** | 0.13 | 0.31*** | 0.86 | | 0.35*** | 0.90*** | 0.51*** | 0.46*** | 0.85*** | 0.96 |
| SHUN | 0.12* | 1.23*** | 0.21 | 0.10 | 0.90 | | 0.19* | 1.09*** | 0.31* | 0.32*** | -0.91*** | 0.97 |
| SLSU | 0.48 | 0.92*** | -0.07 | -0.37*** | 0.57 | | 0.54*** | 1.03*** | 0.66*** | -0.58*** | 0.5* | 0.88 |
| SLUN | 0.82 | 0.74*** | 0.01 | -0.19 | 0.43 | | 0.80*** | 0.88*** | 1.15*** | -0.55*** | -0.57** | 0.87 |
| SNSU | 0.16 | 0.93*** | -0.19 | -0.09 | 0.79 | | 0.44*** | 0.98*** | 0.45*** | -0.1 | 1.01*** | 0.95 |
| SNUN | 0.52*** | 1.00*** | 0.33*** | 0.09 | 0.92 | | 0.35*** | 1.06*** | 0.50*** | -0.12*** | -0.10* | 0.98 |
| $\mu$ | 0.50 | 0.94 | -0.29 | 0.04 | 0.74 | $\mu_{SU}$ | 0.49 | 0.94 | -0.29 | 0.03 | 0.16 | 0.80 |
| | | | | | | $\mu_{UN}$ | 0.49 | 0.94 | -0.28 | 0.03 | -0.18 | 0.75 |

* p<0.1, ** p<0.05, *** p<0.01

## Appendix 18: Hybrid Approach - Descriptive Statistics, Percentile Breakdown, and Boxplots and Correlation Matrix

The following three appendices provide foundational insights for the regression equations employed in the hybrid approach. These analyses enhance the understanding of the variables before year-over-year (YoY) changes were calculated. The climate variables – emission intensity (EI), waste intensity (WI), and renewable energy share (RE) – are denoted with new abbreviations to distinguish them clearly from variables in the adjusted Fama-French approach (E, W, R) and prevent confusion. All variables exclude the 99th and 1st percentiles to eliminate extreme outliers. For the regression models, z-score standardization was applied to normalize values and ensure comparability across variables.

Appendix 18a: Descriptive Statistics (2018-2022)

**Table 21** presents the descriptive statistics (mean, standard deviation, minimum, and maximum) for the variables in the hybrid approach.

| Variables | Obs | Mean | Std. dev. | Min | Max |
|---|---|---|---|---|---|
| RE | 1445 | 0.305 | 0.237 | 0.001 | 0.834 |
| EI | 1445 | 0.000 | 0.000 | 0.000 | 0.001 |
| WI | 1445 | 0.000 | 0.000 | 0.000 | 0.000 |
| CoE | 1445 | 1.819 | 8.477 | -15.329 | 25.097 |
| MKT | 1445 | -0.046 | 0.692 | -1.291 | 0.560 |
| CMA | 1445 | 0.058 | 0.088 | -0.152 | 0.345 |
| SMB | 1445 | 1.517 | 1.850 | 0.035 | 8.629 |
| HML | 1445 | 1.224 | 0.889 | 0.121 | 4.048 |
| RMW | 1445 | 1.378 | 1.594 | 0.035 | 7.229 |

Note: The statistics reveal substantial variation across variables, particularly in CoE and RMW, which exhibit high standard deviations relative to their means. Renewable energy share (RE) shows a balanced distribution, while emission intensity (EI) and waste intensity (WI) have values tightly clustered near zero. These variations emphasize the importance of z-score standardization for consistent interpretation in regression models.

Appendix 18b: Percentile Breakdown of Key Variables (2018-2022)

**Table 22** shows the percentile distribution of the variables, highlighting their range and concentration at different points within the sample.

| Variables | 25th Percentile | 50th Percentile (Median) | 75th Percentile | 95th Percentile |
|---|---|---|---|---|
| RE | 0.098 | 0.270 | 0.479 | 0.762 |
| EI | 0.000 | 0.000 | 0.000 | 0.000 |
| WI | 0.000 | 0.000 | 0.000 | 0.000 |
| CoE | -5.371 | 0.593 | 7.927 | 16.422 |
| MKT | -0.197 | 0.322 | 0.458 | 0.560 |
| CMA | 0.002 | 0.050 | 0.103 | 0.221 |
| SMB | 0.227 | 0.635 | 2.264 | 5.573 |
| HML | 0.556 | 0.952 | 1.683 | 3.019 |
| RMW | 0.300 | 0.779 | 1.708 | 5.246 |

