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THE IMPACT OF CORPORATE SOCIAL RESPONSIBILITY ON FIRM RISK AND VALUATION

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To the memory of my father, for his constant support in all my endeavours.

To my mother, my wife, and my daughter, with love.

Declaration

I declare that this thesis has been written by myself, that the work contained in it is my own, except where expressly stated otherwise in the text, and that this work has not been submitted for any other degree or professional qualification except as stated.

I acknowledge the use of AI-assisted tools, including ChatGPT (OpenAI, California, United States) and Grammarly (Grammarly, Inc., California, United States), in the preparation of this manuscript. These tools were used to support tasks such as language refinement, coding, brainstorming, and improving clarity and presentation. However, I confirm that the ideas, analysis, arguments, and final content of the thesis are entirely my own, and that I have reviewed and take full responsibility for all material presented in this work.

Authorship and Prior Publication Statement

Authorship Contributions

This thesis includes work developed in collaboration with co-authors. The contributions to the jointly authored research are as follows:

Jorge Merladet: Conceptualisation, methodology, software, validation, formal analysis, writing—original draft, writing—review and editing.

Sara Lumbreras: Conceptualisation, methodology, writing—review and editing, supervision.

Andrés Ramos: Conceptualisation, methodology, writing—review and editing, supervision.

Prior Publication

Chapter 2 of this thesis, as well as parts of the Introduction and Conclusions, are based on previously published work by the same authors:

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Chapters 3 and 4 are configured as forthcoming papers by the same authors. All material derived from this publication has been appropriately integrated and adapted within the context of this thesis.

Keywords

Asset Pricing, ESG, Corporate Social Responsibility, Risk, Firm Valuation, Factor Returns, Factor Investing, Cross-sectional Returns, Expected Returns

JEL: G11 Portfolio Choice, Investment Decisions; G12 Asset Pricing; G32 Financial Risk, Risk Management, Value of Firms; M14 Social Responsibility

Abstract

The relationship between firm characteristics, risk, and realised returns remains fragile and sensitive to modelling choices. In particular, the use of ex-post returns as proxies for ex-ante required returns, together with the reliance on segmented portfolio constructions and the limited treatment of interactions, hinders a unified interpretation of asset pricing mechanisms. This is a central question in asset pricing and extends to Corporate Social Responsibility (CSR) as a trait defining the firm. In this context, the literature offers mixed evidence on the relation between CSR and return and risk.

To address these limitations, in the context of factor investing, this thesis develops a new factor model in which factor returns are reformulated as graded factors—cross-sectional slopes— using the full distribution of firms rather than segment averages. This eliminates arbitrary breakpoints, incorporates interactions structurally, and provides a mathematically consistent link between characteristics and returns and risk metrics. Its definition allows for a more advanced and direct analysis of valuation dynamics. By decomposing returns into earnings and price–earnings multiple components and with the implicit cost of capital (ICC) as a forward-looking proxy for required returns, the framework yields a unified model linking cross-sectional and time-series drivers of returns.

Putting the framework to the test, we show that CSR characteristics are robustly associated with lower risk across specifications and time periods, but do not yield stable return premia. Second, we prove that ICC aligns consistently with firm characteristics in theoretically expected directions, supporting its role as a proxy for required returns. Third, our test underscores the importance of interactions in computing jointly operating factors. Fourth, we showcase the need to examine the time profile of factor returns. For example, size and low reinvestment display stable, time-dependent premia, whereas value and greenness are linked to episodic shifts in investor preferences.

We then illustrate the causal channels by decomposing returns into earnings and valuation multiples. Both contribute over long horizons: the overperformance of smaller firms is largely driven by multiple expansion, while that of low-reinvesting firms is more closely tied to realised earnings. The time-series analysis shows that changes in required returns are the primary driver of valuation dynamics, while announcement-related shocks are the main channel through which new information affects prices.

Overall, the thesis contributes to asset pricing by integrating valuation mechanics with factor theory in a consistent causal chain. The results have implications for asset pricing, investment, and corporate finance, providing a more structured basis for risk attribution, valuation, and the interpretation of apparent abnormal returns.

Resumen

La relación entre las características de la firma, el riesgo y los rendimientos observados sigue siendo frágil y sensible a las decisiones de modelización. En particular, el uso de rendimientos ex post como aproximación a los rendimientos requeridos ex ante, la modelización de factores basada en la segmentación de carteras y el tratamiento de las interacciones limitan la eficacia del análisis. Se trata de una cuestión central en la valoración de activos y su aplicación se extiende a los rasgos de responsabilidad social corporativa (RSC). La literatura ofrece conclusiones equívocas sobre la relación entre RSC y los rendimientos y el riesgo.

La tesis desarrolla un modelo alternativo de factores, que los define como pendientes transversales. El nuevo modelo utiliza la distribución completa de la muestra, en lugar de promedios de los segmentos extremos, se eliminan elementos arbitrarios y se incorporan las interacciones de manera estructural. Esta definición permite un análisis más directo y avanzado de los rendimientos. Tomando como proxy del rendimiento requerido el coste implícito del capital (ICC por sus siglas en inglés), proponemos un modelo unificado para explicar la distribución transversal y las variaciones temporales de rendimientos.

Con nuestros resultados probamos que la RSC se asocia con un menor riesgo, pero no genera primas de rentabilidad estables. En segundo lugar, el coste implícito del capital se alinea con las características de riesgo según la teoría, lo que avala su papel como proxy de los rendimientos requeridos. En tercero, nuestro modelo muestra la importancia que adquieren las interacciones entre factores. En cuarto lugar, mostramos la importancia del perfil temporal de las series de factores. Por ejemplo, el tamaño y la reinversión presentan primas de riesgo estables, mientras que el valor y la responsabilidad ambiental se vinculan con cambios episódicos en las preferencias de los inversores.

A continuación, ilustramos el uso del modelo para analizar los canales causales. La descomposición de los rendimientos demuestra que tanto los beneficios como los múltiplos de valoración contribuyen de manera significativa a largo plazo. Por ejemplo: el mejor comportamiento de las empresas pequeñas está impulsado por la expansión de múltiplos, mientras que el de las empresas con baja reinversión está estrechamente ligado al crecimiento de los beneficios. El cambio en el rendimiento requerido es el principal impulsor de las variaciones en la valoración, mientras que los anuncios corporativos constituyen el principal canal por el cual la información corporativa incide en los precios.

En conjunto, esta tesis contribuye a la valoración de activos al integrar mecanismos de valoración y el modelo de factores, lo que configura una cadena causal coherente. Estos resultados tienen implicaciones para la valoración de activos, la inversión y las finanzas corporativas, proporcionando una base más estructurada para la atribución del riesgo, la valoración y la interpretación de rendimientos aparentemente anómalos.

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Introduction

Corporate Social Responsibility (CSR) has been the subject of sustained academic attention for several decades. The recent development and widespread adoption of Environmental, Social, and Governance (ESG) metrics have further enhanced their applicability within investment practice. In parallel, asset pricing research has increasingly relied on factor-based approaches to summarise the cross-section of expected returns. These two developments intersect in a central question: how firm characteristics, such as CSR, influence the firm's expected returns, risk, and valuation.

Most empirical studies addressing this question operate at the firm level and often yield mixed evidence on performance implications. A smaller but growing strand of literature focuses on the relationship between CSR and risk, where empirical findings are more consistent, though still incomplete. This dissertation approaches the CSR–performance relation from a different perspective, examining it through the lens of factor pricing. By leveraging the information-aggregation properties of factors, we aim to mitigate firm-level noise and obtain clearer estimates of how CSR-related characteristics are priced in financial markets.

While preparing the work, we identified a broader methodological issue and proposed a solution. The factor literature itself faces substantial challenges in construction and interpretation. Concerns regarding model specification, robustness, and the integration of cross-sectional and time-series evidence remain unresolved. The dissertation, therefore, develops a unified framework that addresses the measurement of characteristic-based returns, their joint effects, and the interpretation of their economic significance, using conventional risk factors alongside new CSR factors as a central empirical application.

1.1 ESG Metrics in Relation to Returns and Risk

Early reports linking CSR with returns and risk were based on vetoed industries (i.e., *sin stocks*), on metrics that referenced partial aspects of social responsibility, such as GHG emissions, or on binary metrics, such as concerns. The generalisation of environmental, social, and governance (ESG) scores as a wide spectrum proxy for CSR in recent years has opened a new opportunity for the analysis of corporate responsibility, and ESG investing has become increasingly prominent in both academic and practitioner circles. Yet the implication of better social performance for expected returns remains ambiguous. While some studies document positive associations between CSR and performance, others report weak or insignificant relationships (Atz et al., 2023; Rupp & Limpaphayom, 2024). In contrast, the evidence linking

CSR to risk is more consistent, suggesting that firms with stronger CSR profiles tend to exhibit lower exposure to adverse outcomes and greater stability. However, recent contributions emphasise the need for further empirical validation and a deeper understanding of the mechanisms linking CSR with risk (Gillan et al., 2021; Leifhelm et al., 2025; Sassen et al., 2016).

In the second chapter, we thoroughly examine the relationship between CSR and risk. The results indicate that improvements in CSR are associated with reductions in firm risk. This finding carries direct valuation implications, as lower risk translates into higher asset prices. At the same time, it implies lower expected returns, generating a tension between valuation effects and return predictability. This tension highlights the need for a framework that analyses risk and expected return jointly rather than in isolation.

In the third and fourth chapters, we model ESG factors to assess the effects of CSR on returns, and we propose extending the use of factors to risk metrics to benefit from their information-reduction properties. Under the model we develop in these chapters, the tested risk factors for CSR characteristics yield results consistent with the firm-level test and the theoretically predicted results, corroborating our findings on the stability of the risk-reducing effects of CSR, as opposed to one-off repricing effects on returns.

1.2 Challenges in Modelling the Cross-Section of Returns

Factor models have become the dominant framework for studying the cross-section of expected returns. Despite their widespread use, several concerns persist. First, traditional factors such as size and value produce conflicting results across different samples and time periods (Loughran, 2025). Second, the rapid expansion in the number of proposed factors has raised questions about their robustness and empirical validity (Hou et al., 2018). Third, the emergence of a so-called “factor zoo” suggests that selective reporting may have contributed to an overstatement of statistical significance (Harvey & Liu, 2019). Finally, ESG-related characteristics, while broadly analysed at the firm level, remain only partially incorporated into standard factor specifications, comparable to other firm-defining characteristics

These issues reflect deeper limitations in the way factors are constructed. In particular, existing approaches often rely on discretionary design choices and fail to account adequately for interactions among characteristics. We address these limitations by proposing a new factor construction methodology that reduces arbitrariness, improves robustness, and explicitly incorporates interactions. We propose a graded, slope-like design. Its continuous, mathematically consistent design opens multiple analysis possibilities, without sacrificing the informativeness of traditional factor construction. We define, illustrate, and test the proposed model in Chapter Three.

1.3 Interpreting Factor Returns and Causality

Factor research, being a substantial body of work in the domain of finance, has introduced valuable conceptual advances, yet only a minor portion of the work addresses the causality of returns. Led mostly by empirical findings, it generally provides economic interpretations for factor returns. However, the treatment of underlying mechanisms varies considerably. A large share of studies remains primarily empirical, focusing on documenting return patterns, often within specific samples or settings, without explicitly addressing causality (Harvey et al., 2016). Other contributions offer theoretical explanations, yet do not subject the proposed mechanisms to direct empirical testing (Hou et al., 2015). A further strand estimates factor returns at the portfolio level, but examines potential drivers at the firm level, thereby separating the measurement of returns from the validation of their causes (Cochrane, 2011). As a result, the link between characteristics and returns is not always established within a unified empirical framework. The newly proposed model enables direct factor-level causal analysis.

When trying to generalise to draw theoretical conclusions and in addressing causality, a major known issue is the use of realised returns as proxies for expected returns, despite the contradictory nature of the variable and its proxy (Hou et al., 2018). An alternative, better-aligned proxy, the implicit cost of capital, has acquired sufficient support, offering solid evidence when tested in the factor environment (Lee et al., 2021).

Together, a fully articulated factor construction that enables direct decomposition and the option of a more robust proxy for the required returns has created the opportunity for deeper causal analysis to explain the variation of returns. The fourth chapter develops an integrated framework that connects these two dimensions: the cross-sectional characteristics of a firm and the time-series variation of the cross-section. By linking both, we provide an interpretation more coherent with the variable nature of factor returns and allow identification of underlying economic channels. This approach allows examining how firm characteristics influence both risk and expected returns within a unified framework, and we extend the reported factor domain to E, S, and G factors.

1.4 Contributions

This dissertation makes three main contributions that correspond with published or forthcoming papers:

- First, it provides robust evidence that CSR is systematically associated with lower firm risk, reinforcing its role as a risk-reducing characteristic.
- Second, it introduces a novel framework for factor construction that improves the measurement of characteristics in the cross-section of returns.

- Third, it develops an integrated approach to interpreting factor returns in relation to the firm's risk-bearing characteristics, and then links them to underlying economic drivers such as cost of capital and growth expectations.

Taken together, the results reveal a consistent pattern: CSR is associated systematically with reductions in risk, while its impact on expected returns varies over time, reflecting changes in investor preferences. More broadly, the findings demonstrate that ESG characteristics can be analysed within the same framework as traditional risk factors, thereby providing a unified approach to studying their role in asset pricing.

The remainder of this dissertation is organised as follows. Chapters two, three, and four develop the three main contributions. Each of them starts by reviewing the relevant state of the art to build on previous authors' contributions, then proposes the model, tests it, discusses it, and concludes. Finally, our last chapter integrates the conclusions at the broader framework level, together with their implications and limitations, and states possible future research lines.

CSR Provides Sustained Risk Reduction

2.1 Introduction

CSR has attracted sustained academic interest for several decades (Viviers & Eccles, 2012). Initially grounded in ethical considerations, the literature has progressively shifted towards stakeholder-oriented frameworks (Kumar & Srivastava, 2022) and the analysis of corporate decision-making processes (Harjoto & Laksmana, 2018). Despite these developments, there are continuing calls for further research at the intersection with financial economics (Hong et al., 2020). This study is situated at this intersection, where a large share of studies align with industry developments by focusing on the profitability of responsible investing (Dumrose et al., 2022).

Although environmental, social, and governance (ESG) investing is widely acknowledged to influence firm value and is frequently linked to improved financial performance, the evidence on the direction of this effect from a profitability perspective remains inconclusive (Atz et al., 2023; Rupp & Limpaphayom, 2024). By contrast, studies examining the relationship between CSR (corporate social responsibility) and risk yield more consistent results, indicating that stronger CSR profiles are associated with lower risk exposure. The growing body of evidence supporting the role of CSR in risk mitigation calls for further analysis to assess the robustness of this relationship (Leifhelm et al., 2025; Sassen et al., 2016) and to develop a deeper understanding of the mechanisms through which CSR affects risk (Gillan et al., 2021).

Recent work highlights the hedging properties of responsible assets within portfolios (Prol & Kim, 2022; Sun et al., 2024). Other contributions argue that CSR protects against adverse shocks by focusing on downside risk (Hoepner et al., 2023; Jung & Song, 2023; Shafer & Szado, 2020). At the same time, some emphasise its role in lowering firms' cost of capital (Albuquerque et al., 2019; Chollet & Sandwidi, 2018; Dorfleitner & Grebler, 2022; Görgen et al., 2020; Shakil et al., 2025), and others examine its association with firm-specific (idiosyncratic) risk (Fauser & Utz, 2021; Lee & Faff, 2009; Liu et al., 2023; Sassen et al., 2016).

Improvements in CSR affect firm value through two main channels (Breuer et al., 2024; Görgen et al., 2020). First, they reduce corporate risk by lowering the likelihood or impact of adverse outcomes (Albuquerque et al., 2019). Second, they reduce the cost of capital (Pástor et al., 2022), thereby implying lower expected returns. Firm value increases when investor preferences shift, thereby modifying the underlying pricing assumptions (Ma et al., 2023). Within this framework,

existing models predict diminishing returns to CSR as ESG investing becomes more widespread (Pástor et al., 2021).

Our analysis addresses the three questions: a broader consideration of ESG, the causal channels, and the persistence of the effects beyond the maturity of ESG investing, thus contributing to the literature by advancing the understanding of the CSR–risk relationship. We extend prior research, which has often relied on partial measures (e.g. concerns) or specific risk dimensions (e.g. pollution, unethical consumption) (Hoepner et al., 2023; Jo & Na, 2012), by employing broader ESG indicators at the firm-level over a longer sample period beyond the maturity of sustainable investing. Simultaneously, we analyse alternative risk measures, proxying systematic, idiosyncratic, downside or bilateral risk, to shed light on the still unresolved channels linking CSR and risk.

Our analysis shows that, when evaluated through the lens of risk, the effect of CSR has not weakened even as saturation is reached, but rather intensified. In addition, we seek to reconcile the strands of the literature on risk and performance by examining a more comprehensive, recent dataset drawn from a period of broad ESG adoption, which is essential for achieving theoretical consistency.

The next section presents the theoretical framework and develops the hypotheses. Section 3 describes the data, the variables, and the empirical design. Section 4 reports and discusses the results, and the last section concludes.

2.2 The Theoretical Framework

2.2.1 The Evidence about the Link between CSR and Firm Risk

Early contributions document higher costs of capital in industries such as tobacco, alcohol, weapons, or heavily polluting sectors (Hong & Kacperczyk, 2009; Jo & Na, 2012). This pattern has been attributed to investors' moral preferences, which lead them to avoid exposure to these activities. Subsequent studies extend this line of inquiry by showing that firms with a stronger balance of CSR strengths relative to concerns tend to benefit from lower capital costs (El Ghouli et al., 2011; Nguyen & Nguyen, 2015).