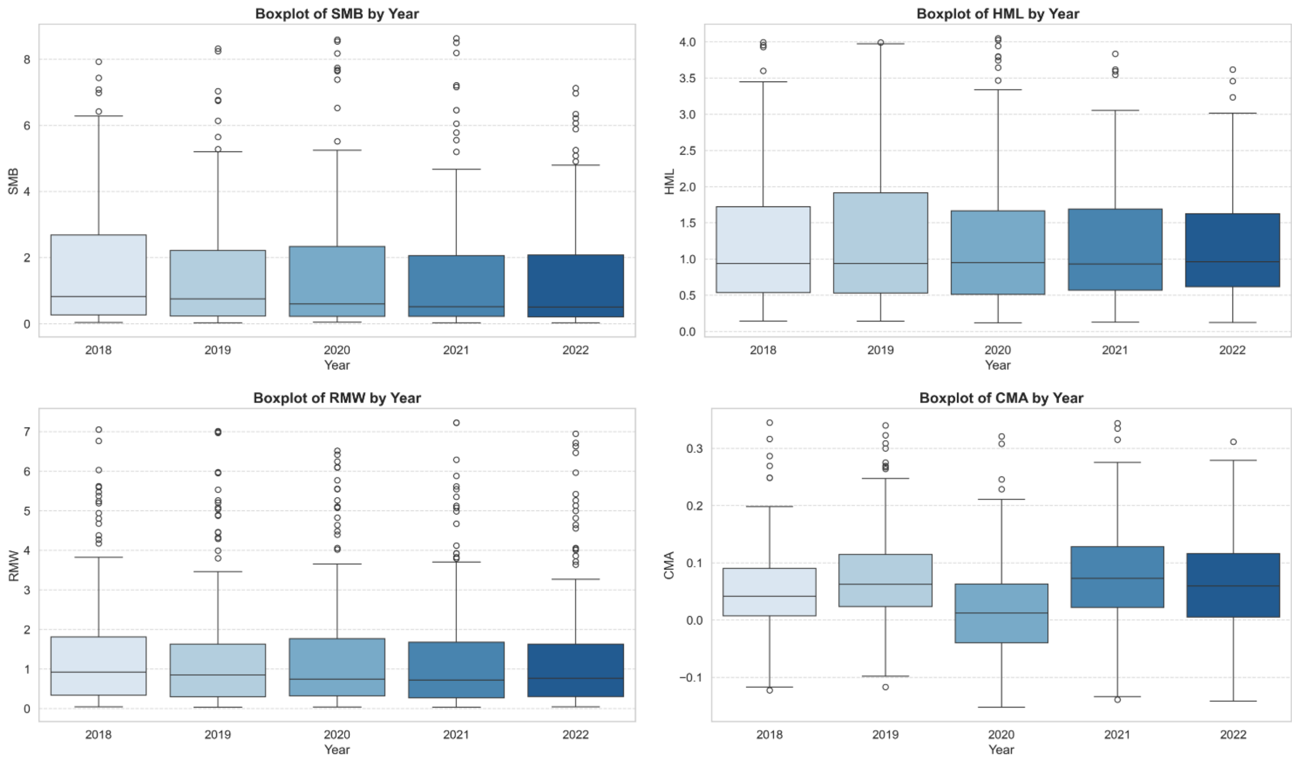
Note: Across the variables, the median values are consistently lower than the mean, indicating positively skewed distributions influenced by extreme upper values. This pattern is evident in variables like CoE, Fama-French factors (e.g., SMB, HML), and renewable energy share (RE), where higher percentiles exhibit disproportionate increases.

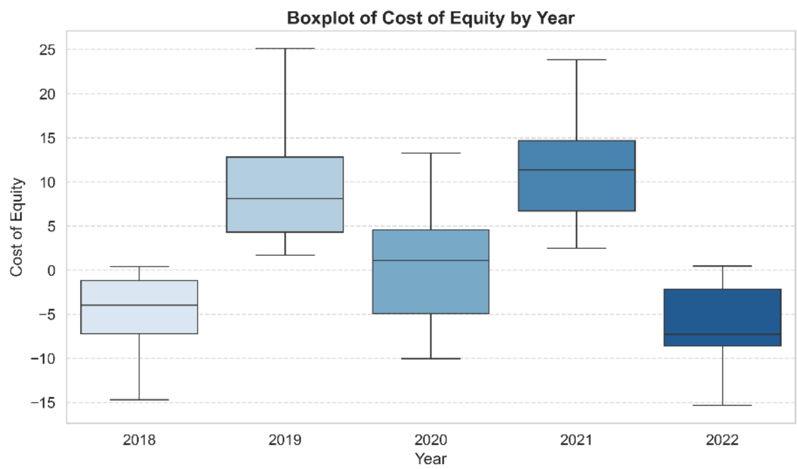
Appendix 18c: Boxplots of the Firm Level – Fama-French Variables and CoE

In addition to the boxplots of the climate variables presented earlier in **Appendix 04**, the regression analysis in the hybrid approach incorporates the adjusted Fama-French variables and the Cost of Equity (CoE). The boxplots for these variables are displayed below in Figure 12, providing insights into their distribution and variability over the years 2018 to 2022.

Figure 12: Distribution Overview – Boxplots of SMB, HML, RMW, CMA and CoE

Figure 12 provides an overview of the distribution of the Fama-French factors (SMB, HML, RMW, CMA) and the Cost of Equity (CoE) across the years 2018 to 2022. Each boxplot highlights the variability, median, interquartile range, and presence of outliers for these variables within the hybrid approach framework.




Note: All variables exhibit distinct patterns, with CoE showing significant variability over time, peaking in 2020 and declining in 2022. Factors like SMB and CMA display notable outliers, reflecting firm-level heterogeneity in size and investment-related characteristics. Despite these variations, applying percentile filtering and standardization ensures robustness and comparability for subsequent regression analyses.