Initial approaches relied on binary CSR indicators based on strengths and concerns. Over time, these measures have been replaced by ESG scores, which provide a more comprehensive assessment by incorporating a broader set of environmental, social, and governance dimensions. These scores not only offer a closer representation of the CSR concept but also better reflect investor behaviour, which increasingly relies on such aggregated measures rather than simple sector exclusions (Krueger et al., 2020).

Despite these advances, substantial disagreement across ESG rating providers continues to raise concerns regarding measurement reliability (Berg et al., 2022). Ongoing

efforts toward standardisation—particularly those associated with the EU Taxonomy—may contribute to a gradual convergence of these measures (Breuer et al., 2024). In the meantime, we address this issue by employing two alternative ESG rating datasets in our empirical analysis.

We therefore formulate the following hypothesis:

H1. CSR reduces risk robustly under alternative model specifications, measurement approaches, industries, and time periods.

2.2.2 The Channels through which the Effect Operates

The dominant framework identifies two primary channels through which CSR affects firm valuation: the reduction in the likelihood of adverse cash-flow outcomes (i.e., the probability distribution of cash flows as weighted by investors) and a decline in the cost of capital (Breuer et al., 2024). However, most existing models isolate only one of these mechanisms, focusing either on reduced cash-flow uncertainty (Hsu et al., 2023) or on a lower cost of capital (Pástor et al., 2021).

Empirically, this separation is reflected in the choice of risk proxies. A large strand of the literature examines downside, or idiosyncratic, risk as a measure of cash-flow uncertainty (Hoepner et al., 2023; Lee & Faff, 2009), while another focuses on systematic risk as a proxy for the cost of capital (Albuquerque et al., 2019; Görgen et al., 2020).

To reconcile the breadth of CSR's impact with the tendency of the literature to emphasise individual channels, we jointly assess the behaviour of complementary risk measures. Specifically, we formulate the following hypotheses:

H2.1. Better CSR is associated with lower systematic and firm-specific risk.

H2.2. Better CSR is associated with lower bilateral and downside risk.

2.2.3 The Persistence of the Effect as ESG Investing Matures

Sustained superior financial performance for firms with stronger CSR, when measured ex post, is difficult to reconcile with the lower cost of capital typically associated with safer firms. Such outcomes are more plausibly interpreted as transitory, reflecting shifts in investor preferences as ESG considerations become increasingly incorporated into asset prices. As ESG investing becomes widespread, this valuation effect is expected to attenuate (Pástor et al., 2022).

In contrast, the risk mitigation channel may remain intact even after the revaluation takes place. That is, while excess returns driven by preference shifts may fade, the underlying reduction in exposure to adverse outcomes need not dissipate. The recent reversal of previously positive flows into ESG funds in the US market (Morningstar, 2024) provides a natural setting to assess the persistence of this mechanism. Accordingly, we test the following hypothesis:

H3. The risk-reducing effect of CSR persists even after ESG investment matures.

2.3 Data and Method

Our sample combines data from Bloomberg and MSCI, covering an average of 1,847 firms over 82 months, and yielding 151,498 firm-month observations from September 2016 to June 2023. The MSCI universe expands over time, from 1,411 firms at the beginning of the period to 2,434 by its end. This time window is selected to limit variation in firm coverage and to avoid methodological revisions in MSCI's database, which were more pronounced between 2012 and 2015. As a robustness check, we replicate the analysis using ESG scores from S&P Robeco.

As reported in Table 2.1, we proxy total risk using two complementary measures: 30-day realised volatility ($SIGMA_S$) and the implied volatility of at-the-money call options ($IVATMC$). The latter captures forward-looking risk expectations embedded in option prices and is widely available for US firms (Hoepner et al., 2023).

Tab. 2.1.: Descriptive statistics

	Mean	Std. Dev.	Min	25%	50%	75%	Max.	n
Risk Variables								
IVATMC	0.511	0.374	0.000	0.297	0.421	0.612	21.642	172,871
SIGMA_S	0.486	0.527	0.000	0.257	0.380	0.572	21.420	203,308
BETA	1.045	0.732	-23.966	0.653	1.009	1.394	21.374	206,547
SIGMA_I	0.436	0.522	0.001	0.217	0.332	0.514	21.389	201,931
IVOTMP	0.550	0.390	0.000	0.324	0.456	0.658	21.642	172,871
SMIRK	0.039	0.112	-4.396	0.010	0.026	0.045	2.525	172,871
SORT	0.320	0.317	0.000	0.162	0.251	0.388	10.583	201,815
MXDD	0.210	0.151	0.000	0.099	0.171	0.282	1.000	193,252
ESG Variables								
ESG	4.827	2.014	0.000	3.300	4.800	6.300	10.000	151,498
ENVIRONMENTAL_PILLAR	4.768	2.089	0.000	3.200	4.600	6.200	10.000	151,498
SOCIAL_PILLAR	4.564	1.483	0.000	3.600	4.500	5.500	10.000	151,477
GOVERNANCE_PILLAR	5.300	1.325	0.000	4.500	5.400	6.200	10.000	151,477
Control Variables								
BS_TOT_ASSET	10171.782	40122.064	0.000	470.569	1616.926	6007.178	1772124	209,094
MTB	3.206	2.511	0.001	1.425	2.426	4.237	17.163	175,096
OPERATING_ROA	0.054	0.093	-0.221	0.009	0.059	0.108	0.302	170,281
CAPASSETS	0.008	0.007	-0.001	0.003	0.006	0.012	0.031	183,908
RMOM	217.101	3757.176	-97.366	-16.401	-1.704	14.651	162229	205,698
DEBT_TO_ASSET	0.272	0.212	0.000	0.077	0.260	0.415	0.941	205,746
DVD_PAYOUT_RATIO	0.157	0.242	-0.221	0.000	0.000	0.269	1.261	156,841
EQY_INST_PCT	0.770	0.341	0.000	0.542	0.858	1.024	1.745	202,914

Note: Risk and ESG variables are defined in the main text. Control variables include total assets (BS_TOT_ASSET) as a proxy for firm size, market-to-book ratio (MTB), return on assets ($OPERATING_ROA$) to capture profitability, capital expenditures scaled by assets ($CAPASSETS$) to reflect investment intensity, relative market momentum ($RMOM$), leverage ($DEBT_TO_ASSET$), dividend payout ratio (DVD_PAYOUT_RATIO), and institutional ownership (EQY_INST_PCT). n denotes the number of observations.

To isolate idiosyncratic from systematic risk, the literature typically defines idiosyncratic risk as the residual component obtained after modelling expected returns with a chosen asset pricing framework (Chollet & Sandwidi, 2018). We adopt the Capital Asset Pricing Model (CAPM) (Lintner, 1965; Sharpe, 1964):

$$r_{i,t} = \alpha_i + \beta_i r_{m,t} + \varepsilon_{i,t} \quad (2.1)$$

where $r_{i,t}$ denotes the return of stock i at time t , α_i is the intercept, β_i measures exposure to the market factor, $r_{m,t}$ is the market return, and $\varepsilon_{i,t}$ captures the idiosyncratic component.

Assuming returns are normally distributed with mean μ_i and volatility σ_i , the residual term can be expressed as a standardised disturbance:

$$r_{i,t} = \mu_i + \sigma_i \varepsilon_{i,t}, \quad \varepsilon_{i,t} \sim \mathcal{N}(0, 1) \quad (2.2)$$

Substituting the market return in equation 2.1 with its stochastic representation yields:

$$r_{i,t} = \alpha_i + \beta_i \mu_m + \beta_i \sigma_m \varepsilon_{m,t} + \varepsilon_{i,t} \quad (2.3)$$

where μ_m and σ_m denote the mean and volatility of market returns, respectively. Taking the variance of both sides, and noting that α_i , β_i , μ_m , and σ_m are constant over time, we obtain:

$$\text{Var}(r_{i,t}) = \beta_i^2 \sigma_m^2 \text{Var}(\varepsilon_{m,t}) + \text{Var}(\varepsilon_{i,t}) \quad (2.4)$$

Assuming $\varepsilon_{m,t} \sim \mathcal{N}(0, 1)$, this simplifies to:

$$\sigma_{T,i}^2 = \beta_i^2 \sigma_M^2 + \sigma_{I,i}^2 \quad (2.5)$$

where $\sigma_{T,i}^2$ denotes the total variance of stock i , decomposed into systematic risk ($\beta_i^2 \sigma_M^2$) and idiosyncratic risk ($\sigma_{I,i}^2$). Solving for the idiosyncratic volatility yields:

$$\sigma_{I,i} = \sqrt{\sigma_{T,i}^2 - \beta_i^2 \sigma_M^2} \quad (2.6)$$

This decomposition allows us to isolate the portion of total risk that is not explained by market-wide movements.

As a forward-looking proxy for downside risk, we employ the implied volatility of out-of-the-money put options (*IVOTMP*) (Kräussl et al., 2023), together with the lower segment of the volatility smile (*SMIRK*) (Ilhan et al., 2021; Kräussl et al., 2023; Shafer & Szado, 2020). The *SMIRK* measure, introduced by Shafer and Szado, 2020 for its resemblance to one half of a conventional volatility smile, is

defined as the difference between the implied volatility of out-of-the-money puts (*IVOTMP*) and that of at-the-money calls (*IVATMC*). This metric captures asymmetry in the implied volatility structure and provides a direct indication of market expectations regarding downside risk.

To complement these forward-looking measures, we construct a historical proxy based on the second lower partial moment, which captures the dispersion of returns falling below a specified threshold. We set this threshold at zero, thereby isolating the variability of negative returns and avoiding the introduction of external benchmarks. Originally developed in the late 1970s (Bawa & Lindenberg, 1977; Price et al., 1982), this measure has been only sparsely applied in the asset pricing literature (Hoepner et al., 2023). We denote it by *SORT*, as it corresponds to the denominator of the Sortino ratio (Sortino & Meer, 1991), a widely used performance metric that emphasises downside risk.

Downside risk is particularly relevant given its central role in the debate on the nature of the CSR–risk relationship. To further capture this dimension, we include maximum drawdown (*MXDD*), defined as the largest peak-to-trough decline in a firm’s price over a specified period, a measure widely used in the mutual fund industry. Compared with model-dependent metrics such as cumulative abnormal returns, *MXDD* is model-free and depends solely on the chosen time horizon. We compute *MXDD* over 60- and 180-day windows and perform robustness checks using alternative specifications.

In addition, we use β as a proxy for systematic risk. As indicated in equation 2.5, systematic risk is given by $\beta_i \sigma_M$. Since σ_M is common across firms within a given period, variation in systematic risk across firms is fully captured by differences in β_i . Consequently, percentage changes in β_i provide a valid measure of the relative contribution of systematic risk in the empirical analysis.

Our empirical analysis begins by sorting firms into quintiles based on their ESG ratings. We then compare mean risk levels across groups, test for statistical significance, and assess whether risk declines monotonically across ESG segments (Shafer & Szado, 2020). In contrast to studies centred on portfolio optimisation, our objective is to evaluate implications for firm valuation. Accordingly, all firms are given equal weight, thereby limiting distortions arising from the concentration of market value in a small number of large firms.

We estimate panel regressions of the form:

$$\text{RISK}_{it} = \beta_0 + \beta_1 \text{ESG}_{it-1} + \beta_2 X_{it-1} + \gamma_i + \delta_t + \varepsilon_{it} \quad (2.7)$$

where RISK_{it} denotes the risk of firm i at time t , measured using eight alternative proxies; β_0 is the intercept, and β_1 captures the effect of CSR, proxied by the aggregate ESG score. X_{it} represents the vector of control variables, γ_i denotes firm fixed effects controlling for time-invariant unobserved heterogeneity, and δ_t captures time fixed effects common to all firms. The term ε_{it} is the error term.

To assess the robustness of our findings, we vary the specification of fixed effects across firm, sub-industry, and industry levels. We further examine heterogeneity across industries and time periods, employ an alternative ESG data source (Berg et al., 2022; Chollet & Sandwidi, 2018), and test the stability of the results by restricting the sample to firms with a minimum number of observations.

2.4 Results and Discussion

2.4.1 CSR Reduces Risk Consistently across Specifications

Using the quintile-sorting approach, firms in the highest ESG group exhibit significantly lower risk than those in the lowest groups (Table 2.2). Based on Newey–West standard errors, these differences are statistically significant and consistently negative across all risk measures. Risk declines strongly monotonically across ESG categories, with only one exception: a single one of the 28 adjacent differences is positive, and its magnitude is negligible relative to the average of the negative differences.

Tab. 2.2.: Segment analysis of eight risk measures

	quintile	ESG	IVATMC	SIGMA_S	BETA	SIGMA_I	IVOTMP	SMIRK	SORT	MXDD
(L)	1 (L)	2.103	0.543	0.476	1.201	0.418	0.583	0.040	0.323	0.222
	2	3.748	0.504	0.445	1.152	0.388	0.547	0.043	0.302	0.209
	3	4.882	0.467	0.412	1.083	0.357	0.507	0.040	0.280	0.193
	4	6.008	0.436	0.396	1.058	0.341	0.474	0.039	0.270	0.187
(H)	5 (H)	7.638	0.379	0.356	0.974	0.304	0.415	0.036	0.242	0.167
	H-L	5.525	-0.155	-0.114	-0.223	-0.108	-0.158	-0.003	-0.076	-0.052
	t	1172.287	-75.179	-44.814	-109.422	-58.838	-68.844	-11.528	-36.177	-39.769

Note: This table reports the mean values of all variables across ESG quintiles. The sample is sorted into five groups based on ESG scores. *IVATMC* and *SIGMA_S* proxy total risk; *BETA* captures systematic risk; *SIGMA_I* measures idiosyncratic risk; *IVOTMP*, *SORT*, and *MXDD* represent downside risk; and *SMIRK* captures the downside risk premium. *H – L* denotes the difference between the highest (quintile five) and lowest (quintile one) ESG groups. *t*-statistics are computed using Newey–West standard errors. All *H – L* differences are statistically significant at the 1% level.

Our regression results confirm a statistically significant relationship between CSR and risk across all measures (Table 2.3). The estimated coefficients are consistently negative and remain significant across alternative model specifications, including the inclusion of entity fixed effects, time fixed effects, and control variables.

At the industry level, based on the GICS industry group classification, five of the 21 industries do not display statistically significant coefficients. Among the remaining 16 industries, the estimates are negative and significant at the 1% level, further supporting the robustness of the CSR–risk relationship (Table 2.4).

Tab. 2.3.: Regression analysis of eight risk measures

Dep. Variable	IVATMC (1)	SIGMA_S (2)	BETA (3)	SIGMA_I (4)	IVOTMP (5)	SMIRK (6)	SORT (7)	MXDD (8)
Intercept	0.6667*** (135.49)	0.5130*** (127.37)	1.0537*** (128.19)	0.4713*** (115.60)	0.6963*** (140.92)	0.0296*** (15.803)	0.3462*** (109.32)	0.2433*** (132.87)
ESG	-0.0120*** (-36.788)	-0.0083*** (-27.310)	-0.0190*** (-24.934)	-0.0077*** (-24.870)	-0.0125*** (-35.200)	-0.0005*** (-3.7272)	-0.0058*** (-24.753)	-0.0034*** (-19.501)
BS_TOT_ASSET	-4.319e-07*** (-17.469)	-2.647e-07*** (-12.720)	-8.236e-08*** (-3.0027)	-2.836e-07*** (-13.077)	-4.656e-07*** (-17.045)	-3.378e-08*** (-9.1538)	-1.886e-07*** (-12.951)	-1.277e-07*** (-11.371)
MTB	-0.0034*** (-8.9147)	0.0001 (0.3240)	0.0177*** (22.586)	-0.0013*** (-3.6782)	-0.0044*** (-11.140)	-0.0010*** (-8.3170)	-0.0022*** (-9.9350)	-0.0038*** (-22.633)
OPERATING_ROA	-0.7062*** (-59.977)	-0.6288*** (-54.558)	-1.2255*** (-48.023)	-0.5816*** (-49.746)	-0.7322*** (-58.966)	-0.0260*** (-5.5416)	-0.4175*** (-51.480)	-0.3142*** (-53.484)
CAPASSETS	0.0192 (0.1615)	0.5109*** (5.1389)	1.5112*** (5.7695)	0.4539*** (4.5040)	0.1609 (1.2818)	0.1416*** (3.2289)	0.5426*** (6.6432)	0.5291*** (9.3489)
RMOM	4.639e-07** (2.1149)	-8.6e-09 (-0.0268)	-1.457e-06*** (-3.5992)	2.232e-07 (0.6635)	4.35e-07* (1.9297)	-2.895e-08 (-0.1347)	-2.885e-07 (-1.4068)	-2.867e-07* (-1.9390)
DEBT_TO_ASSET	0.0616*** (11.882)	0.0608*** (14.263)	0.1471*** (15.018)	0.0511*** (11.793)	0.0558*** (10.130)	-0.0059*** (-2.8856)	0.0483*** (15.620)	0.0406*** (17.356)
DVD_PAYOUT	-0.1791*** (-65.631)	-0.1347*** (-49.851)	-0.3020*** (-47.318)	-0.1251*** (-45.499)	-0.1805*** (-59.379)	-0.0014 (-1.1217)	-0.0811*** (-38.793)	-0.0502*** (-33.913)
EQY_INST_PCT	-0.1166*** (-25.759)	-0.0461*** (-14.054)	0.1253*** (18.375)	-0.0585*** (-17.602)	-0.0964*** (-21.331)	0.0202*** (13.484)	-0.0252*** (-10.095)	-0.0215*** (-13.971)
Effects	Entity Time	Entity Time	Entity Time	Entity Time	Entity Time	Entity Time	Entity Time	Entity Time
n	91590	95114	95114	94410	91590	91590	95104	92348
R-squared	0.1791	0.1254	0.0898	0.1118	0.1644	0.0053	0.1011	0.1131
F-statistic	2215.2***	1512.0***	1040.7***	1317.1***	1997.3***	53.8***	1185.5***	1305.5***