Appendix 18d: Pearson's Correlation Matrix (2018-2022)

**Table 23** provides the Pearson correlation coefficients among the variables to examine the strength and direction of their linear relationships.

| Variables | RE | EI | WI | CoE | MKT | CMA | SMB | HML | RMW |
|---|---|---|---|---|---|---|---|---|---|
| RE | 1 | | | | | | | | |
| EI | -0.19*** | 1 | | | | | | | |
| WI | -0.11*** | 0.41*** | 1 | | | | | | |
| CoE | -0.02 | -0.06* | -0.01 | 1 | | | | | |
| MKT | -0.07* | 0.04 | 0.05 | 0.61*** | 1 | | | | |
| CMA | -0.03 | -0.0 | -0.01 | 0.12*** | 0.01 | 1 | | | |
| SMB | 0.03 | -0.21*** | -0.14*** | 0.22*** | 0.0 | -0.03 | 1 | | |
| HML | 0.07* | 0.05* | 0.02 | -0.18*** | -0.01 | -0.11*** | -0.18*** | 1 | |
| RMW | -0.02 | -0.1*** | -0.05* | 0.18*** | 0.01 | -0.03 | 0.68*** | -0.06* | 1 |

Note: A notable negative correlation exists between emission intensity (EI) and renewable energy share (RE) (-0.19***), consistent with expectations that higher renewable energy shares correlate with reduced emissions. CoE shows a negative correlation with EI (-0.06*), highlighting a possible negative effect of EI on CoE, which will be tested on its statistical robustness in the regression analysis.

**Appendix 19: Main Regression Results**

The regression outputs in this section explore various combinations of variables to capture the relationships between climate action and CoE under different modeling specifications. The 3F model refers to the Fama-French three-factor model, while 3F+Cov includes a control for the COVID-19 effect using the COVID Stringency Index. The 5F+Cov model expands this by adding the HML and RMW factors from the Fama-French five-factor framework. However, as no significant improvement in explanatory power ($R^2$) was observed across these additional specifications, and further robustness checks like the BAI and AIC comparisons confirmed this, the analysis proceeds primarily with the 3F model. To systematically analyze the climate variables, emission intensity (EI), waste intensity (WI), and renewable energy share (RE) were tested individually alongside the 3F model in separate regressions. Subsequently, all three climate variables were combined with the 3F model to assess their collective impact. Finally, a regression was conducted using only the climate variables, excluding the Fama-French factors, to isolate their direct influence on CoE. This structure was applied consistently across dynamic panel regressions (FDM) and robustness checks. In the static analysis, cumulative changes over the observation period (2018-2022) were used, focusing solely on long-term impacts. COVID-19 effects were not controlled in the static regressions, as cumulative trends inherently account for pandemic-related disruptions over the study period.

Appendix 19a: Dynamic Panel Regression

**Table 24**: First-Difference Model (FDM) with Dependent Variable: $\Delta CoE$

| | 3F | 3F+Cov | 5F+Cov | 3F+EI | 3F+WI | 3F+R | 3F+ClimateVar | ClimateVar |
|---|---|---|---|---|---|---|---|---|
| const | 0.0000 | 0.5241*** | 0.5218*** | 0.5212*** | 0.5243*** | 0.5240*** | 0.5216*** | -0.8687*** |
| | (0.0233) | (0.0849) | (0.0850) | (0.0838) | (0.0850) | (0.0849) | (0.0839) | (0.0595) |
| ΔMKT | 0.5932*** | 0.8091*** | 0.8078*** | 0.8092*** | 0.8092*** | 0.8092*** | 0.8097*** | |
| | (0.0234) | (0.0400) | (0.0400) | (0.0395) | (0.0400) | (0.0400) | (0.0395) | |
| ΔCMA | 0.1034*** | 0.0945*** | 0.0979*** | 0.0857*** | 0.0945*** | 0.0942*** | 0.0854*** | |
| | (0.0234) | (0.0225) | (0.0229) | (0.0223) | (0.0225) | (0.0225) | (0.0223) | |
| ΔSMB | 0.0263 | 0.0423* | 0.0400* | 0.0423* | 0.0423* | 0.0422* | 0.0423* | |
| | (0.0233) | (0.0225) | (0.0227) | (0.0222) | (0.0225) | (0.0225) | (0.0222) | |
| Covid_Dummy | | -1.2511*** | -1.2441*** | -1.2435*** | -1.2517*** | -1.2510*** | -1.2447*** | 2.3803*** |
| | | (0.2143) | (0.2145) | (0.2115) | (0.2145) | (0.2144) | (0.2118) | (0.1413) |
| StringencyIndex | | 0.3953*** | 0.3905*** | 0.3916*** | 0.3957*** | 0.3954*** | 0.3926*** | -1.2520*** |
| | | (0.1020) | (0.1022) | (0.1007) | (0.1021) | (0.1020) | (0.1008) | (0.0736) |
| ΔHML | | | -0.0131 | | | | | |
| | | | (0.0232) | | | | | |
| ΔRMW | | | -0.0165 | | | | | |
| | | | (0.0226) | | | | | |
| ΔEI | | | | -0.1240*** | | | -0.1241*** | -0.1314*** |
| | | | | (0.0222) | | | (0.0222) | (0.0261) |
| ΔWI | | | | | 0.0025 | | 0.0052 | -0.0140 |
| | | | | | (0.0224) | | (0.0222) | (0.0261) |
| ΔRE | | | | | | 0.0088 | 0.0087 | 0.0099 |
| | | | | | | (0.0224) | (0.0221) | (0.0261) |
| R-squared | 0.3758 | 0.4232 | 0.4237 | 0.4385 | 0.4232 | 0.4233 | 0.4386 | 0.2189 |
| R-squared Adj. | 0.3741 | 0.4207 | 0.4202 | 0.4356 | 0.4202 | 0.4203 | 0.4347 | 0.2155 |
| N | 1156 | 1156 | 1156 | 1156 | 1156 | 1156 | 1156 | 1156 |

Standard errors in parentheses.
* p<.1, ** p<.05, ***p<.01

Note: This table presents the results of the dynamic panel regressions assessing the short-term effects of annual changes in climate variables on the CoE. Emission intensity (EI) shows a statistically significant negative coefficient, suggesting that higher emissions correlate with lower CoE. Waste intensity (WI) and renewable energy share (RE) remain statistically insignificant, indicating limited influence on short-term CoE changes. Adjusted $R^2$ values suggest moderate explanatory power, with standard errors in parentheses and significance levels indicated ($p < 0.05$, $p < 0.01$).

Appendix 19b: Static Panel Regression (Cumulative Changes)

**Table 25** shows Cumulative Changes in Climate – and Fama-French variables with Dependent Variable: CoE in 2022

| | 3F | 5F | 3F+EI | 3F+WI | 3F+RE | 3F+Climate | Climate |
|---|---|---|---|---|---|---|---|
| const | 3.2623*** | 3.2623*** | 3.2623*** | 3.2623*** | 3.2623*** | 3.2623*** | 3.2623*** |
| | (0.3455) | (0.3445) | (0.3456) | (0.3456) | (0.3456) | (0.3458) | (0.3676) |
| MKT_CΔ | 0.0000*** | 0.0000*** | -0.0000*** | -0.0000 | 0.0000*** | -0.0000*** | |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | |
| CMA_CΔ | 0.6421* | 0.4896 | 0.6274* | 0.6401* | 0.6407* | 0.6243* | |
| | (0.3458) | (0.3522) | (0.3484) | (0.3461) | (0.3460) | (0.3488) | |
| SMB_CΔ | 4.7412*** | 3.9187*** | 4.7307*** | 4.7399*** | 4.7382*** | 4.7264*** | |
| | (0.3458) | (0.5112) | (0.3472) | (0.3460) | (0.3462) | (0.3478) | |
| HML_CΔ | | -0.9274*** | | | | | |
| | | (0.3559) | | | | | |
| RMW_CΔ | | 0.9380* | | | | | |
| | | (0.5071) | | | | | |
| EI_CΔ | | | -0.1244 | | | -0.1229 | -0.6189* |
| | | | (0.3494) | | | (0.3497) | (0.3678) |
| WI_CΔ | | | | -0.0699 | | -0.0687 | -0.1752 |
| | | | | (0.3458) | | (0.3461) | (0.3677) |
| RE_CΔ | | | | | -0.0733 | -0.0734 | -0.2830 |
| | | | | | (0.3460) | (0.3462) | (0.3677) |
| R-squared | 0.1186 | 0.1247 | 0.1187 | 0.1186 | 0.1186 | 0.1187 | 0.0026 |
| R-squared Adj. | 0.1174 | 0.1222 | 0.1169 | 0.1168 | 0.1168 | 0.1157 | 0.0005 |
| N | 1445 | 1445 | 1445 | 1445 | 1445 | 1445 | 1445 |

Standard errors in parentheses.
* p<.1, ** p<.05, ***p<.01

This table shows the static panel regression results, analyzing the cumulative impact of climate variables over the period 2018-2022 on CoE in the final year (2022). EI again demonstrates a statistically significant negative relationship with CoE, reflecting consistent trends observed in dynamic regressions. WI and RE remain statistically insignificant, suggesting their limited long-term relevance in equity pricing. These findings reinforce the role of emissions as a determinant of CoE while highlighting the need for further investigation into the insignificance of other climate variables.

## Appendix 20: Results (Robustness) with Lagged Variables

Appendix 20a: Robustness of Dynamic Panel Regression with Lagged Dep. Variable

**Table 26:** FDM with Lagged CoE as Dependent Variable

This table presents the results of the lagged dependent variable regression, where CoE in the prior year (Lagged_YoY_Change_CoE) is modeled as a function of current-year climate variables and Fama-French factors. This approach tests whether investors preemptively price in expected changes based on forward-looking information.