Note: This table reports coefficients from panel regressions of eight risk measures on ESG scores, including the control variables defined in Table 2.1. *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Tab. 2.4.: Risk regressed on ESG for 21 industry groups

Industry group	Energy	Materials	Capital Goods	Commercial & Professional Services	Transportation	Automobiles & Components	Consumer Durables & Apparel
GICS code	1010	1510	2010	2020	2030	2510	2520
ESG	-0.0400*** (-15.806)	-0.0104*** (-12.248)	-0.0126*** (-20.181)	-0.0004 (-0.3292)	-0.0021 (-1.5186)	-0.0065*** (-2.7611)	-0.0074*** (-7.5434)
n	5243	8859	13855	5184	2346	2154	4602
R-squared	0.2284	0.2276	0.2623	0.3019	0.2382	0.3774	0.2190
F-statistic	169.3***	286.6***	543.5***	244.5***	78.2***	138.8***	140.3***

Industry group	Consumer Services	Consumer Discretionary Dist. and Retail	Consumer Staples Distribution and Retail	Food, Beverage & Tobacco	Household & Personal Products	Health Equipment Services	Care & Pharmaceuticals, Biotechnology & Life Sciences
GICS code	2530	2550	3010	3020	3030	3510	3520
ESG	-0.0111*** (-6.9346)	-0.0171*** (-8.8068)	-0.0007 (-0.5186)	-0.0039*** (-2.6361)	-0.0025 (-0.3630)	0.0037*** (3.4225)	-0.0122*** (-6.7241)
n	3685	5055	1809	3090	680	6870	4967
R-squared	0.2795	0.2150	0.2587	0.2812	0.2918	0.2873	0.2463
F-statistic	154.8***	150.9***	66.5***	130.2***	27.0***	303.4***	177.0***

Industry group	Software & Services	Technology Hardware & Equipment	Semiconductors & Semiconductor Equipment	Telecommunic. Services	Media & Entertainment	Utilities	Real Estate
GICS code	4510	4520	4530	5010	5020	5510	6020
ESG	-0.0173*** (-13.204)	-0.0119*** (-8.9730)	-0.0081*** (-8.5431)	-0.0039 (-0.5912)	-0.0185*** (-11.958)	-0.0154*** (-12.946)	-0.0099*** (-3.8529)
n	4199	5226	3164	1069	3954	4329	1250
R-squared	0.2634	0.2300	0.2766	0.3650	0.2707	0.2280	0.2186
F-statistic	163.1***	170.3***	130.6***	62.4***	159.1***	139.0***	36.0***

Note: This table reports coefficients from panel regressions of the risk measure *IVATMC* on ESG scores for firms within each industry group. Control variables are defined in Table 2.1 (omitted here for brevity). *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

We find support for our first hypothesis. The results are consistent with recent evidence showing that improvements in CSR—captured through comprehensive ESG scores—are associated with a systematic reduction in risk, even in the context of evolving investor preferences and regulatory developments (Kräussl et al., 2023; Shafer & Szado, 2020).

From a sectoral perspective, earlier studies conducted during the initial stages of ESG adoption (Krueger et al., 2020) found that the risk-reducing effects of CSR were limited or uneven across sectors. In particular, some contributions identified the effect primarily in controversial industries (Harjoto & Laksmana, 2018), while others reported mixed or even conflicting results depending on the proxy employed (Jo & Na, 2012; Nguyen & Nguyen, 2015). Additional evidence suggested that the relationship was confined to specific firm types, such as large manufacturing companies (Cai et al., 2016). By contrast, in a more mature ESG environment, our findings indicate a consistent and monotonic reduction in risk across sectors.

2.4.2 CSR Relates Closely to Systematic and Idiosyncratic Risk

As shown in equation 2.5, total risk can be decomposed into systematic and idiosyncratic components. For the average firm, this decomposition yields $0.486^2 \approx 1.045^2 \times 0.163^2 + 0.436^2$ (Table 2.2). Approximately one-seventh of total risk is attributable to systematic risk (the first term), while the remaining six-sevenths correspond to idiosyncratic risk (the second term).

Moving from the lowest to the highest ESG quintile, total risk declines by 0.114, corresponding to a reduction of approximately 23%. This decrease is associated with a reduction in systematic risk of 0.223 (about 21%) and a reduction in firm-specific risk of 0.108 (about 25%). Overall, these results indicate proportionally similar declines across total, systematic, and idiosyncratic risk.

Applying the regression framework to total, systematic, and idiosyncratic risk measures, and standardising variables in logarithms to account for differences in scale and dispersion, yields statistically significant coefficients for ESG across all specifications. The estimated coefficients are of comparable magnitude across total, systematic, and idiosyncratic risk measures, as reported in Table 2.5.

In summary, the reduction in idiosyncratic risk is larger in absolute terms than that of systematic risk, reflecting its higher initial level. However, when risk reductions are expressed relative to the average firm's baseline or standardised across measures, both components contribute to the overall effect to a similar extent.

2.4.3 The effect on Downside and Bilateral Components of Risk

To examine the effect of CSR on bilateral and downside risk components, we rearrange the definition of *SMIRK* as follows:

Tab. 2.5.: Risk regressed on ESG using log-standard values

Dep. Variable	lnIVATMC (1)	lnSIGMA_S (2)	lnBETA (3)	lnSIGMA_I (4)	lnIVOTMP (5)	lnSMIRK (6)	lnSORT (7)	lnMXDD (8)
ESG	-0.0225*** (-13.524)	-0.0199*** (-10.220)	-0.0215*** (-8.3539)	-0.0179*** (-8.0548)	-0.0205*** (-11.713)	-0.0154*** (-5.4580)	-0.0180*** (-8.6611)	-0.0138*** (-5.7373)
n	23526	24245	22771	23928	23513	20867	24138	23084
R-squared	0.2744	0.1395	0.0631	0.1260	0.2650	0.0581	0.1005	0.0939
F-statistic	979.75***	432.80***	168.90***	379.70***	933.56***	141.47***	296.97***	263.48***

Note: This table reports coefficients from panel regressions of eight log-standardised risk measures on ESG scores, including log-standardised control variables defined in Table 2.1, for firms within each industry group. *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

$$\text{RISK}_{\text{downside}} = \text{RISK}_{\text{bilateral}} + \text{Downside Premium} \quad (2.8)$$

In terms of the empirical measures used in this study, this decomposition can be written as:

$$IVOTMP = IVATMC + SMIRK \quad (2.9)$$

For the average firm, the relationship is given by $0.550 = 0.511 + 0.039$, while the observed reduction in risk is $-0.158 \approx -0.155 + (-0.003)$ (Table 2.2). This implies that downside risk (*IVOTMP*) declines by 28.7% relative to its mean, total risk (*IVATMC*) by 30.3%, and the downside premium (*SMIRK*) by only 7.7%. Although the reduction in the downside premium is statistically significant relative to its initial level, it is quantitatively small compared to the decline in bilateral risk. Hence, the bulk of the reduction in downside risk is driven by its bilateral component.

When estimating the regression model with log-standardised risk variables, effect sizes can be directly compared through the coefficients. The results in Table 2.5 show similar magnitudes: -0.0205 for *IVOTMP*, -0.0225 for *IVATMC*, and -0.0154 for *SMIRK*. These estimates indicate that the effect on downside risk is comparable to that on its bilateral and premium components, with the bilateral component playing at least an equally important role.

Overall, we find strong support for H2.1 and H2.2. The evidence shows that CSR reduces investors' perceived exposure to adverse outcomes, as reflected in downside and idiosyncratic risk measures that proxy for cash-flow (numerator) effects, both in forward-looking indicators (e.g., implied metrics) and realised ex post outcomes (e.g., drawdowns and observed volatility). At the same time, CSR lowers the cost of capital (denominator effect), as evidenced by the reduction in systematic risk. Taken together, these findings motivate a reformulation of the CSR-risk relationship that is consistent with our results and more closely aligned with the theoretical framework in (Breuer et al., 2024), emphasising its broad impact on overall firm risk rather than isolating it within specific components.

2.4.4 The Time Series of the Effects of CSR on Risk

The estimated β_1 coefficients in later years (-0.0125 to -0.0140) are substantially larger in magnitude than those observed at the beginning of the sample period (-0.0033 to -0.0090). Notably, the coefficient for 2020—when financial markets were affected by the COVID-19 shock—reaches its largest value at -0.0176 (Table 2.6).

Tab. 2.6.: Risk regressed on ESG for each of the years

Year Dep. Variable	2016 IVATMC	2017 IVATMC	2018 IVATMC	2019 IVATMC	2020 IVATMC	2021 IVATMC	2022 IVATMC	2023 IVATMC
ESG	-0.0033*** (-3.3281)	-0.0050*** (-9.8786)	-0.0058*** (-8.0078)	-0.0090*** (-15.994)	-0.0176*** (-14.514)	-0.0140*** (-16.749)	-0.0125*** (-15.079)	-0.0128*** (-10.335)
n	3505	11473	12284	13127	14042	14983	15493	6683
R-squared	0.1903	0.1934	0.1222	0.2396	0.1585	0.1998	0.2651	0.2808
F-statistic	87.9***	301.8***	187.7***	454.5***	290.7***	411.7***	615.1***	283.8***

Note: This table reports coefficients from panel regressions of risk, measured by *IVATMC*, on ESG scores, including the control variables defined in Table 2.1. *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

The estimated coefficient capturing risk reduction nearly doubles in the post-2020 period relative to earlier years, increasing from -0.0069 to -0.0135 . The structural break associated with the COVID-19 shock, spanning February to August 2020, is statistically significant (Chow test: $F = 1,100.8$, $p < .01$) (Table 2.7).

The increase in magnitude—by a factor ranging from 1.53 to 2.67—is both economically large and statistically significant across measures of total risk (*IVATMC*, *SIGMA_S*), idiosyncratic risk (*SIGMA_I*), and downside risk (*IVOTMP*, *SORT*, and *MXDD*). Although β is slightly lower in the later period (multiplying factor 0.91), once the increase in market volatility is taken into account, the implied reduction in systematic risk, $\beta\sigma_M$, is approximately 46% stronger in the later period. This pattern suggests that the risk-mitigating role of CSR becomes more pronounced during periods of heightened uncertainty.

While the heightened protection observed during the COVID-19 crisis aligns with prior research suggesting CSR's mitigating role during systemic events (Albuquerque et al., 2020; Sun et al., 2024), the sustained intensification of this effect over time is a novel finding. Unlike the temporary impact of CSR on higher returns, this pattern indicates a persistent impact consistent with a stable shift in risk perception linked to CSR (Pástor et al., 2022). Investor focus on environmental, social, and governance risks may stem from several factors, including improved disclosure practices, the proliferation of ESG scores, ongoing regulatory changes (i.e. EU Taxonomy), and evolving market norms. Identifying and ranking these factors and their relative contributions presents a valuable opportunity for future research.

Tab. 2.7.: Increased sensitivity of risk to ESG and breakpoint test

	IVATMC	SIGMA_S	BETA	SIGMA_I
Before	-0.0069	-0.0057	-0.0176	-0.0055
Conf Interval	[-0.0076, -0.0063]	[-0.0064, -0.0051]	[-0.0198, -0.0154]	[-0.0062, -0.0048]
After	-0.0135	-0.009	-0.016	-0.0084
Conf Interval	[-0.0144, -0.0125]	[-0.0099, -0.0080]	[-0.0182, -0.0138]	[-0.0094, -0.0075]
After/Before	1.96	1.58	0.91	1.53
Chow test (F)	1100.8***	819.6***	1566.7***	623.4***

Dependent variable	IOTMP	SMIRK	SORT	MXDD
Before	-0.0072	-0.0003	-0.004	-0.0027
Conf Interval	[-0.0079, -0.0065]	[-0.0005, -0.0000]	[-0.0046, -0.0035]	[-0.0032, -0.0023]
After	-0.0142	-0.0008	-0.0061	-0.0033
Conf Interval	[-0.0153, -0.0132]	[-0.0012, -0.0003]	[-0.0068, -0.0054]	[-0.0038, -0.0027]
After/Before	1.97	2.67	1.53	1.22
Chow test (F)	926.8***	115.6***	577.0***	640.8***

Note: This table reports coefficients from panel regressions of eight risk measures on ESG scores, controlling for variables defined in Table 2.1, for the "Before" (September 2016–January 2020) and "After" (August 2020–June 2023) periods. Confidence intervals are reported at the 95% level. ***, **, and * denote statistical significance of the Chow test *F*-statistic at the 1%, 5%, and 10% levels, respectively.

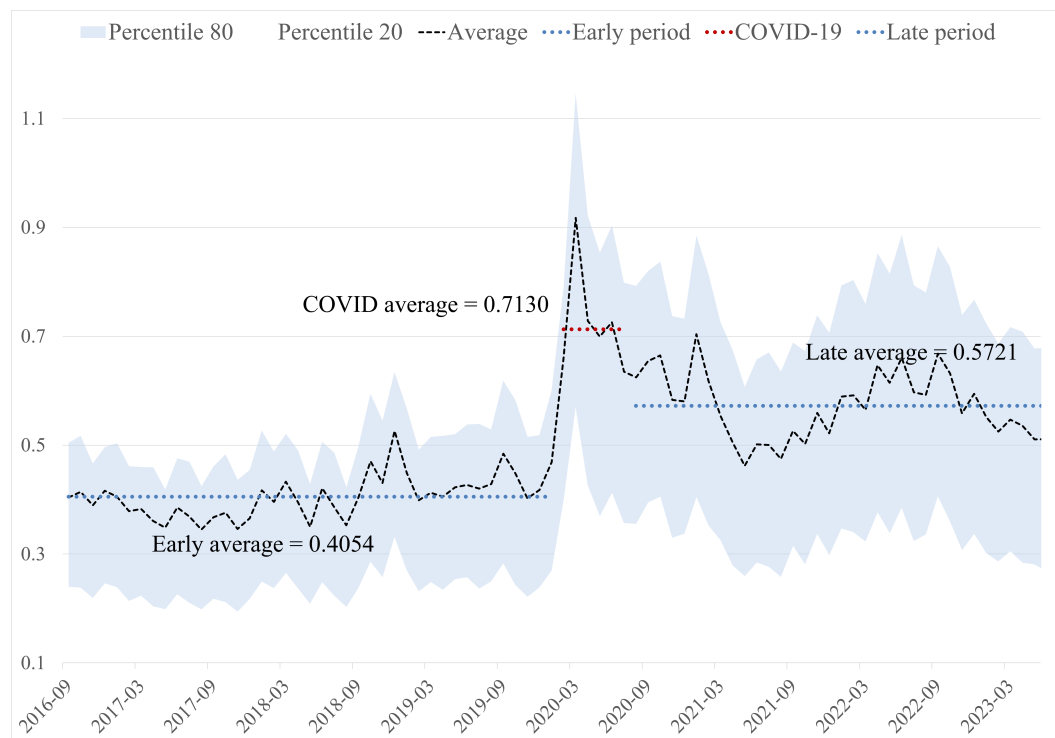


Fig. 2.1.: Time series of risk measured by IVATMC

2.5 Conclusion

Our results show that improvements in CSR are associated with reductions across all risk measures. CSR mitigates risks typically classified in the literature as downside or idiosyncratic—such as litigation risk, stranded assets, or technological disruption—as much as it lowers the cost of capital. We further show that broad-based measures of total risk provide a more accurate representation of CSR's impact than metrics that isolate downside risk, idiosyncratic risk, or the cost of capital. This comprehensive effect is consistent with investors reassessing the weighting of cash-flow scenarios (a numerator effect) and firm risk in determining required returns (a denominator effect), as documented in investor surveys (Krueger et al., 2020) and formalised in our theoretical framework (Breuer et al., 2024; Zhang et al., 2024).

The persistence of the risk reduction effect contrasts with the more variable evidence on performance outcomes (Ardia et al., 2023; Pástor et al., 2022). These findings highlight the need for further research on the long-term effects of CSR on risk. If future work confirms the sustained intensity of this relationship, improved CSR performance would directly contribute to firms' core objectives by mitigating risk and should be fully incorporated into managerial decision-making and asset valuation (Breuer et al., 2024; Shakil et al., 2025).

Our study is subject to several limitations, particularly regarding the sample period and the measurement of ESG performance. Overall risk levels increased during the sample period, and we cannot rule out that the benefits of CSR may weaken in lower-risk environments. To address concerns about discrepancies across ESG ratings, we replicate our analysis using two alternative data sources (Berg et al., 2022).

An additional limitation concerns the composition of the sample. Although our empirical specifications include industry controls and separate analyses by sector, we do not formally analyse the overall sectoral composition of the sample or the implications of its unbalanced coverage over time as the MSCI universe expands. Consequently, we cannot completely rule out potential coverage or survivorship effects, which may be explored in future research.