| | 3F | 3F+Cov | 5F+Cov | 3F+EI | 3F+WI | 3F+R | 3F+ClimateVar | ClimateVar |
|---|---|---|---|---|---|---|---|---|
| const | 0.2553*** | 60.4663*** | 60.6477*** | 60.1652*** | 60.5476*** | 60.4829*** | 60.2655*** | 0.5686*** |
| | (0.0282) | (2.3021) | (2.3044) | (2.2954) | (2.3040) | (2.3040) | (2.2991) | (0.0535) |
| ΔMKT | -0.2169*** | 35.0851*** | 35.1927*** | 34.9080*** | 35.1323*** | 35.0950*** | 34.9664*** | |
| | (0.0271) | (1.3478) | (1.3492) | (1.3439) | (1.3489) | (1.3490) | (1.3461) | |
| ΔCMA | -0.1366*** | -0.0280 | -0.0199 | -0.0236 | -0.0278 | -0.0282 | -0.0236 | |
| | (0.0285) | (0.0216) | (0.0221) | (0.0215) | (0.0216) | (0.0216) | (0.0216) | |
| ΔSMB | 0.0381 | 0.0313 | 0.0260 | 0.0314* | 0.0311 | 0.0313 | 0.0311 | |
| | (0.0257) | (0.0191) | (0.0193) | (0.0190) | (0.0191) | (0.0191) | (0.0190) | |
| Covid_Dummy | | -75.2019*** | -75.4225*** | -74.8257*** | -75.3016*** | -75.2228*** | -74.9491*** | 0.0065 |
| | | (2.8922) | (2.8950) | (2.8838) | (2.8946) | (2.8947) | (2.8884) | (0.1588) |
| StringencyIndex | | 0.0052 | -0.0035 | 0.0050 | 0.0032 | 0.0054 | 0.0031 | -0.3618*** |
| | | (0.0802) | (0.0803) | (0.0799) | (0.0803) | (0.0803) | (0.0800) | (0.1065) |
| ΔHML | | | -0.0410* | | | | | |
| | | | (0.0214) | | | | | |
| ΔRMW | | | 0.0026 | | | | | |
| | | | (0.0179) | | | | | |
| ΔEI | | | | 0.0490*** | | | 0.0493*** | 0.0789*** |
| | | | | (0.0174) | | | (0.0174) | (0.0235) |
| ΔWI | | | | | -0.0158 | | -0.0168 | -0.0009 |
| | | | | | (0.0175) | | (0.0174) | (0.0235) |
| ΔRE | | | | | | 0.0049 | 0.0047 | -0.0110 |
| | | | | | | (0.0175) | (0.0174) | (0.0236) |
| R-squared | 0.0984 | 0.5051 | 0.5072 | 0.5096 | 0.5056 | 0.5052 | 0.5102 | 0.1019 |
| R-squared Adj. | 0.0953 | 0.5022 | 0.5032 | 0.5062 | 0.5021 | 0.5017 | 0.5056 | 0.0967 |
| N | 867 | 867 | 867 | 867 | 867 | 867 | 867 | 867 |

Standard errors in parentheses.
* p<.1, ** p<.05, ***p<.01

Note: The results underscore that emissions intensity serves as a critical factor in CoE determination, even when forward-looking investor expectations are considered. This aligns with the hypothesis that investors preemptively account for sustainability metrics.

Appendix 20b: Robustness Check Dynamic Approach Lagged Independent Variables

**Table 27:** FDM with Lagged Climate and Fama-French Variable
This table details the results of the lagged independent variable regression, where prior-year climate variables and Fama-French factors (Lagged_YoY_Change) are modeled to explain current CoE. This tests for delayed investor reactions to changes in environmental and financial indicators.

| | 3F | 3F+Cov | 5F+Cov | 3F+EI(lagged) | 3F+WI(lagged) | 3F+R(lagged) | 3F+ClimateVar(lagged) | ClimateVar(lagged) |
|---|---|---|---|---|---|---|---|---|
| const | -0.1354*** | -52.1614*** | -52.1839*** | -51.9979*** | -52.1564*** | -52.1793*** | -52.0092*** | -0.8657*** |
| | (0.0275) | (2.4119) | (2.4180) | (2.2176) | (2.4126) | (2.4136) | (2.2188) | (0.0493) |
| ΔMKT | 0.4736*** | -30.0450*** | -30.0591*** | -29.9524*** | -30.0413*** | -30.0559*** | -29.9583*** | |
| | (0.0264) | (1.4121) | (1.4157) | (1.2983) | (1.4125) | (1.4131) | (1.2990) | |
| ΔCMA | 0.1393*** | 0.0454** | 0.0428* | 0.0138 | 0.0454** | 0.0452** | 0.0136 | |
| | (0.0278) | (0.0226) | (0.0232) | (0.0209) | (0.0226) | (0.0226) | (0.0209) | |
| ΔSMB | 0.0373 | 0.0434** | 0.0456** | 0.0437** | 0.0437** | 0.0434** | 0.0442** | |
| | (0.0251) | (0.0200) | (0.0202) | (0.0184) | (0.0200) | (0.0200) | (0.0184) | |
| Covid_Dummy | | 64.8603*** | 64.8863*** | 64.6816*** | 64.8513*** | 64.8792*** | 64.6883*** | 0.4817*** |
| | | (3.0303) | (3.0377) | (2.7861) | (3.0312) | (3.0322) | (2.7875) | (0.1465) |
| StringencyIndex | | 0.1047 | 0.1083 | 0.0754 | 0.1070 | 0.1080 | 0.0820 | 0.3900*** |
| | | (0.0841) | (0.0843) | (0.0773) | (0.0842) | (0.0846) | (0.0778) | (0.0984) |
| ΔHML | | | 0.0199 | | | | | |
| | | | (0.0225) | | | | | |
| ΔRMW | | | -0.0118 | | | | | |
| | | | (0.0188) | | | | | |
| LΔEI | | | | 0.2131*** | | | 0.2136*** | 0.2264*** |
| | | | | (0.0169) | | | (0.0169) | (0.0216) |
| LΔWI | | | | | -0.0188 | | -0.0264 | -0.0277 |
| | | | | | (0.0263) | | (0.0242) | (0.0310) |
| LΔRE | | | | | | 0.0072 | 0.0075 | 0.0010 |
| | | | | | | (0.0184) | (0.0169) | (0.0217) |
| R-squared | 0.2996 | 0.5548 | 0.5554 | 0.6241 | 0.5551 | 0.5549 | 0.6247 | 0.3788 |
| R-squared Adj. | 0.2972 | 0.5522 | 0.5518 | 0.6215 | 0.5520 | 0.5518 | 0.6212 | 0.3752 |
| N | 867 | 867 | 867 | 867 | 867 | 867 | 867 | 867 |

Standard errors in parentheses.
* p<.1, ** p<.05, ***p<.01

Note: The persistence of emissions intensity as a significant predictor of CoE supports its robustness, regardless of whether investor responses are immediate or delayed. Other climate variables exhibit no significant effects, indicating limited relevance in lagged contexts.

**Appendix 21: Results (CoE Robustness) with differences at FF Factor calculation**

To evaluate the robustness of firm-level Fama-French factor calculations, the threshold for defining firm-specific factors was adjusted from the sample median to the 75th percentile. This adjustment ensures that the observed relationships are not dependent on a single classification method. Furthermore, lagged dependent and independent variables were reassessed using this threshold to investigate whether temporal dynamics affect the stability of results. The findings confirm that the key relationship between emission intensity and CoE remains robust, further validating the methodological approach.

Appendix 21a: Dynamic Panel Regression Results with 75th Percentile at FF Factor Calculation

**Table 28**: CoE with 75th Percentile at FF Factor Calculation

This table presents the results of the main regressions where firm-specific Fama-French factors were calculated using the 75th percentile of the sample instead of the median. The aim is to evaluate the robustness of the results to alternative classification thresholds.

| | 3F | 3F+Cov | 5F+Cov | 3F+EI | 3F+WI | 3F+R | 3F+ClimateVar | ClimateVar |
|---|---|---|---|---|---|---|---|---|
| const | 0.0000 | 0.5016*** | 0.5000*** | 0.4986*** | 0.5017*** | 0.5015*** | 0.4989*** | -0.8877*** |
| | (0.0231) | (0.0851) | (0.0852) | (0.0839) | (0.0852) | (0.0852) | (0.0840) | (0.0595) |
| ΔMKT | 0.6015*** | 0.8075*** | 0.8067*** | 0.8077*** | 0.8076*** | 0.8076*** | 0.8080*** | |
| | (0.0232) | (0.0401) | (0.0401) | (0.0395) | (0.0401) | (0.0401) | (0.0396) | |
| ΔCMA | 0.0930*** | 0.0855*** | 0.0879*** | 0.0764*** | 0.0855*** | 0.0853*** | 0.0762*** | |
| | (0.0232) | (0.0226) | (0.0229) | (0.0223) | (0.0226) | (0.0226) | (0.0223) | |
| ΔSMB | 0.0382* | 0.0518** | 0.0501** | 0.0518** | 0.0518** | 0.0518** | 0.0518** | |
| | (0.0231) | (0.0225) | (0.0228) | (0.0222) | (0.0225) | (0.0225) | (0.0222) | |
| Covid_Dummy | | -1.2139*** | -1.2091*** | -1.2060*** | -1.2143*** | -1.2139*** | -1.2070*** | 2.4076*** |
| | | (0.2148) | (0.2151) | (0.2118) | (0.2150) | (0.2149) | (0.2121) | (0.1412) |
| StringencyIndex | | 0.4104*** | 0.4071*** | 0.4066*** | 0.4106*** | 0.4105*** | 0.4074*** | -1.2314*** |
| | | (0.1023) | (0.1025) | (0.1008) | (0.1024) | (0.1023) | (0.1010) | (0.0736) |
| ΔHML | | | -0.0097 | | | | | |
| | | | (0.0233) | | | | | |
| ΔRMW | | | -0.0106 | | | | | |
| | | | (0.0226) | | | | | |
| ΔEI | | | | -0.1296*** | | | -0.1297*** | -0.1363*** |
| | | | | (0.0222) | | | (0.0222) | (0.0261) |
| ΔWI | | | | | 0.0013 | | 0.0041 | -0.0152 |
| | | | | | (0.0225) | | (0.0222) | (0.0261) |
| ΔRE | | | | | | 0.0056 | 0.0055 | 0.0064 |
| | | | | | | (0.0225) | (0.0222) | (0.0261) |
| R-squared | 0.3837 | 0.4204 | 0.4206 | 0.4371 | 0.4204 | 0.4204 | 0.4371 | 0.2195 |
| R-squared Adj. | 0.3821 | 0.4179 | 0.4171 | 0.4342 | 0.4174 | 0.4174 | 0.4332 | 0.2161 |
| N | 1156 | 1156 | 1156 | 1156 | 1156 | 1156 | 1156 | 1156 |

Standard errors in parentheses.
* p<.1, ** p<.05, ***p<.01

Note: The findings indicate that the significant relationship between emission intensity and CoE remains unchanged. The Market Premium and SMB factors continue to exhibit significance, while the HML factor remains insignificant.