The focus on US firms reflects the relative maturity of ESG investing in this market, which has recently experienced net outflows, providing a suitable setting to test the persistence of the effects identified. Future research could extend the analysis to other regions and sectors, examine the individual environmental, social, and governance dimensions separately, and explore whether the risk-reducing effects of CSR differ across the distribution of risk or under alternative market conditions. Differences in regulatory frameworks, market fragmentation, and investor protection may further influence the generalizability of these relationships, thereby enhancing the external validity of CSR's role in asset pricing.

A New Model for the Cross-section of Returns and Risk

3.1 Introduction

In asset pricing, research on factors has expanded markedly. According to Scopus, 865 articles on factors or factor investing were published in 2025 alone, reflecting a sustained upward trend. What originated with the Capital Asset Pricing Model in the 1960s (Lintner, 1965; Sharpe, 1964) was subsequently extended by the Arbitrage Pricing Theory (Ross, 1976) and later operationalised empirically in the multifactor models of Eugene F. Fama and Kenneth R. French (Fama & French, 1993, 2015).

The ability of factors to summarise systematic variation in the cross-section of returns is widely recognised, and their contribution remains extensively cited. Building on this framework, the literature has proposed numerous additional factors, employing increasingly sophisticated econometric techniques and incorporating insights from behavioural finance. More recently, machine learning approaches and institutional applications have further reinforced the central role of factor returns in contemporary research.

However, the two core pillars of this literature—size and value—on which it is firmly grounded, present conflicting evidence. Over the past decade, both strategies have experienced extended periods of underperformance, in contrast with theoretical expectations (Loughran, 2025). A second major concern relates to the proliferation of the so-called “factor zoo” (Harvey & Liu, 2019), comprising hundreds of proposed return predictors, many of which do not survive more stringent testing procedures (Hou et al., 2018). Third, some contributions extend this critique further, arguing that empirical results often rely on discretionary modelling choices and may be affected by publication bias, whereby only favourable outcomes are reported (Harvey et al., 2016).

The literature has long emphasised that empirical asset pricing depends on broad, inductive search procedures, rendering results vulnerable to specification risk (Fama & French, 1993; Harvey et al., 2016; Schwert, 2003). A review of prior studies shows that calls for more stringent econometric standards have become increasingly prominent (Harvey et al., 2016; Hou et al., 2020). The prevailing model’s known weaknesses include the static factor values and the lack of consideration of factor interactions. In response, some authors propose variations or more elaborate factor constructions by adjusting factor calculations dynamically to market conditions

(DeMiguel et al., 2024), more developed segmentation techniques to better capture interactions among factors (Jagannathan et al., 2025), robustness tests with alternative variables and models (Pástor et al., 2022), or complementary firm-level analyses of the time-series (Cochrane, 2011). We contend that the intensifying debate surrounding factor models reflects a more fundamental issue: the construction of factors itself remains inherently fragile.

We introduce a new framework for constructing factors that enables objective computation. In contrast to traditional segment-based portfolio factors, graded factors quantify the influence of firm characteristics on returns and can be standardised to facilitate comparisons of effect magnitudes across factors. In addition, they can be decomposed to analyse underlying causal relationships and allow for the joint examination of multiple interacting factors.

3.2 The State of the Art in Factor Calculation

Traditionally, factor returns are obtained by constructing portfolios that sort stocks according to a given characteristic and then computing the return spread between portfolios formed from high- and low-exposure groups. This approach entails ranking firms based on variables such as size, book-to-market, or momentum, partitioning the cross-section into segments, and forming a long-short portfolio that takes a long position in the highest segment and a short position in the lowest.

Implementing this methodology involves a number of design choices that differ across studies: the definition and transformation of the characteristic, the selection of breakpoints for portfolio formation (e.g., 30/70 or 20/80 splits), whether sorting is conducted univariately or within multidimensional grids (such as the standard 2×3 framework of Fama and French), the weighting scheme within portfolios (equal- or value-weighted), the rebalancing frequency, and the treatment of overlapping or composite signals. These apparently minor design decisions can materially affect factor performance (Harvey et al., 2016; Loughran, 2025), and relevant information is lost in the high-minus-low calculation, as it disregards the central section of the sample (Hou et al., 2020). Further layers of discretion arise when factor construction is based on composite indices that blend different managerial or behavioural aspects, when the index value continuum is replaced by rank metrics in a mix of managerial or performance-related measures (Daniel et al., 2020; Stambaugh & Yuan, 2017).

The extensive testing increases the likelihood of false discoveries in expected returns: researchers evaluate a large number of candidate factors, yet only those that yield statistically significant outcomes are reported (Harvey et al., 2016). In line with this concern, a comprehensive study compiling hundreds of return predictors finds that most fail to produce consistent results upon replication (Hou et al., 2020).

Re-sorting portfolios to capture interactions among the characteristics under study is frequently required within the prevailing methodology, yet this procedure may generate counterintuitive and undesirable outcomes. When factor returns are defined as the difference between the average returns of the highest and lowest segments—each

internally value-weighted—an inconsistency emerges: the aggregation does not incorporate the relative weights of the underlying subsegments when combining them. As a result, identical weights are effectively assigned to the value-weighted returns of both small and large firms. This compromises the coherence of the weighting scheme (Loughran, 2025).

Taken together, these findings have raised more fundamental questions about the construction and evaluation of factors. Adding to the concerns about arbitrary sorting decisions, selection biases, and the salient empiricism, we group authors' responses to model weaknesses around three main strands: (1) the need for dual time-series and cross-sectional analyses, (2) the consideration of the simultaneous effects of factors, (3) model architectures based on theoretical propositions, and (4) models that consider continuous, rather than discrete characteristics.

The integration of cross-sectional and time-series analyses of returns has been the aim of notable studies. At the inception of factor investing, Fama and MacBeth focused on the effects on beta larger risks and used firm-based regressions. By averaging the slope coefficients, which were held constant for the period, they proved the relation between higher risk and higher returns (Fama & MacBeth, 1973). The two-pass (time-series and cross-sectional) regressions alleviated the time-invariant constraint for the coefficients and improved the prediction on the basis of characteristics (Lewellen, 2015). The model was further elaborated using the principal component analysis, an information-aggregation technique, to produce a three-pass model that grouped variables into fewer composites that represent unobservable latent variables to predict returns (Kelly & Pruitt, 2015; Light et al., 2017). Finally, some recent work focuses specifically on the persistence of cross-sectional returns (Monge et al., 2025), showcasing the importance of the time perspective. Our model aims to integrate both dimensions in a mathematically consistent way, enabling direct time-series analysis.

In contrast, our proposed model explicitly states each of the characteristics. Choosing only observable, risk-defining observable characteristics, its direct, explicit formulation allows for the interpretation and evaluation of the persistence of the effects of each of them. With a mathematically consistent formulation, the use of graded factors extends to their decomposition and the analysis of causality.

In an effort to disentangle the joint effects of value and greenness, Jagannathan, Meier, and Sokolovski adopt a framework that partitions the sample into quadrants based on greenness, size, and value (Jagannathan et al., 2025). Identifying the large-value segment as the region that best balances green and brown firms, they first compare the returns of large-value-green firms with those of large-value-brown firms, and subsequently contrast large-growth-green firms with large-value-green firms. Through this sequential approach, excess returns are attributed in two stages: initially to the value–growth dimension, and then to the green–brown differential. In their results, the value–growth characteristic accounts for the majority of the observed effects. However, in this methodology, alternative segment definitions yield different inferences.

In response to the large number of data-driven studies, some authors base their models on theoretical arguments (Hou et al., 2015) or incorporate economic behaviour into their models (Bryzgalova et al., 2023). To avoid discretisation, in a different direction, some authors model firm characteristics directly, departing from the factor strand (DeMiguel et al., 2020), sacrificing the information-reduction properties of factors in exchange for fewer discretionary partitions (Bryzgalova et al., 2023).

Factor models frequently evolve to portfolio trading models. In some models closely connected to the practice of investing, we observe continuous modelling in their consideration of transaction costs, even in weighting adjustments to broader market risk (DeMiguel et al., 2020). Despite this, they still operate firm characteristics as discretely segmented return differentials. Their application is highly followed by the investing community. By considering factors aligned with their chosen strategy, trading costs, and market conditions, they develop their own trading models (DeMiguel et al., 2024; Frazzini & Pedersen, 2014).

In the search for factor models that address these limitations, we note that Pástor, Stambaugh, and Taylor (PST) examine the robustness of their conventionally constructed green-minus-brown factor (GMB) by introducing a slope-type factor that relates firm greenness to returns. Within their framework, expected returns on green assets are modelled as a function of investor preferences, implying lower long-run returns consistent with their reduced risk profile. They argue that any excess returns associated with green firms should persist only during periods of shifting preferences (Pástor et al., 2021). Consistent with this mechanism, PST document that the short-term ex post returns of green firms decline as ESG investing matures. By contrast, the risk-mitigating effect of greenness appears to be more persistent. Our results reinforce this latter point, showing that the risk reduction associated with CSR endures even after the maturation of ESG investment (Merladet et al., 2025).

In a widely cited test, the same authors analyse green-minus-brown returns — traditionally defined as the return spread between portfolios formed from the greener and browner thirds of firms — against a composite index incorporating environmentally related news, earnings-based variables, and capital flows into responsible investing. They show that the relative performance of green stocks is strongly associated with the intensity of such news (Pástor et al., 2022). To support the causal interpretation, they employ two complementary approaches: firm-level return regressions and a newly introduced slope-type factor. This factor, which is particularly relevant to our analysis, departs from the conventional two-portfolio construction by assigning returns along a continuous gradient based on each firm's degree of greenness, rather than contrasting two discrete segments. It is also shown to explain variation in value and momentum returns within the sample period.

We extend this line of reasoning by generalising the underlying calculation to construct informative features for analysing both cross-sectional and time-series returns, while preserving their information-reduction properties. Building on this foundation, we introduce a model that:

- reduces discretionary choices in its parametrisation, such as breakpoint selection, segmentation frequency, or grid design in multi-characteristic settings,
- incorporates information from the full cross-section rather than relying on selected subsamples, thereby reducing potential biases,
- is specified in a parsimonious and broadly applicable manner across firms and over time, avoiding dependence on particular samples, segments, or periods,
- captures a firm's excess performance relative to any given characteristic in a formulation that is theoretically consistent with its intended measurement,
- provides a mathematically rigorous construction that can be extended to the time dimension for causal analysis, and
- enables the joint analysis of interacting factors within a structured and objective framework,

The next section presents the construction of the proposed factors, their variations, and their core properties. As this chapter's contribution is primarily methodological, that section focuses on the development of the framework, while the subsequent sections illustrate its application to size, value, and green factors. Using these three benchmark factors, we demonstrate how the proposed approach captures their effects on firm returns and their interactions, providing new insights into long-standing issues and highlighting the potential of graded factors.

3.3 Modelling Graded Factors

A factor, in its simplest form, captures the excess returns earned by firms exhibiting a given characteristic relative to those with lower exposure or without it. Not all attributes are suitable for defining a factor: they must meaningfully describe firms, be measurable across a broad cross-section, and have a rationale to explain differences in returns (Harvey et al., 2016). In addition, they should be economically interpretable and provide a theoretically coherent link between firms' decisions and their outcomes (Hou et al., 2015).

In this chapter, we focus on three characteristics: size, proxied by market capitalisation; value, proxied by the book-to-market ratio (BTM); and greenness, proxied by a composite index combining the environmental pillar score with the weight assigned to environmental concerns in ESG-based measures of corporate social responsibility.

To formalise the model, let $G_{i,t}$ denote the value of a given characteristic for firm i at time t . For each period—specifically, each month-end—we compute its cross-sectional average $\bar{G}_t$ using weights $w_{i,t}$, such that $\sum_i w_{i,t} = 1$, yielding $\bar{G}_t = \sum_i w_{i,t} G_{i,t}$.

We then define the centred characteristic $g_{i,t}$ by demeaning the raw measure $G_{i,t}$ relative to its value-weighted cross-sectional mean, so that $g_{i,t} = G_{i,t} - \bar{G}_t$, with the property that $\sum_i w_{i,t} g_{i,t} = 0$.

If we estimate a linear relationship using ordinary least squares (OLS), where the dependent variable is the return of firm i at time t , $r_{i,t}$, and the explanatory variable is the centred characteristic $g_{i,t}$, then the sensitivity of returns to the characteristic is captured by the slope coefficient of the cross-sectional regression. Following PST, we define the graded factor f_t as this slope, obtained from a no-intercept regression of $r_{i,t}$ on $g_{i,t-1}$:

$$f_t = \frac{\sum_i g_{i,t-1} r_{i,t}}{\sum_i g_{i,t-1}^2} \quad (3.1)$$

Note that returns in period t are matched with characteristics measured at $t - 1$ to ensure temporal precedence; accordingly, characteristics are indexed at $t - 1$ and returns at t . The numerator corresponds to the sum of the cross-products between $g_{i,t-1}$ and $r_{i,t}$, while the denominator is the sum of squared $g_{i,t-1}$. The resulting expression can be interpreted as a slope, and, as such, a second-moment calculation suffices to compute it. No breakpoint definitions or discretionary parameters are required.

The interpretation of this factor is linear: it not only captures the excess performance of smaller firms relative to larger ones, but also quantifies the observed excess return associated with a one-unit increase in the underlying characteristic across the cross-section. The characteristic may represent a measure of greenness, a unit of size or value (e.g., the BTM ratio), or any attribute reflecting the firm's risk profile. We now proceed to outline the main properties of graded factors.

In a sufficiently large cross-section of firms, the density of observations approximates a continuum, rendering it unnecessary to approximate the slope using a simpler two-portfolio average, as is implicitly done in traditional segment-based constructions. With modern computational capabilities, estimating the slope is in fact no more demanding—and often simpler—than performing the sorting and averaging procedures required by conventional methods.

3.3.1 Standardization

When comparing the magnitude of different factors, the underlying characteristic must be standardised to ensure that factor units are comparable. Let σ_t denote the cross-sectional standard deviation of the characteristic $G_{i,t}$ at time t . The standardised characteristic for each firm and period is then given by $z_{i,t} = \frac{G_{i,t} - \bar{G}_t}{\sigma_t}$.

Substituting this expression into equation 3.1, we obtain the factor associated with the standardised characteristic, denoted f_t^z :

$$f_t^z = \frac{\sum_i z_{i,t-1} r_{i,t}}{\sum_i z_{i,t-1}^2} \quad (3.2)$$

$$= \frac{\frac{1}{\sigma_{t-1}} \sum_i (G_{i,t-1} - \bar{G}_{t-1}) r_{i,t}}{\frac{1}{\sigma_{t-1}^2} \sum_i (G_{i,t-1} - \bar{G}_{t-1})^2} \quad (3.3)$$

$$= \sigma_{t-1} \frac{\sum_i g_{i,t-1} r_{i,t}}{\sum_i g_{i,t-1}^2} \quad (3.4)$$

Equivalently, $f_t^z = \sigma_{t-1} f_t$, providing a simple transformation that makes factor magnitudes directly comparable, while maintaining a clear correspondence between the standardised factors and their underlying characteristics.

3.3.2 Additivity in the Characteristic

Consider a setting in which large firms in the sample appear to earn a performance premium. A straightforward interpretation would attribute this premium to firm size itself. However, large firms are not uniformly distributed across the economy; instead, they are disproportionately concentrated in sectors such as technology, software, pharmaceuticals, and telecommunications. If these sectors outperform during the sample period, part of the observed premium attributed to size may in fact reflect sectoral exposure rather than a pure size effect. The graded framework enables us to disentangle the causes. Specifically, the size characteristic $G_{i,t}$ can be decomposed into an across-sector component and a within-sector component, $G_{i,t} = G_{i,t}^{across} + G_{i,t}^{within}$.

The across component reflects the performance attributable to the sectoral concentration of large firms, whereas the within component captures whether larger firms outperform smaller ones within the same sector, holding sector membership fixed. This additive decomposition enables a clear separation between composition effects and the intrinsic premium associated with the characteristic.

We exploit this property in a sectoral decomposition framework, although it extends more generally to the analysis of component effects for any characteristic or to the construction of composite factors. This requires identifying a characteristic $G_{i,t}$ that can be expressed as the sum of C additive components $G_{i,t}^{(c)}$, where each component is indexed by c : $G_{i,t} = \sum_{c=1}^C G_{i,t}^{(c)}$. An equivalent representation holds for the demeaned characteristic, $g_{i,t} = \sum_{c=1}^C g_{i,t}^{(c)}$.

Substituting this decomposition into the factor definition yields:

$$f_t = \frac{\sum_i \left(\sum_c g_{i,t-1}^{(c)} \right) r_{i,t}}{\sum_i g_{i,t-1}^2} \quad (3.5)$$

As shown in A.1, the composite factor f_t can be expressed as a weighted average of the C component factors $f_t^{(c)}$, where the weights correspond to the adjusted variance contribution of each component $V_{c,t}$ relative to the total adjusted variance V_t :

$$f_t = \sum_{c=1}^C \frac{V_{c,t}}{V_t} f_t^{(c)} \quad (3.6)$$

Two remarks are required regarding the weighting ratio $\frac{V_{c,t}}{V_t}$. First, most studies aim to represent the aggregate market portfolio weight characteristics by market capitalisation. Under this approach, the centred characteristic $g_{i,t}^{(c)}$ is defined relative to the value-weighted average $\bar{G}_{c,t}$. Assuming that the number of observations N is identical across all components and for the composite, and noting that variance is invariant to demeaning, the variance of the centred characteristic $g_{c,t}$ coincides with that of the raw characteristic $G_{c,t}$, denoted $\sigma^2(G_{c,t})$. This variance can be expressed as the sum of squared deviations from the simple (unweighted) mean $\mu_{c,t}$, which differs from the value-weighted average $\bar{G}_{c,t}$. The squared difference between these two averages constitutes the re-centring term in the “adjusted variance” used for weighted factors:

$$V_{c,t} = \sigma^2(G_{c,t}) + (\mu_{c,t} - \bar{G}_{c,t})^2 \quad (3.7)$$

This correction term raises the question of whether the characteristic’s mean should be computed with weights or left unweighted, and, if weighting is applied, whether the slope should also give greater weight to larger firms. When characteristics are unweighted—or when both the characteristic and the slope are consistently weighted—the correction term vanishes. We do not favour weighted slopes, as they effectively amplify the influence of large firms twice: first through the value-weighted mean used to centre the characteristic, and again through the weighting embedded in the slope estimation. More broadly, the widespread practice of weighting characteristics in factor construction appears most appropriate when the objective is to assess how signals translate into returns at the market level, where large firms dominate and where the perspective aligns with that of a representative investor holding market-like portfolios. For broader applications, the weighted model outperforms the unweighted model only rarely (DeMiguel et al., 2009).

By contrast, an unweighted slope combined with an unweighted characteristic may be more suitable when analysing firm-level effects, including applications such as stock selection. In this setting, the decomposition simplifies to the unadjusted variance-share representation of the component factors in the composite:

$$f_t = \sum_{c=1}^C \frac{\sigma_{c,t}^2}{\sigma_t^2} f_t^{(c)} \quad (3.8)$$

A second remark concerns the aggregation of variances. In our illustrative setting, the factors are orthogonal by construction; however, the framework also accommodates

correlated components, as orthogonality is not required. When components are not orthogonal, it follows that $V_t \neq \sum V_{c,t}$, since covariance (cross-component) terms arise, as detailed in A.2.

The economic interpretation of the graded factor model is direct, and all its components are meaningful. The graded factor return f_t represents the reward per unit of the cross-sectional characteristic (the signal), and each component contributes proportionally according to the strength of its own signal $\tilde{f}_t^{(c)}$ —that is, the extent to which its dispersion covaries with returns—and to its share in the dispersion of the aggregate signal, $\frac{V_{c,t}}{V_t}$, corresponding to its contribution to the total variance. The de-centring adjustment is required only when the characteristic's mean is value-weighted.

3.3.3 Multiple Interacting Factors

The gradient-based construction of factors also allows us to isolate the effect of each characteristic in the presence of strong interactions among them, as discussed earlier. The same principle underlying multiple regression—namely, the identification of partial effects—applies to graded factors when estimating simultaneous cross-sectional slopes.

Let X_t denote the matrix of firm characteristics at time t , and let r_t be the vector of firm returns. Our objective is to estimate the slope of the OLS-fitted hyperplane of r_t on X_t , which yields the vector of partial graded factors $\tilde{F}_t$ (Greene, 2012):

$$\tilde{F}_t = (X_t' X_t)^{-1} X_t' r_t \quad (3.9)$$

In the expression above, the elements of the vector $\tilde{F}_t$ represent the partial effects of factors acting jointly at time t . Their computation depends exclusively on second moments, as detailed in A.2 for the two- and three-factor cases. To illustrate this, we expand the matrix formulation in a two-factor setting, where size is indexed by m and value by v . For each period t , the partial factor associated with size is denoted $\tilde{f}_{m,t}$, and that associated with value by $\tilde{f}_{v,t}$. These depend solely on the combination of cross-sectional variances $\sigma_{m,t}^2, \sigma_{v,t}^2$ and covariances such as $\text{Cov}(g_{m,t}, r_t)$ and $\text{Cov}(g_{m,t}, g_{v,t})$, among others:

$$\begin{aligned} \tilde{f}_{m,t} &= \frac{\sigma_{v,t}^2 \text{Cov}(g_{m,t}, r_t) - \text{Cov}(g_{m,t}, g_{v,t}) \text{Cov}(g_{v,t}, r_t)}{\sigma_{m,t}^2 \sigma_{v,t}^2 - \text{Cov}(g_{m,t}, g_{v,t})^2} \\ \tilde{f}_{v,t} &= \frac{\sigma_{m,t}^2 \text{Cov}(g_{v,t}, r_t) - \text{Cov}(g_{m,t}, g_{v,t}) \text{Cov}(g_{m,t}, r_t)}{\sigma_{m,t}^2 \sigma_{v,t}^2 - \text{Cov}(g_{m,t}, g_{v,t})^2} \end{aligned} \quad (3.10)$$

Having defined our framework, we will now compute the factors.

3.4 Data

Our dataset consists of 3,000 non-banking companies listed in the US from December 2014 to June 2025. The data were sourced from Bloomberg, and the ESG scores and weights from MSCI. The availability of reliable environmental scores, which are necessary to investigate the relationship between the green factor and established benchmark factors, limits the ability to retrieve earlier data. Companies are categorised into industry groups at the six-digit level based on the GICS classification. Descriptive statistics are presented in Table 3.1.

3.4.1 Data Transformation

As discussed earlier, a valid firm characteristic should be observable across a broad cross-section of firms, should have an economic interpretation, and be capable of explaining ex-ante variation in returns. Size and value remain the most commonly studied characteristics. These also raise two unresolved issues: their interaction, given that size enters the construction of both, and the unexpected underperformance of value stocks during the sample period. The environmental characteristic is introduced both to illustrate the properties of the proposed factors using data of a different nature and to contribute to the ongoing debate on the green factor. The size and value characteristics, $G_{m,i,t}$ and $G_{v,i,t}$, are defined as the logarithm of market capitalisation and the logarithm of the book-to-market ratio, respectively. The environmental characteristic, $G_{e,i,t}$, is constructed following (Pástor et al., 2022):

$$G_{e,i,t} = \frac{-(10 - E_{score}) \times E_{weight}}{100} \quad (3.11)$$

Where E_{score} refers to MSCI's environmental pillar score, and E_{weight} to MSCI's weight for the environmental pillar in the overall ESG composite index, to adapt the score obtained in the environmental assessment to the relative importance of environmental issues for each of the firms. As described earlier, each absolute characteristic $G_{k,i,t}$ is demeaned by its average to obtain the corresponding relative characteristics $g_{k,i,t}$. Monthly returns $r_{i,t}$ are winsorised at the 1st and 99th percentiles to avoid overreliance on extreme values (Hou et al., 2015). We calculate weighted and unweighted factors.

In addition to the graded factor, we also produce the corresponding traditional segment factors for comparison purposes: the small-minus-big (SMB), the high-minus-low BTM (HML), and the green-minus-brown (GMB) factors. To minimise intervention, firms are sorted into small/big, value/growth, and green/brown portfolios each month according to the tercile they belong to, with the remaining returns of the central tercile excluded from the calculations.

We will evaluate the correspondence between observed risk measures, such as 30-day historical volatility (sigma), implicit at-the-money call volatility (ivol), and historical

Tab. 3.1.: Descriptive statistics

	n	mean	std	min	25	median	75	max
Primary Data								
rit	311,725	0.118473	26.23934	-0.99992	-0.06957	0.000888	0.073884	10499
market cap	311,625	12,548	78,699	0	236	1,269	5,492	4,340,028
BTM	303,082	0.768314	29.61607	2.77E-06	0.169088	0.368589	0.669703	10000
E_score	197,347	4.933423	2.140743	0	3.4	4.8	6.4	10
E_weight	197,347	25.5773	17.20943	5	10	22	38	84
sigma	311,044	0.642143	1.533045	0	0.26982	0.40822	0.651143	65.13812
ivol	252,605	0.58927	0.635609	0.0001	0.29269	0.425276	0.666499	46.66338
sort	309,928	0.533872	0.751399	0.000111	0.247909	0.378952	0.598763	15.87252
Centered characteristics								
gmit	311,625	6.13E-17	2.37434	-7.59255	-1.59878	-0.13588	1.559298	14.23973
gvit	301,919	-6.8E-18	1.304969	-7.834	-0.55734	0.217793	0.807508	6.002823
geit	198,394	1.6E-17	1.105454	-4.57334	-0.60218	0.1789	0.89975	2.107622
Graded factor returns								
fm_t	129	0.001894	0.00763	-0.01647	-0.00238	0.00142	0.006131	0.046878
fv_t	129	0.000314	0.008386	-0.02294	-0.00528	-0.0003	0.00481	0.025283
fe_t	127	-0.00028	0.011485	-0.03644	-0.00736	0.001125	0.007663	0.031945
Segment factor returns								
SMB	129	0.004527	0.037703	-0.07584	-0.01904	0.00118	0.02095	0.18907
HML	129	0.002616	0.028763	-0.09528	-0.01615	0.001726	0.019351	0.084097
GMB	127	-0.0023	0.021673	-0.07112	-0.01786	-0.00233	0.011097	0.056199
Graded factor risks								
fm_sgma	129	0.133508	0.0353	0.079339	0.1044	0.13369	0.155256	0.20312
fm_ivol	129	0.040941	0.041534	-0.03647	0.015895	0.030838	0.075639	0.122445
fm_sort	129	0.10111	0.025839	0.057353	0.079395	0.099905	0.119371	0.153544
fv_sgma	129	-0.02958	0.026708	-0.09454	-0.04914	-0.03463	-0.0053	0.031334
fv_ivol	129	0.022169	0.020542	-0.01378	0.003134	0.021273	0.036728	0.088005
fv_sort	129	-0.02299	0.020875	-0.05941	-0.03961	-0.02671	-0.00468	0.030355
fe_sgma	127	0.010142	0.019003	-0.07635	0.000262	0.010444	0.021267	0.055081
fe_ivol	127	0.02073	0.021166	-0.03453	0.005689	0.016906	0.038743	0.061817
fe_sort	127	0.007978	0.017071	-0.06952	-4.4E-05	0.007609	0.018397	0.049792

Note: rit is the total return of firm i in month t, calculated as the total return index for the shares of the firm in t divided by the total return in t-1, assuming full reinvestment of gross dividends. Market cap is the market capitalisation in million USD, and BTM is the inverse of the price-to-book ratio. E_score is the score of the environmental pillar, and E_weight is the weight of the pillar (MSCI). sigma is the 30-day volatility, ivol is the implied volatility of the at-the-money call options maturing in two months, and sort is the standard deviation of the firm's negative-only returns. We calculate centred characteristics and factor returns in the table as described in the main body of the text (here, value-weighted).

downturn-only volatility (sort), and proxies for risk (Kräussl et al., 2023; Merladet et al., 2025).

3.4.2 Ex-post Returns

In our data, we analyse the distribution of returns across three size terciles. We compare the ex-post return distributions over the period for each of them relative to the overall distribution. As shown in Table 3.2, the probability of falling below the average minus five sigma, four sigma, and three sigma thresholds for firms in the upper size tercile (the low SMB, low-risk segment) is significantly lower than for small firms (the high-risk segment).

More specifically, the likelihood of falling below 3σ is 1.32% for smaller firms, 0.49% for mid-size firms, and only 0.10% for larger firms, showcasing the heavier tails in the distribution of smaller firms, which is also consistent with higher ex-ante risk.

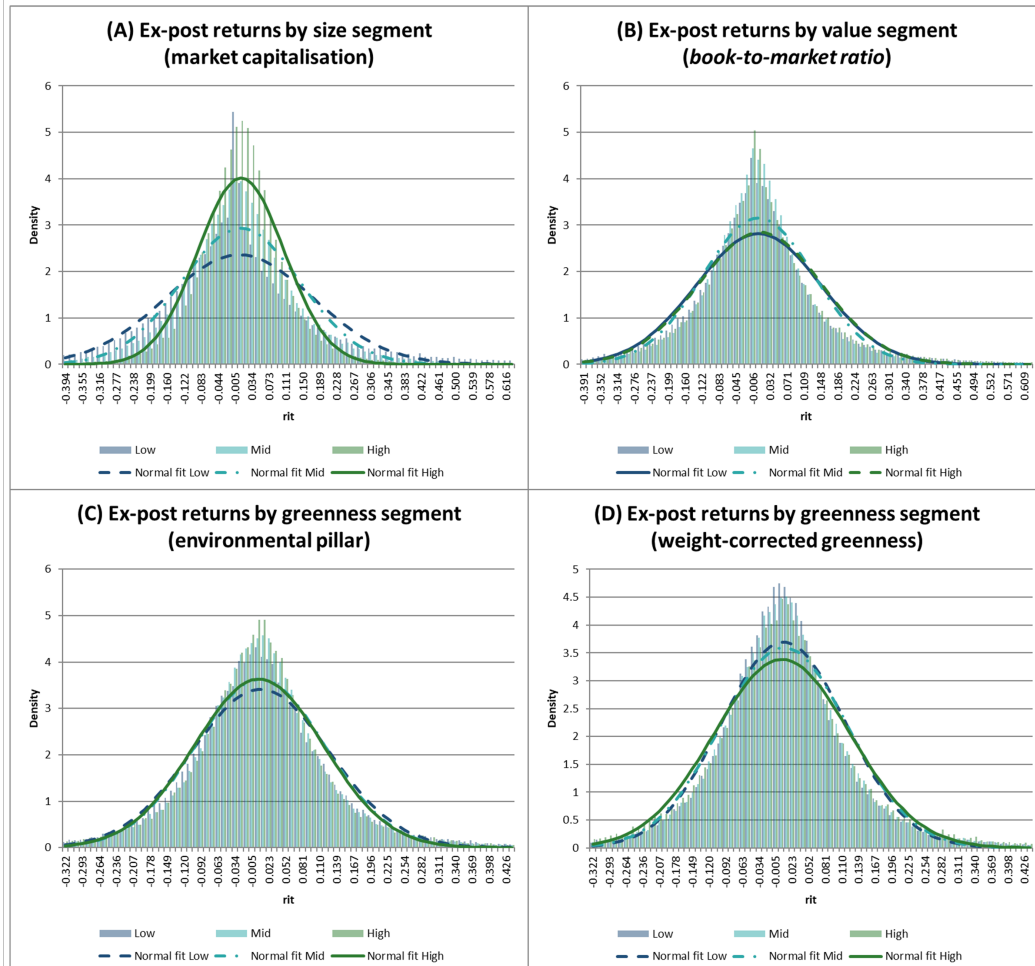
The three segments are ordered as expected, and alternative measures (percentiles, standard deviation, excess kurtosis) also show greater return dispersion for the higher-risk segments. Figure 3.1 displays a normal distribution fitted to the returns: the higher-risk segment also exhibits greater dispersion than the mid- and low-risk segments. The ex-post returns of size-segmented portfolios align with theoretical expectations, supporting the view that size is a consistent characteristic of factor returns.

Tab. 3.2.: Extreme values by segments

segment	n	mean	std	skewness	kurtosis	$p(<\mu-5\sigma)$	$p(<\mu-3\sigma)$	$p(>\mu+3\sigma)$	$p(>\mu+5\sigma)$
Size									
Low (1)	103,037	0.01695	0.22716	1.51257	4.98770	0.00154	0.01320	0.04097	0.01673
Mid (2)	103,125	0.00680	0.14202	0.37180	1.41875	0.00031	0.00488	0.01064	0.00259
High (3)	103,074	0.00856	0.09605	0.14134	0.93868	0.00007	0.00095	0.00201	0.00041
Global	309,236	0.00952	0.15517	0.84623	3.21541	0.00064	0.00634	0.01787	0.00657
Value									
Low (1)	100,660	0.00937	0.16482	0.88852	3.37050	0.00103	0.00811	0.02041	0.00792
Mid (2)	100,581	0.00688	0.13512	0.60967	2.47131	0.00035	0.00421	0.01251	0.00407
High (3)	100,678	0.01290	0.16118	0.94831	3.37651	0.00060	0.00657	0.02033	0.00762
Global	301,919	0.00967	0.15387	0.83214	3.15123	0.00066	0.00629	0.01775	0.00653
Green									
Low (1)	67,981	0.01078	0.12952	0.48103	1.54088	0.00049	0.00677	0.01577	0.00441
Mid (2)	65,572	0.00963	0.12026	0.39103	1.64679	0.00076	0.00671	0.01318	0.00354
High (3)	64,627	0.00756	0.12174	0.40187	1.87729	0.00060	0.00659	0.01397	0.00405
Global	198,180	0.00934	0.12396	0.42857	1.68156	0.00062	0.00669	0.01433	0.00401

Note: Moments (mean, standard deviation, skewness, kurtosis) are computed on winsorised returns to mitigate the influence of extreme outliers. We compute tail probabilities on raw returns and evaluate them relative to a common global reference distribution. Skewness measures asymmetry (positive values indicate a heavier right tail). Excess kurtosis measures tail thickness relative to the normal distribution (zero under normality). Positive excess kurtosis indicates fat tails and a higher likelihood of extreme outcomes.

Examining value, its support is well rooted in the literature. Theoretically, growth (i.e., low BTM) companies possess a longer maturity of their cash flows into the



Note: The figure shows the histograms of raw returns and the fitted normal curves for the three segments of high, mid and low size (panel A), value (panel B), and greenness (panels C and D). In panel C, greenness is measured by the firm's environmental pillar on the date in question. In panel D, greenness is measured by the composite index of the pillar score and the weight assigned to the pillar by the rater as described in the main body of the text.