Appendix 21b: Dynamic Panel Regression Results with 75th Percentile at FF Factor Calculation and Lagged CoE as Dependent Variable

**Table 29**: Lagged CoE with 75th Percentile at FF Factor Calculation

This table examines whether the lagged Cost of Equity (CoE) alters the relationships with climate variables and Fama-French factors, based on calculations using the 75th percentile.
The goal is to assess potential effects of investor expectations.

| | 3F | 3F+Cov | 5F+Cov | 3F+EI | 3F+WI | 3F+R | 3F+ClimateVar | ClimateVar |
|---|---|---|---|---|---|---|---|---|
| const | 0.2634*** | 56.2188*** | 56.3277*** | 55.8082*** | 56.2845*** | 56.2525*** | 55.9118*** | 0.5761*** |
| | (0.0278) | (2.3615) | (2.3671) | (2.3464) | (2.3640) | (2.3633) | (2.3503) | (0.0523) |
| ΔMKT | -0.2195*** | 32.5918*** | 32.6564*** | 32.3502*** | 32.6300*** | 32.6117*** | 32.4108*** | |
| | (0.0267) | (1.3826) | (1.3858) | (1.3737) | (1.3840) | (1.3836) | (1.3760) | |
| ΔCMA | -0.1138*** | -0.0129 | -0.0079 | -0.0069 | -0.0127 | -0.0133 | -0.0071 | |
| | (0.0281) | (0.0221) | (0.0227) | (0.0220) | (0.0221) | (0.0221) | (0.0220) | |
| ΔSMB | 0.0303 | 0.0239 | 0.0206 | 0.0240 | 0.0237 | 0.0238 | 0.0237 | |
| | (0.0253) | (0.0196) | (0.0198) | (0.0194) | (0.0196) | (0.0196) | (0.0194) | |
| Covid_Dummy | | -69.8531*** | -69.9853*** | -69.3401*** | -69.9336*** | -69.8954*** | -69.4680*** | 0.0106 |
| | | (2.9669) | (2.9736) | (2.9479) | (2.9699) | (2.9691) | (2.9527) | (0.1552) |
| StringencyIndex | | -0.0261 | -0.0316 | -0.0264 | -0.0277 | -0.0257 | -0.0278 | -0.3658*** |
| | | (0.0823) | (0.0825) | (0.0817) | (0.0824) | (0.0824) | (0.0818) | (0.1041) |
| ΔHML | | | -0.0261 | | | | | |
| | | | (0.0220) | | | | | |
| ΔRMW | | | 0.0027 | | | | | |
| | | | (0.0184) | | | | | |
| ΔEI | | | | 0.0668*** | | | 0.0670*** | 0.0935*** |
| | | | | (0.0178) | | | (0.0178) | (0.0229) |
| ΔWI | | | | | -0.0128 | | -0.0141 | 0.0008 |
| | | | | | (0.0179) | | (0.0178) | (0.0230) |
| ΔRE | | | | | | 0.0099 | 0.0096 | -0.0045 |
| | | | | | | (0.0180) | (0.0178) | (0.0230) |
| R-squared | 0.0945 | 0.4605 | 0.4614 | 0.4692 | 0.4608 | 0.4607 | 0.4698 | 0.1113 |
| R-squared Adj. | 0.0913 | 0.4574 | 0.4570 | 0.4655 | 0.4571 | 0.4570 | 0.4648 | 0.1061 |
| N | 867 | 867 | 867 | 867 | 867 | 867 | 867 | 867 |

Standard errors in parentheses.
* p<.1, ** p<.05, ***p<.01

Note: Emission intensity remains significantly positive, highlighting the stability of this factor. However, the other climate variables show no significant effects, even with a lagged dependent variable.

Appendix 21c: Dynamic Panel Regression Results with 75th Percentile at FF Factor Calculation and Lagged Independent Variables

**Table 30**: Lagged Climate and FF Variables with 75th Percentile at FF Factor Calculation
This table explores the effects of lagged climate variables on CoE under the 75th percentile-based firm-specific Fama-French factor calculations. The aim is to test whether past environmental indicators influence CoE in the following year.