Fig. 3.1.: Ex-post returns by characteristic and segment

future to repay the initial investment and the price of the firm than value firms (van Binsbergen, 2026). They are, therefore, more exposed to potential deviations. The higher growth of low BTM companies is expected to offset their higher risk, i.e., greater dispersion of returns, through higher returns over time.

However, the ex-post statistics and figures show that the middle segment is the most stable across most metrics, indicating that both high- and low-growth firms are riskier than firms around the median BTM. In 3.2, we observe that ex-post returns of the firms in the “mid” value segment fall below 3σ in only 0.42% of the registered firm-months, while the “low” and “high” segments account for 0.81% and 0.66% of the cases, respectively.

Skewness, kurtosis, and standard deviation support the same conclusion: the middle segment represents the lowest risk of the three. The risk of the growth segment is theoretically grounded, but the results also suggest that deep-value firms are riskier investments than mid firms. Potential explanations for it fall beyond the scope of our study: the segment may be related to poor profitability or highly variable results, or other reasons may be hypothesised. Independent of potential causes, we do not find sufficient support for the value to expect monotonic excess returns in the cross-section of firms.

Regarding greenness, as measured by the unweighted environmental pillar score, all three segments exhibit distributions with similarly heavy tails. In Figure 3.1, the low-greenness curve is only slightly below the high-greenness curve. This ambiguous outcome changes when returns are distributed according to PST’s greenness metric, which combines E-score and E-weight. Then, contrary to expectations, the greener tercile exhibits greater dispersion of results, not less, during the sample period.

The three characteristics, market capitalisation, BTM, and E_{score} do interact modestly with each other: the correlations among them range from -0.12 to 0.14 , and the centred characteristics $g_{m,i,t}$, $g_{v,i,t}$, and $g_{e,i,t}$, from -0.22 to 0.17 (see Table 3.3, Panel A).

3.5 Graded and Segment Factor Returns

Calculating excess returns under the traditional segment construction, we observe that HML, with an average monthly return of -0.0057 , has a modest and yet the highest t-statistic (t-stat = -1.45) (Table 3.4). Across the nine 3-year rolling periods in our sample, value has produced mildly significant negative returns ($t > 2$) in three of them. The cumulative negative return is notable at -57% over ten years. In Figure 3.2, we observe that, except for the first two years, the time series is reasonably linear, showing a downward trend with only one drawback period (2020-2022). Unlike HML, neither SMB (-27% cumulative over the period) nor GMB ($+12\%$ cumulative over the period) has shown stable trends or produced effects of comparable statistical significance. Segment factors are notably more correlated than their base characteristics ($\rho = -0.51$ to $+0.49$).

Tab. 3.3.: Correlation

Panel A Primary data and centred characteristics (firm-level, average monthly cross-sectional correlations)											
	rit	market cap	BTM	E_score	E_wgt	sigma	ivol	sort	gmit	gvit	geit
rit											
market cap	-0.003										
BTM	-0.009	-0.039									
E_score	-0.002	0.136	-0.115								
E_weight	0.000	-0.039	0.164	-0.324							
sigma	0.193	-0.047	0.100	-0.104	-0.132						
ivol	-0.006	-0.109	0.137	-0.094	-0.153	0.497					
sort	0.123	-0.069	0.116	-0.101	-0.117	0.811	0.531				
gmit	0.062	-0.367	0.154	-0.277	-0.034	0.336	0.530	0.425			
gvit	0.001	-0.101	0.330	-0.114	0.210	-0.070	0.054	-0.061	0.173		
geit	-0.002	0.089	-0.184	0.653	-0.866	0.043	0.067	0.034	-0.105	-0.217	

Panel B Graded and segmented factor returns (market-level; time-series correlations)						
	fm_t	fv_t	fe_t	SMB	HML	GMB
fm_t						
fv_t	0.830					
fe_t	-0.680	-0.819				
SMB	0.897	0.853	-0.592			
HML	0.467	0.751	-0.798	0.487		
GMB	-0.374	-0.454	0.513	-0.410	-0.507	

Panel C Graded factor risks (market-level; time-series correlations)									
	fm_sgm	fm_ivol	fm_sort	fv_sgm	fv_ivol	fv_sort	fe_sgm	fe_ivol	fe_sort
fm_sgm									
fm_ivol	0.342								
fm_sort	0.957	0.415							
fv_sgm	0.030	0.772	0.114						
fv_ivol	-0.093	0.802	-0.010	0.951					
fv_sort	0.042	0.781	0.154	0.988	0.945				
fe_sgm	-0.433	-0.839	-0.498	-0.825	-0.753	-0.824			
fe_ivol	-0.165	-0.845	-0.222	-0.758	-0.805	-0.753	0.884		
fe_sort	-0.427	-0.859	-0.520	-0.823	-0.763	-0.841	0.987	0.876	

Note: Firm-level correlations are the average of cross-sectional monthly correlations during the period. Market-level factor correlations are the correlations of the time series.

Tab. 3.4.: Significance and stability of graded and segmented factors. Average factor returns by characteristic

3-year to	Segment (value weighted)			Graded (value weighted)			Graded (equally weighted)		
	SMB	HML	GMB	size	value	green	size	value	green
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2017	-0.0002	-0.0038	0.0024	0.0003	0.0004	-0.0002	0.0011	0.0005	-0.0002
(t-stat)	(-0.04)	(-0.84)	(0.79)	(0.45)	(0.30)	(-0.15)	(2.11)	(0.39)	(-0.12)
2018	0.0021	-0.0041	0.0002	0.0003	0.0000	-0.0002	0.0009	-0.0003	0.0000
(t-stat)	(0.49)	(-0.85)	(0.04)	(0.51)	(-0.01)	(-0.13)	(1.56)	(-0.19)	(0.04)
2019	-0.0016	-0.0113	0.0013	-0.0004	-0.0032	0.0021	0.0005	-0.0027	0.0018
(t-stat)	(-0.36)	(-4.09)	(0.33)	(-0.69)	(-2.63)	(1.77)	(0.66)	(-2.59)	(1.94)
2020	0.0026	-0.0163	-0.0020	0.0006	-0.0025	0.0027	0.0025	-0.0031	0.0029
(t-stat)	(0.38)	(-2.16)	(-0.36)	(0.53)	(-1.11)	(1.22)	(1.88)	(-2.13)	(2.37)
2021	0.0020	-0.0100	-0.0042	0.0005	-0.0011	0.0014	0.0032	-0.0003	0.0005
(t-stat)	(0.18)	(-1.02)	(-0.93)	(0.23)	(-0.32)	(0.43)	(1.30)	(-0.17)	(0.26)
2022	0.0022	-0.0004	-0.0084	0.0011	0.0013	-0.0030	0.0032	0.0013	-0.0034
(t-stat)	(0.19)	(-0.03)	(-1.68)	(0.60)	(0.39)	(-0.76)	(1.35)	(0.64)	(-1.11)
2023	-0.0045	0.0063	-0.0033	-0.0003	0.0011	-0.0031	0.0011	0.0034	-0.0045
(t-stat)	(-0.54)	(0.72)	(-0.71)	(-0.20)	(0.43)	(-0.90)	(0.59)	(2.54)	(-1.58)
2024	-0.0058	-0.0009	0.0012	-0.0003	0.0001	-0.0011	0.0016	0.0021	-0.0027
(t-stat)	(-1.11)	(-0.12)	(0.25)	(-0.35)	(0.05)	(-0.32)	(1.56)	(1.79)	(-0.89)
2025	-0.0065	-0.0105	0.0111	-0.0006	-0.0015	0.0045	0.0028	0.0012	0.0013
(t-stat)	(-0.93)	(-2.19)	(3.26)	(-0.61)	(-0.78)	(2.34)	(2.05)	(1.18)	(0.65)
2015-2025	-0.0015	-0.0057	0.0012	0.0001	-0.0005	0.0006	0.0019	0.0003	-0.0003
(t-stat)	(-0.39)	(-1.45)	(0.50)	(0.18)	(-0.46)	(0.43)	(2.40)	(0.33)	(-0.26)

Note: The periods are three-year periods ending in December of the year shown in the row heading. We choose longer periods to provide sustained, significant averages. The main body shows average factor returns for the characteristic heading in each column within the method, as well as in the headings. Under each average factor return, the table shows the t-statistic. For autocorrelation, we calculate t-statistics using Newey-West standard errors.

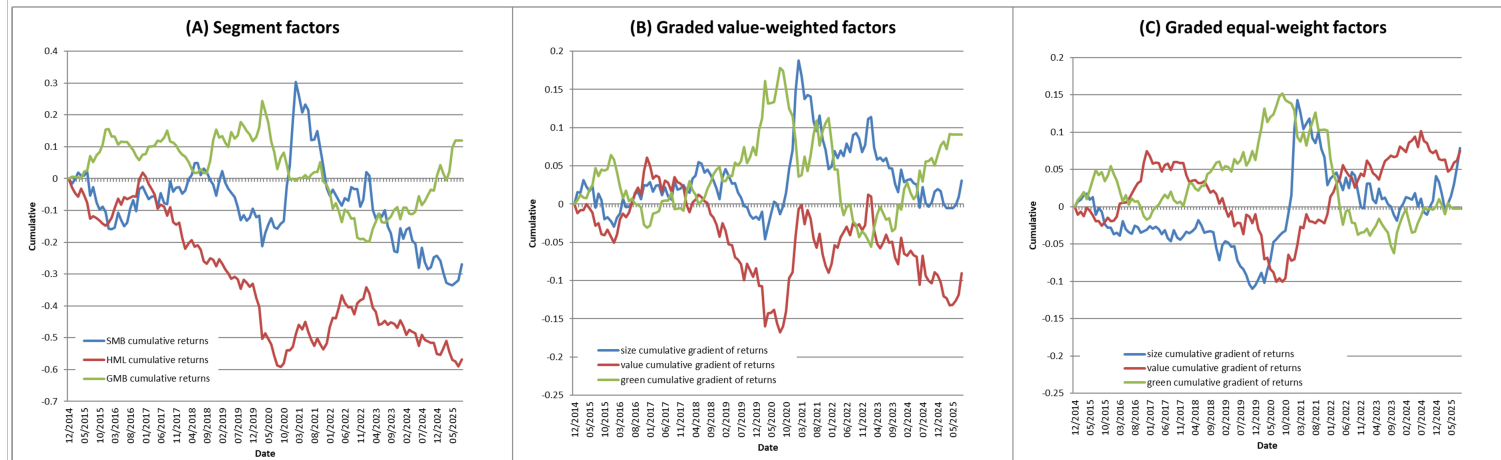
Graded factors are strongly correlated to their segment counterparts: the graded market capitalisation factor ($f_{m,t}$ or 'size') and SMB are correlated at 0.90, the value factor ($f_{v,t}$ or 'value') and HML at 0.75, and the environmental factor ($f_{e,t}$ or 'green') and GMB at 0.51 (Table 3, Panel B). In Figure 3.2, we see similar short-term profiles corresponding to monthly variations, but different overall balances reflecting varying underlying trends and return weightings.

The statistics show lower significance, particularly for value returns, and much smaller magnitudes (Table 3.4). $f_{m,t} = 0.0001$ can be interpreted as the relationship between an increase in size and average monthly realised returns, meaning that investing in a firm that is 100% larger yields an additional 0.01% (1 basis point or 1 b.p.) per month, equivalent to a mere 3% over ten years. Similarly, for value ($f_{v,t}$) investing in a firm that doubles its BTM ratio results in lower monthly returns of 6 b.p., equivalent to a -9% over the extended period. For the green $f_{e,t}$, investing in a greener firm by one point on the score scale improves monthly performance by 6 b.p. and results in a 9% increase over the longer period.

Because the measures are built differently, the average monthly excess returns under both methodologies are not fully comparable; yet, the difference between the observed values suggests that segment factors, the difference in the average of extreme subsamples, may have a signal-enhancing effect. Without amplification, their magnitude would have been smaller and statistically less significant.

Turning to unweighted factor returns, the size factor becomes positive and statistically significant ($t = 2.40$), remaining positive across all three-year periods. As noted earlier, this factor, in our view, better captures the effects of size and should be interpreted as an average of 19 b.p. in additional returns for firms one size smaller. The green factor is now modestly negative but not statistically significant across the sample period ($t = -0.26$), and it frequently changes sign.

The correlation among the pairs in the realm of graded factors is intense. $f_{m,t}$ and $f_{v,t}$ show direct correlation of 0.83, and the environmental factor correlates inversely with the other to -0.68 (size) and 0.82 (value). Had it not been for the fact that the newly modelled factors are built on excess returns, defined as firms' returns minus the beta-adjusted market return, these values would suggest a common, time-driven force. Since the base returns are net of the market effect, we must assume either a different omitted variable or strong interactions among the explanatory variables (the factors). We will look next at their behaviour relative to risk metrics.



Note: The charts show cumulative returns under different model specifications. Chart A shows the difference in adjusted returns (raw returns minus the risk-free rate) between the top and bottom segments (terciles) for the three factors, using the small-minus-big (SMB), value-minus-growth (HML), and green-minus-brown specifications. Chart B shows the value-weighted graded factors of excess returns (raw returns minus beta-adjusted market returns) for size (measured by market capitalisation), value (by book-to-market, BTM), and greenness (by the weight-adjusted environmental pillar). Chart C shows the equally weighted graded returns. To make comparisons more direct, we align the graded factors with the segment factors: a positive size factor refers to the overperformance of smaller companies, a positive value factor to the overperformance of lower BTM companies, and a positive green factor to the overperformance of green companies. We rescale the charts to show similar dispersion of results, not the same scale. Segment factors and graded factors do not measure the same concept. Segment factors' metric is the difference in performance between two portfolios, while graded factors measure a gradient relative to each unit of the underlying characteristic. To compare the intensity of factors based on differently scaled characteristics, we calculate the factors using cross-sectionally standardised characteristics, so the unit of reference is each characteristic's standard deviation. Size and BTM are logged.

Fig. 3.2.: Cumulative factor returns for size, value, and greenness under different model specifications (cross-sectionally standardised)

3.6 Factors on Risk Variables

In one study, the authors calculate the time series of risk metrics for the long and short legs of the upper and lower segments of greenness (Pástor et al., 2022). In Figure 3.3, we observe a difference in historical volatility between the upper and lower size segments, but the equivalent patterns for value and greenness are less clear.

In a more direct approach, the graded factor method also enables us to apply factor calculations to risk metrics rather than return metrics. Our ‘risk factors’ represent the actual variations in risk metrics relative to the characteristic; they link the cross-section of the characteristics to ex-post risk metrics observed for each firm. We proxy risk using volatility (*sigma*), implicit volatility in at-the-money call options (*ivol*), and downward volatility (*sort*).

Table 3.5 (Panel A) shows strong, robust relationships between size-risk and greenness-risk across different metrics and time periods. Analysing size, smaller firms exhibit notable and significant increases in their risk metrics. A 50% reduction in size leads to a 13 percentage-point rise in volatility (*sigma*), a 4.2 percentage-point increase in implied volatility, and a 10 percentage-point rise in downward volatility. In Figure 3.4A, we observe the time series of the size risk factor.

The fact that the higher risk inherent in small firms (risk factors) is not rewarded in segment-factor configurations and is only weakly rewarded in value-weighted graded factors (only in the graded equal-weighted construction is the cost of risk compensated for by realised returns) is inconsistent with expectations and calls for deeper analysis.

Value firms experience lower volatility and lower sort (i.e., the standard deviation of negative-only returns, defined in Chapter 2) by 3 and 2 percentage points, respectively, but higher implicit volatility by 2 percentage points, possibly because value firms are smaller and their option markets may be penalised for lower investor attention and liquidity. The evidence, however inconclusive, is suggestive of value firms being safer than growth firms, which compares with also ambiguous ex-post returns.

Greenness is associated with smaller but significant increases in risk: 1% higher volatility, 2% higher implied volatility, and 0.8% higher downside risk. The evidence for value is less clear, as it is associated with lower historical and downward volatilities but larger implied volatility.

The higher risk observed for greener firms in two of the models does not reconcile with their lower expected transition risk. When we compare our test with regression studies that show the risk-reducing effect of greenness, we see that these firm-level tests control for sector, whereas classical factor models do not. By recalculating the environmental risk factor using the within characteristic, we obtain highly significant ($t = -12.8$ to -14.5) and robust risk-reduction effects ranging from 2.9 to 5.0 percentage points across the three risk metrics (see Table 5, Panel B). This result aligns our risk factors with the rating methodology, which is reassuring.

Figure 3.4A shows the cross-sectionally standardised effects of the characteristics, and Figure 3.4B shows their analogous within-sector effects. These can be interpreted as the effect of a one-standard-deviation change in the characteristic. The new model allows us to control for sectoral differences and to investigate the effects of sector composition.

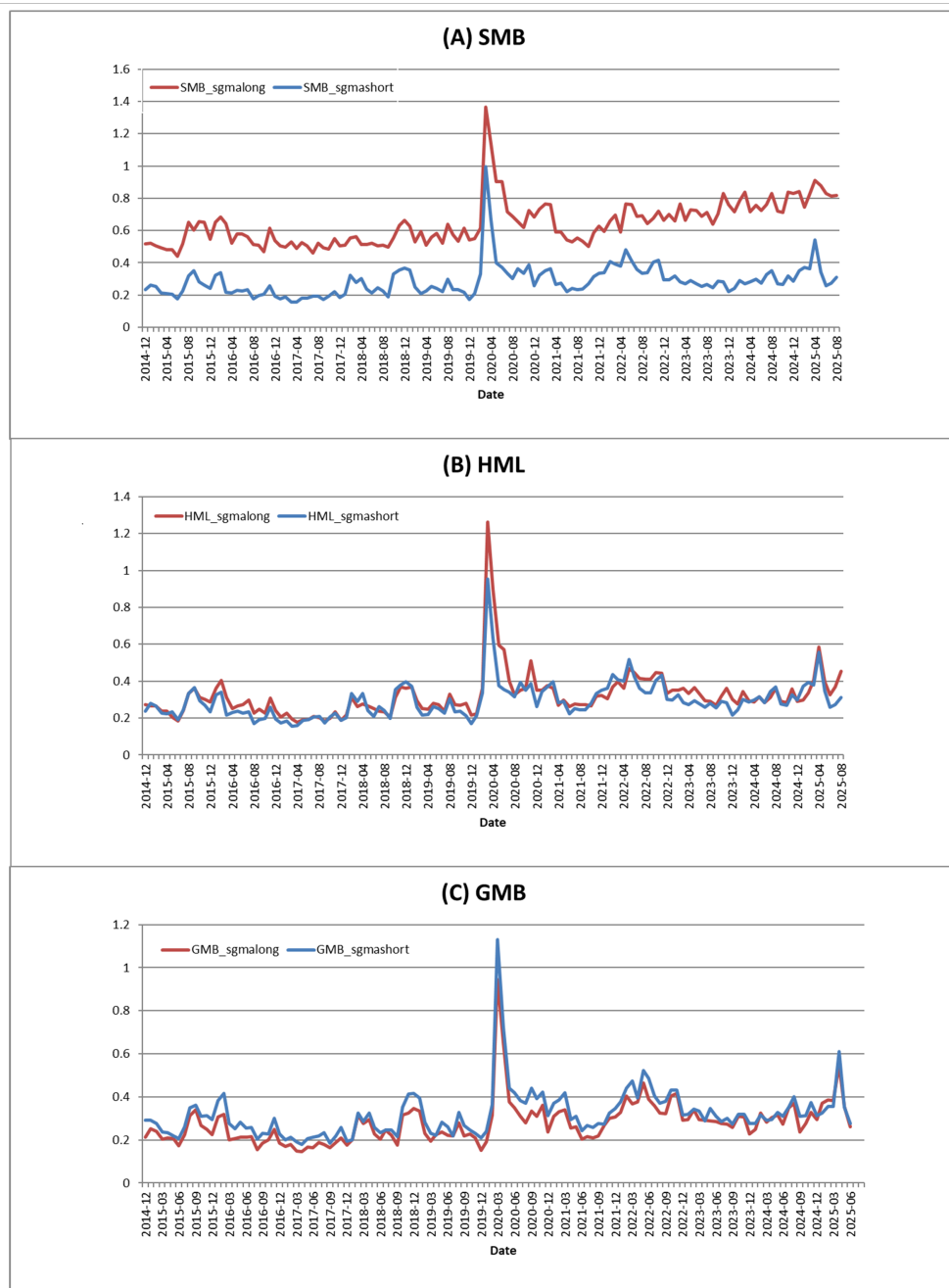


Fig. 3.3.: Volatility of the long and short legs of size, value, and greenness factors

Tab. 3.5.: Stability of risk factors proxied by three different metrics. Average factor risks (equally-weighted)

PANEL A - Average Total Risk Factors									
3-year to	size	Sigma value	green	size	IVOL value	green	size	Sort value	green
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2017	0.1774	-0.0569	0.0021	-0.0005	0.0136	0.0090	0.1327	-0.0422	0.0011
(t-stat)	(33.92)	(-14.46)	(0.98)	(-0.08)	(3.71)	(4.99)	(41.71)	(-18.34)	(0.56)
2018	0.1608	-0.0484	0.0071	0.0141	0.0113	0.0135	0.1229	-0.0390	0.0053
(t-stat)	(27.83)	(-31.95)	(2.87)	(4.37)	(3.03)	(6.26)	(30.03)	(-21.56)	(2.74)
2019	0.1473	-0.0418	0.0108	0.0265	0.0108	0.0181	0.1142	-0.0333	0.0080
(t-stat)	(41.72)	(-14.77)	(8.20)	(8.98)	(3.11)	(15.62)	(38.55)	(-15.66)	(6.88)
2020	0.1373	-0.0271	0.0007	0.0312	0.0253	0.0087	0.1046	-0.0221	-0.0011
(t-stat)	(43.09)	(-3.91)	(0.13)	(10.98)	(3.50)	(1.59)	(36.07)	(-3.77)	(-0.21)
2021	0.1228	-0.0250	-0.0036	0.0321	0.0228	0.0039	0.0948	-0.0208	-0.0032
(t-stat)	(17.79)	(-3.99)	(-0.71)	(12.12)	(2.84)	(0.79)	(22.97)	(-3.85)	(-0.68)
2022	0.1054	-0.0200	0.0023	0.0381	0.0214	0.0103	0.0809	-0.0159	0.0020
(t-stat)	(15.44)	(-3.22)	(0.32)	(7.26)	(2.58)	(1.38)	(18.12)	(-2.82)	(0.31)
2023	0.0976	-0.0178	0.0201	0.0559	0.0193	0.0291	0.0756	-0.0138	0.0180
(t-stat)	(26.07)	(-2.70)	(4.07)	(6.34)	(2.82)	(5.08)	(28.51)	(-2.29)	(4.37)
2024	0.1016	-0.0050	0.0295	0.0836	0.0327	0.0444	0.0768	-0.0033	0.0244
(t-stat)	(30.20)	(-1.28)	(14.31)	(11.55)	(8.33)	(19.29)	(27.35)	(-0.98)	(10.57)
2025	0.1078	-0.0009	0.0286	0.1012	0.0404	0.0488	0.0806	-0.0012	0.0236
(t-stat)	(52.83)	(-0.44)	(11.99)	(22.27)	(21.77)	(20.97)	(53.93)	(-0.50)	(9.35)
2015-2025	0.1330	-0.0293	0.0103	0.0415	0.0224	0.0209	0.1007	-0.0228	0.0082
(t-stat)	(22.33)	(-6.65)	(3.47)	(5.86)	(6.70)	(5.71)	(23.47)	(-6.69)	(3.17)
PANEL B - Average Within Risk Factors									
3-year to	size	Sigma value	green	size	IVOL value	green	size	Sort value	green
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2017	0.1728	-0.0422	-0.0217	-0.0124	0.0245	-0.0307	0.1279	-0.0317	-0.0204
(t-stat)	(32.91)	(-13.55)	(-11.03)	(-2.52)	(8.78)	(-13.01)	(41.10)	(-12.69)	(-10.28)
2018	0.1559	-0.0341	-0.0203	-0.0001	0.0242	-0.0310	0.1180	-0.0279	-0.0185
(t-stat)	(27.01)	(-16.08)	(-8.82)	(-0.05)	(9.91)	(-14.96)	(29.06)	(-11.61)	(-8.59)
2019	0.1422	-0.0270	-0.0184	0.0106	0.0260	-0.0295	0.1093	-0.0217	-0.0182
(t-stat)	(39.18)	(-11.07)	(-10.94)	(4.16)	(8.32)	(-18.90)	(35.49)	(-12.19)	(-10.41)
2020	0.1322	-0.0162	-0.0292	0.0144	0.0381	-0.0504	0.0997	-0.0145	-0.0269
(t-stat)	(42.67)	(-3.48)	(-5.12)	(5.67)	(6.93)	(-5.07)	(36.62)	(-3.91)	(-5.94)
2021	0.1180	-0.0176	-0.0390	0.0154	0.0327	-0.0644	0.0901	-0.0157	-0.0345
(t-stat)	(17.26)	(-3.50)	(-8.23)	(6.32)	(4.34)	(-7.59)	(22.40)	(-3.94)	(-10.12)
2022	0.1003	-0.0148	-0.0424	0.0195	0.0285	-0.0727	0.0759	-0.0123	-0.0370
(t-stat)	(14.29)	(-2.81)	(-12.84)	(4.56)	(3.60)	(-12.94)	(15.66)	(-2.76)	(-14.46)
2023	0.0921	-0.0110	-0.0370	0.0366	0.0290	-0.0615	0.0698	-0.0079	-0.0321
(t-stat)	(24.26)	(-1.69)	(-17.14)	(4.51)	(3.76)	(-26.79)	(24.23)	(-1.37)	(-18.04)
2024	0.0957	0.0033	-0.0397	0.0629	0.0465	-0.0607	0.0706	0.0035	-0.0339
(t-stat)	(28.20)	(0.82)	(-12.14)	(8.20)	(8.35)	(-37.06)	(23.50)	(1.06)	(-14.45)
2025	0.1020	0.0085	-0.0448	0.0810	0.0577	-0.0619	0.0747	0.0065	-0.0369
(t-stat)	(50.60)	(5.75)	(-13.85)	(18.97)	(44.75)	(-32.50)	(49.85)	(3.32)	(-13.37)
2015-2025	0.1279	-0.0185	-0.0323	0.0249	0.0348	-0.0500	0.0955	-0.0147	-0.0286
(t-stat)	(21.23)	(-4.87)	(-12.80)	(3.83)	(10.16)	(-13.02)	(21.90)	(-4.92)	(-14.47)

Note: The periods are three-year periods ending in December of the year shown in the row heading. We choose longer periods to provide sustained, significant averages. The main body shows average factor returns for the characteristic heading in each column within the method, as well as in the headings. Under each average factor return, the table shows the t-statistic. For autocorrelation, we calculate t-statistics using Newey-West standard errors.

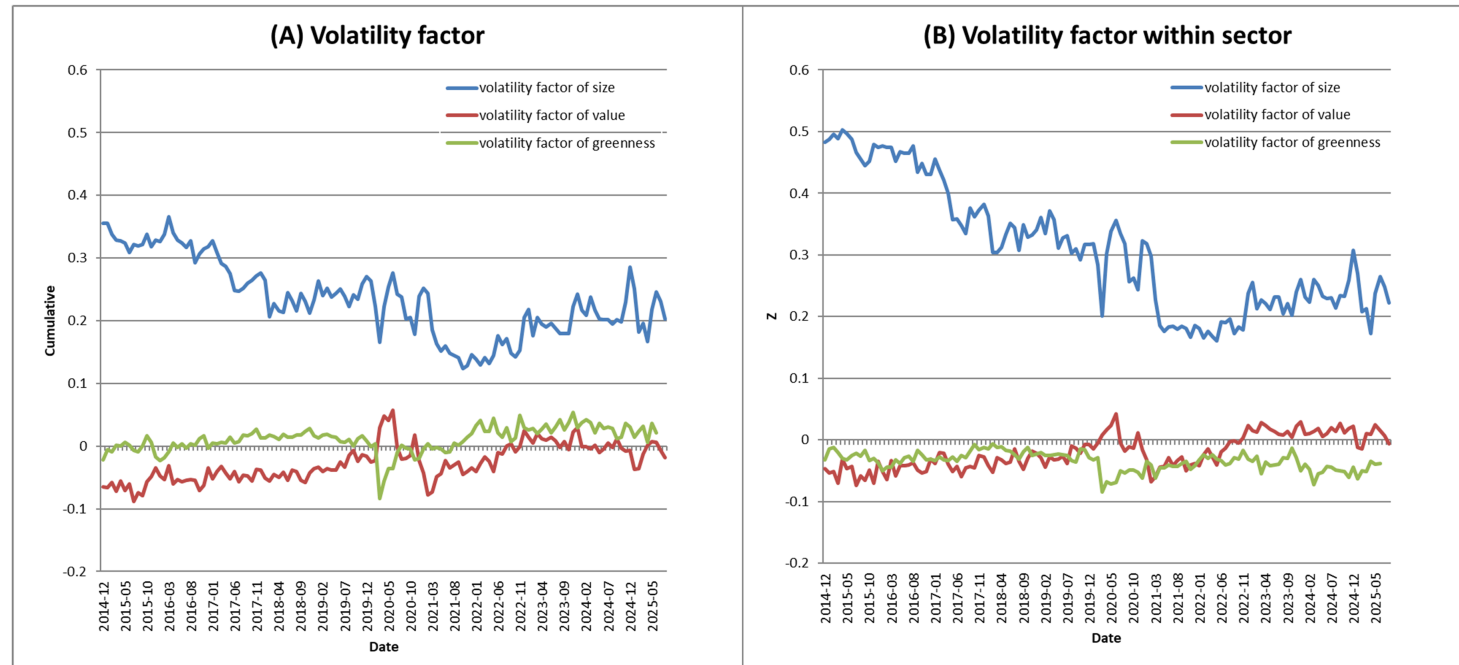


Fig. 3.4.: Volatility factors and volatility within factors (equally-weighted, cross-sectionally standardised)

3.7 Sector Effects

The potential effects of belonging to the firm's sector extend beyond their direct effect on the greenness-risk pair. We have also found a strong correlation in the small-value pair, and we are interested in whether the underlying sectoral affiliation truly explains the returns, rather than the characteristics themselves.

When we rank our average signals by sector for size, value, and greenness, not surprisingly, we find that the size and value ranks show a strong negative correlation (Spearman correlation = -0.54), and we observe that firms are more frequently highly ranked for greenness at the top end of the size distribution than at the bottom (Spearman = 0.36). Table 3.6 lists the rank values for the top 10 and bottom 10 sectors by size.

We split each factor into two additive parts, as previously described, by dividing the characteristic into within- and across-sector components. The characteristic within its sector is the difference between the firm's characteristic and the sector's (unweighted) average. The characteristic across relates the returns to the sector's average characteristic. The additive nature of our factor construction allows us to reconcile excess returns with the contributions of the within- and across-sector components (Table 3.7).

At first glance, sector-free within factors do not change significantly. The decomposition shows that the sector weight by size is 12.5%, with the firm-specific component at 87.5% on average during the study period, and in terms of value, it is 12.7%/87.3%. Given the industry rank, the sectoral contribution in size and value factor returns is surprisingly small.

The sector-driven component is much higher for the green factor (71.6%), while the firm-specific contribution is more modest (28.4%). The green factor's composition may be influenced by its peculiar construction, but it also relates to the nature of greenness, which is closely linked to the businesses involved. Across the three characteristics considered, the across factor does not gain sample-long significance.

Our overall results remain subdued, with no clear evidence of sectoral dominance or persistent excess returns across the three categories. Our findings up to this point emphasise the volatile nature of excess returns: they occur only at specific moments and within specific subsegments, vanishing when generalised over time or across sectors. Our characteristics are largely independent, but their factor returns are not. Decomposing their components into sectoral and firm-specific parts shows no compensation for the risk of investing in smaller firms, nor does it align with the common understanding that value firms were especially unfavoured during this period. We observe strong evidence of a relationship between size and value that cannot be explained by considering only one factor at a time.

These results are particularly relevant for the environmental characteristic, whose variation is largely driven by sectoral differences. Consequently, the within-sector

specification provides the appropriate basis for the subsequent multivariate analysis, where greenness exhibits its strongest explanatory power after controlling simultaneously for the remaining characteristics.

Tab. 3.6.: Sectors ranked by average characteristic (GICS subindustry classification)

Sector rank	market capitalisation	book-to-market	environmental score
Top ten by size			
Technology Hardware, Storage & P.	1	131	28
Systems Software	2	138	138
Broadline Retail	3	133	39
Interactive Media & Services	4	123	3
Semiconductors	5	122	140
Automobile Manufacturers	6	100	12
Integrated Oil & Gas	7	41	72
Consumer Staples Merchandise Retail	8	115	21
Pharmaceuticals	9	110	35
Managed Health Care	10	76	44
Bottom 10 by size			
Consumer Electronics	130	82	117
Security & Alarm Services	131	48	68
Diversified Metals & Mining	132	90	9
Silver	133	12	25
Diversified Real Estate Activities	134	71	99
Coal & Consumable Fuels	135	4	10
Commercial Printing	136	57	107
Real Estate Operating Companies	137	24	118
Paper Products	139	19	132
Textiles	140	6	129

Note: Spearman correlation size/value -0.54, size/green 0.36, value/green -0.25.