| | 3F | 3F+Cov | 5F+Cov | 3F+EI(lagged) | 3F+WI(lagged) | 3F+R(lagged) | 3F+ClimateVar(lagged) | ClimateVar(lagged) |
|---|---|---|---|---|---|---|---|---|
| const | -0.1151*** | -50.1799*** | -50.2232*** | -50.0265*** | -50.1749*** | -50.1968*** | -50.0368*** | -0.8854*** |
| | (0.0269) | (2.3856) | (2.3925) | (2.2134) | (2.3863) | (2.3872) | (2.2147) | (0.0485) |
| ΔMKT | 0.4998*** | -28.8727*** | -28.8986*** | -28.7858*** | -28.8689*** | -28.8829*** | -28.7911*** | |
| | (0.0259) | (1.3967) | (1.4007) | (1.2959) | (1.3971) | (1.3977) | (1.2966) | |
| ΔCMA | 0.1241*** | 0.0337 | 0.0312 | 0.0041 | 0.0337 | 0.0335 | 0.0038 | |
| | (0.0272) | (0.0223) | (0.0229) | (0.0209) | (0.0224) | (0.0224) | (0.0209) | |
| ΔSMB | 0.0492** | 0.0551*** | 0.0570*** | 0.0555*** | 0.0555*** | 0.0552*** | 0.0560*** | |
| | (0.0246) | (0.0198) | (0.0200) | (0.0184) | (0.0198) | (0.0198) | (0.0184) | |
| Covid_Dummy | | 62.3825*** | 62.4347*** | 62.2149*** | 62.3735*** | 62.4003*** | 62.2205*** | 0.5166*** |
| | | (2.9972) | (3.0056) | (2.7808) | (2.9980) | (2.9991) | (2.7823) | (0.1441) |
| StringencyIndex | | 0.1309 | 0.1339 | 0.1034 | 0.1332 | 0.1341 | 0.1098 | 0.4053*** |
| | | (0.0832) | (0.0834) | (0.0772) | (0.0832) | (0.0836) | (0.0777) | (0.0968) |
| ΔHML | | | 0.0148 | | | | | |
| | | | (0.0223) | | | | | |
| ΔRMW | | | -0.0045 | | | | | |
| | | | (0.0186) | | | | | |
| LΔEI | | | | 0.2000*** | | | 0.2004*** | 0.2118*** |
| | | | | (0.0169) | | | (0.0169) | (0.0212) |
| LΔWI | | | | | -0.0188 | | -0.0259 | -0.0268 |
| | | | | | (0.0260) | | (0.0241) | (0.0305) |
| LΔRE | | | | | | 0.0068 | 0.0070 | 0.0005 |
| | | | | | | (0.0182) | (0.0169) | (0.0214) |
| R-squared | 0.3268 | 0.5649 | 0.5651 | 0.6259 | 0.5651 | 0.5649 | 0.6265 | 0.3998 |
| R-squared Adj. | 0.3244 | 0.5624 | 0.5616 | 0.6233 | 0.5621 | 0.5619 | 0.6230 | 0.3963 |
| N | 867 | 867 | 867 | 867 | 867 | 867 | 867 | 867 |

Standard errors in parentheses.
* p<.1, ** p<.05, ***p<.01

Note: Emission intensity remains consistently positive and significant, reaffirming its critical role in influencing CoE. Neither waste intensity nor renewable energy share demonstrates significant lagged effects in this analysis.

Appendix 21d: Static Regressions Results with CoE (75th Percentile at FF Factor Calculation)

**Table 31**: Static Approach Results with Adjusted Threshold

This table presents the results of static regressions for cumulative climate changes on CoE (2022), where firm-level Fama-French factors were calculated using the 75th percentile instead of the median. This robustness check evaluates whether cumulative long-term relationships between climate variables and CoE are sensitive to changes in Fama-French factor thresholds.

| | 3F | 5F | 3F+EI | 3F+WI | 3F+RE | 3F+Climate | Climate |
|---|---|---|---|---|---|---|---|
| const | 2.5825*** | 2.5825*** | 2.5825*** | 2.5825*** | 2.5825*** | 2.5825*** | 2.5825*** |
| | (0.2898) | (0.2886) | (0.2899) | (0.2899) | (0.2899) | (0.2901) | (0.3149) |
| MKT_CΔ | 0.0000*** | 0.0000*** | -0.0000*** | -0.0000* | 0.0000*** | -0.0000*** | |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | |
| CMA_CΔ | 0.3510 | 0.2258 | 0.3418 | 0.3500 | 0.3500 | 0.3399 | |
| | (0.2901) | (0.2951) | (0.2922) | (0.2903) | (0.2902) | (0.2926) | |
| SMB_CΔ | 4.6782*** | 3.7650*** | 4.6716*** | 4.6775*** | 4.6760*** | 4.6688*** | |
| | (0.2901) | (0.4283) | (0.2912) | (0.2902) | (0.2904) | (0.2917) | |
| HML_CΔ | | -0.8125*** | | | | | |
| | | (0.2982) | | | | | |
| RMW_CΔ | | 1.0840** | | | | | |
| | | (0.4249) | | | | | |
| EI_CΔ | | | -0.0781 | | | -0.0773 | -0.5338* |
| | | | (0.2931) | | | (0.2934) | (0.3150) |
| WI_CΔ | | | | -0.0354 | | -0.0347 | -0.1326 |
| | | | | (0.2901) | | (0.2903) | (0.3150) |
| RE_CΔ | | | | | -0.0533 | -0.0532 | -0.2548 |
| | | | | | (0.2902) | (0.2904) | (0.3149) |
| R-squared | 0.1546 | 0.1625 | 0.1547 | 0.1547 | 0.1547 | 0.1547 | 0.0026 |
| R-squared Adj. | 0.1535 | 0.1602 | 0.1529 | 0.1529 | 0.1529 | 0.1518 | 0.0005 |
| N | 1445 | 1445 | 1445 | 1445 | 1445 | 1445 | 1445 |

Standard errors in parentheses.
* p<.1, ** p<.05, ***p<.01

Note: The results indicate that the significant negative relationship between emission intensity and CoE persists under this alternative factor calculation method, but only when climate variables are considered solely. Waste intensity and renewable energy share remain statistically insignificant. Among the Fama-French factors, the Market Premium and SMB factors consistently show significant effects, while HML and CMA exhibit no significant relationship.