3.8 The Simultaneous Effects of Size, Value, and Greenness

A previous study isolated the effects of size and value by identifying market sub-segments where similar-sized, value- and growth-oriented firms coexist with green and brown firms. By segmenting them, they compared their relative performances (Jagannathan et al., 2025). Our gradient method allows us to consider simultaneous partial effects for each variable. In columns (1) to (3), Table 3.8 presents size-value-green factor returns for the equally weighted graded factors, thereby avoiding any potential interaction of size in the weightings; in columns (4) to (6), it

Tab. 3.7.: Significance and stability of across and within factor returns

3-year to	Graded (equally weighted)			Graded (across)			Graded (within)		
	size	value	green	size	value	green	size	value	green
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2017	0.0011	0.0005	-0.0002	0.0000	0.0013	-0.0001	0.0012	0.0005	-0.0003
(t-stat)	(2.11)	(0.39)	(-0.12)	(0.01)	(0.26)	(-0.08)	(2.46)	(0.54)	(-0.24)
2018	0.0009	-0.0003	0.0000	0.0002	0.0021	0.0003	0.0010	-0.0005	-0.0009
(t-stat)	(1.56)	(-0.19)	(0.04)	(0.17)	(0.41)	(0.18)	(1.81)	(-0.52)	(-0.82)
2019	0.0005	-0.0027	0.0018	0.0001	-0.0045	0.0021	0.0005	-0.0025	0.0010
(t-stat)	(0.66)	(-2.59)	(1.94)	(0.07)	(-1.51)	(1.68)	(0.78)	(-2.70)	(1.06)
2020	0.0025	-0.0031	0.0029	0.0032	-0.0085	0.0037	0.0024	-0.0023	0.0009
(t-stat)	(1.88)	(-2.13)	(2.37)	(1.11)	(-1.90)	(2.37)	(1.92)	(-1.83)	(0.76)
2021	0.0032	-0.0003	0.0005	0.0007	-0.0016	0.0003	0.0034	-0.0001	0.0009
(t-stat)	(1.30)	(-0.17)	(0.26)	(0.17)	(-0.31)	(0.15)	(1.44)	(-0.09)	(0.44)
2022	0.0032	0.0013	-0.0034	0.0018	0.0028	-0.0043	0.0033	0.0012	-0.0013
(t-stat)	(1.35)	(0.64)	(-1.11)	(0.46)	(0.43)	(-1.10)	(1.42)	(0.79)	(-0.57)
2023	0.0011	0.0034	-0.0045	-0.0015	0.0089	-0.0054	0.0013	0.0026	-0.0023
(t-stat)	(0.59)	(2.54)	(-1.58)	(-0.54)	(2.13)	(-1.45)	(0.73)	(2.44)	(-1.17)
2024	0.0016	0.0021	-0.0027	0.0011	0.0047	-0.0026	0.0016	0.0017	-0.0029
(t-stat)	(1.56)	(1.79)	(-0.89)	(0.44)	(1.05)	(-0.65)	(1.51)	(1.90)	(-2.14)
2025	0.0028	0.0012	0.0013	0.0023	-0.0006	0.0026	0.0029	0.0014	-0.0016
(t-stat)	(2.05)	(1.18)	(0.65)	(0.65)	(-0.16)	(0.92)	(2.19)	(1.46)	(-1.50)
2015-2025	0.0019	0.0003	-0.0003	0.0010	0.0003	-0.0002	0.0020	0.0003	-0.0006
(t-stat)	(2.40)	(0.33)	(-0.26)	(0.66)	(0.12)	(-0.13)	(2.58)	(0.45)	(-0.68)
Variance share				0.1254	0.1271	0.7164	0.8746	0.8729	0.2836

Note: The periods are the three-year periods ending in December of the year shown in the row heading. The main body shows average factor returns for the characteristic heading in each column within the method, as well as in the headings. Under each average factor return, the table shows the t-statistic. Variance share is the average variance of the across and within calculations relative to the total factor's variance.

shows the simultaneous effects of the three factors, and in columns (7) to (9), the simultaneous effects within each factor. The combined explanatory power of the returns is attributed to each factor without any discretion involved.

In the results, size becomes highly significant when both value and greenness are considered simultaneously ($t=3.19$). A company half the size should warrant 18 basis points of additional return, a substantial premium equivalent to over 2% per annum. From a time perspective, size is statistically significant in three periods ($t > 3$) and close to significant in another period ($t > 2$), having a positive value across the sample, which demonstrates its stability. Contrary to popular belief, and in line with the theoretical framework, smaller firms do earn a risk premium. Figure 3.5A shows the stable trend expected in a sustained premium for size.

Value indicates a lower risk profile and, consequently, lower returns. Our findings align with that view. They estimate the average monthly lower return at -24 b.p., or 2.8% per annum, but its consistency and statistical significance are insufficient to draw a solid conclusion. We observe in Figure 3.5A a small, unstable premium during 2015-2019, followed by a negative shift in relevant intensity from 2019 to 2021, only partly reversed in 2022. The data on value do not support a clear time-related premium; rather, they suggest a shift in preferences.

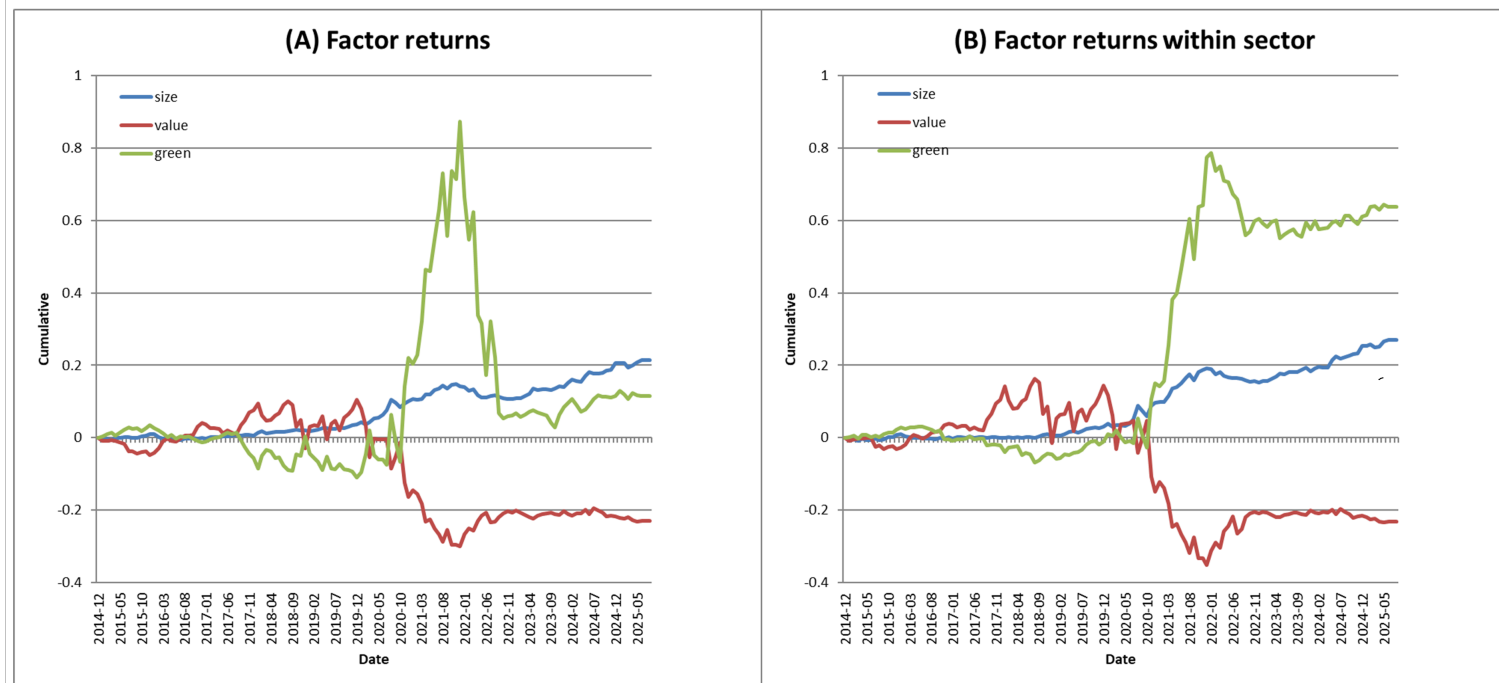
As anticipated in the previous section, greenness displays a clearer explanatory power only after sector effects have been neutralised. When considered alongside the remaining characteristics, it reveals a notable excess return (54 b.p., or 6.6% p.a.) with modest statistical significance ($t = 1.50$). This effect was particularly strong during the 2019-2021 period, but its instability lessens its significance. The timing of this excess return has been documented in the literature, and it may well correspond to a preference shift (Pástor et al., 2022).

Studying the time series of cumulative returns for green, we observe a similar pattern, suggestive of a preference shift during 2020 and 2021, only partly reversed in 2022 in the within characteristic (Figure 3.5B). Following this specific impact, only a barely noticeable trajectory of return and risk remains.

Tab. 3.8.: Graded (equally-weighted) factors vs simultaneous partial factors, and simultaneous within factors

3-year to	Graded (univariate)			Graded (multivariate)			Graded (multivariate within)		
	size	value	green	size	value	green	size	value	green
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2017	0.0011	0.0005	-0.0002	0.0002	0.0023	-0.0016	0.0000	0.0031	-0.0006
(t-stat)	(2.11)	(0.39)	(-0.12)	(0.44)	(0.97)	(-0.85)	(0.02)	(1.26)	(-0.57)
2018	0.0009	-0.0003	0.0000	0.0003	0.0013	-0.0006	0.0000	0.0014	-0.0019
(t-stat)	(1.56)	(-0.19)	(0.04)	(0.58)	(0.33)	(-0.18)	(-0.06)	(0.30)	(-1.55)
2019	0.0005	-0.0027	0.0018	0.0013	0.0014	-0.0030	0.0010	0.0026	-0.0004
(t-stat)	(0.66)	(-2.59)	(1.94)	(3.49)	(0.41)	(-0.90)	(2.29)	(0.58)	(-0.30)
2020	0.0025	-0.0031	0.0029	0.0030	-0.0080	0.0091	0.0034	-0.0085	0.0072
(t-stat)	(1.88)	(-2.13)	(2.37)	(2.66)	(-1.51)	(1.07)	(2.53)	(-1.28)	(1.11)
2021	0.0032	-0.0003	0.0005	0.0036	-0.0108	0.0211	0.0061	-0.0142	0.0250
(t-stat)	(1.30)	(-0.17)	(0.26)	(3.39)	(-2.03)	(2.11)	(4.15)	(-2.07)	(2.64)
2022	0.0032	0.0013	-0.0034	0.0020	-0.0095	0.0095	0.0039	-0.0108	0.0189
(t-stat)	(1.35)	(0.64)	(-1.11)	(1.27)	(-1.56)	(0.67)	(1.82)	(-1.33)	(1.70)
2023	0.0011	0.0034	-0.0045	0.0011	-0.0010	-0.0007	0.0024	-0.0014	0.0111
(t-stat)	(0.59)	(2.54)	(-1.58)	(0.90)	(-0.21)	(-0.06)	(1.34)	(-0.22)	(1.10)
2024	0.0016	0.0021	-0.0027	0.0017	0.0034	-0.0139	0.0013	0.0060	-0.0054
(t-stat)	(1.56)	(1.79)	(-0.89)	(1.36)	(1.12)	(-1.62)	(0.97)	(1.44)	(-1.59)
2025	0.0028	0.0012	0.0013	0.0035	-0.0019	0.0015	0.0036	-0.0020	0.0007
(t-stat)	(2.05)	(1.18)	(0.65)	(4.58)	(-1.49)	(0.71)	(5.02)	(-1.76)	(0.58)
2015-2025	0.0019	0.0003	-0.0003	0.0018	-0.0024	0.0021	0.0023	-0.0025	0.0054
(t-stat)	(2.40)	(0.33)	(-0.26)	(3.19)	(-1.09)	(0.50)	(3.17)	(-0.88)	(1.51)

Note: The periods are the three-year periods ending in December of the year shown in the row heading. The main body shows average factor returns for the characteristic heading in each column within the method, as well as in the headings. Under each average factor return, the table shows the t-statistic.



Note: Figure A represents the time series of the multivariate factors: size, value, and greenness. The factor represents the excess return on the market obtained per unit of the underlying characteristic. In this chart, the characteristics have not been cross-sectionally standardised. This chart does not aim to compare their relative intensities across factors, but rather the time series of each factor. Figure B depicts the within-sector factor returns.

Fig. 3.5.: Cumulative factor returns for size, value, and greenness under different model specifications (cross-sectionally standardised)

3.9 Spanning and Explanatory Power of Graded and Segment Factors

3.9.1 Alternative Model Definitions and Tests

After reviewing the model's results, one question remains: Does the proposed model provide information comparable to that of existing asset pricing models? This contribution can be evaluated along two related dimensions: spanning and explanatory power. Spanning assesses whether the returns generated by the proposed factors can be replicated by a linear combination of the time series of factor spreads. If the portfolio returns are fully spanned by the factors, their incremental contribution will drain the value of the independent term (alpha) and make it indistinguishable from zero. Explanatory power, in contrast, refers to the model's ability to account for the cross-sectional variation in expected returns. A model with greater explanatory power achieves a higher cross-sectional R^2 .

However, in testing both models, we need to address their different formulations. To begin with, in the classical environment, Fama and French Fama and French (2015) specify their asset pricing model as the regression of the returns of a set of purpose-built test sub-portfolios in excess of the risk-free asset, $R_{pt} - R_{ft}$, on the broad market performance, $R_{Mt} - R_{ft}$, and the pre-calculated factors SMB, HML, RMW, and CMA. That is:

$$R_{pt} - R_{ft} = \alpha_p + b_p(R_{Mt} - R_{ft}) + s_pSMB_t + h_pHML_t + r_pRMW_t + c_pCMA_t + \epsilon_{pt} \quad (3.12)$$

The factors SMB, HML, RMW, and CMA, or only SMB and HML in their earlier simplified versions, are calculated as the difference between the average return of a market segment at the top and bottom of the characteristic: market capitalisation for SMB and the BTM ratio for HML. In this equation, the factor loadings s_p , h_p , r_p , and c_p are firm-specific but time-invariant.

Test assets are created as segments of the market portfolio mimicking the division used to calculate the factors themselves. In the simplest models with two or three factors, the market portfolio is partitioned into 3 x 3, 5 x 5, or 4 x 4 x 2 segments, yielding 9, 25, or 32 segments, respectively. This resorting procedure aims to clear interactions among the factors. However, excessive sample fractionation leads to poor diversification and unstable performance. To prevent it, instead of creating a full segmentation, third and subsequent partitions are typically handled by averaging the returns of segments with the high characteristic minus the returns of segments with the low characteristic, rather than creating fully separated compartments.

In the classical framework, the test aims to minimise the pricing errors α_i in a regression in which the dependent variable is the return of each one of the sorted portfolios used in calculating the factors, the *test assets*, and the independent variables are the factors themselves. The proof shows whether any linear combination of the factors

can track the return variability of the test assets. The model's span is demonstrated by introducing successive factors to decrease the alphas and improve the model's fit.

The factors are interpreted as diversified portfolios that proxy for exposures to underlying unknown state variables, and the key question is whether a given set of factors can jointly eliminate alphas across the test assets. The reference statistics are the absolute value of alpha, $|\alpha_i|$, or alpha relative to the average returns, and the GRS test (Gibbons et al., 1989), which evaluates the likelihood that alpha = 0 across the sub-portfolios generated for the test.

In contrast, the graded factor approach shifts the unit of analysis to the firm level and directly explains excess returns as a function of characteristics in a regression-like setting. Rather than exhausting alphas in portfolio time-series regressions, the focus is on cross-sectional fit, evaluated by metrics such as R-squared and adjusted R-squared, to show the explanatory power of the cross-sectional variation. The two approaches therefore differ fundamentally: one tests whether factors explain returns indirectly through portfolios, while the other evaluates how well characteristics match returns directly at the firm level.

3.9.2 Testing under the Classical Framework

To cross-test both factors, we need to adapt each calculation to the other factor's testing environment. To start, we test the three-factor model's performance in the classical environment. We create the test assets by sorting three characteristics and three segments $3 \times 3 \times 3$. Thus, we generate 27 assets over 113 months. When the test assets are regressed on the SMB, HML, and GMB factors calculated in isolation the classical way, the average monthly absolute alpha is 0.0132, with a model fit of Adjusted $R^2 = 31.0\%$, as shown in the first and third data columns of Table 3.9 Panel A. Its GRS p-value indicates that, jointly, the alpha coefficients are different from zero, which is not surprising given that only three factors are considered in this abbreviated model, prepared to illustrate the proposed model construction.

After calculating the factors by sorting all three characteristics and averaging the returns of the corresponding segments, the alpha declines only slightly to 0.0127, and the model's explanatory power remains at adjusted $R^2 = 30.1\%$.

To incorporate our graded factors into the environment, we need to create a setup that mirrors the previous one, minimising alpha in the linear combination of factor returns in the equation explaining test asset returns. In our model, according to its definition, the factor returns $F_{k,t}^{graded}$ are the factor (our cross-sectional slope) times the demeaned characteristic, multiplying the factor formula 4.1 by $g_{k,i,t-1}$, we get

$$F_{k,t}^{graded} = \frac{\sum_i w_{i,t-1} g_{k,i,t-1} r_{it}}{\sum_i w_{i,t-1} |g_{k,i,t-1}|} \quad (3.13)$$

In this formula, the returns are weighted by

$$\tilde{w}_{k,t}^{(k)} = \frac{\sum_i w_{i,t-1} g_{k,i,t-1}}{\sum_i w_{i,t-1} |g_{k,i,t-1}|} \quad (3.14)$$

In our equally weighted specification, every $w_{i,t-1} = 1$, so the returns are weighted by the demeaned characteristic, producing a long leg when $g_{k,i,t}$ is positive and a short leg when it is negative. Thus, graded factor returns are constructed as equally weighted long–short portfolios in which each firm’s position is proportional to its demeaned characteristic exposure, thereby producing a continuous analogue of the traditional discrete high-minus-low factors to capture the covariance between returns and the underlying characteristic. Then these graded factor returns are tested exactly like the classical factors in the time-series test against the test assets (portfolio segments) $R_{p,t}$, leaving the coefficients β_p free to optimise the fit of the model:

$$R_{p,t} = \alpha_p + \beta_p F_t^{\text{graded}} + \varepsilon_{p,t} \quad (3.15)$$

The test results (Table 3.9, Panel A) include an absolute alpha of 0.0069, substantially smaller than its segment counterpart, an adjusted R^2 of 26.3%, slightly lower, and a similar GRS test with a p-value of 0.003, far from the alpha zero hypothesis. Obtaining parameters similar to those observed in the segment model is a satisfying result, given that the segment factors are derived from the same sorting used to calculate them, whereas graded factors are objectively calculated from the full sample across the full cross-section. The multivariate factors yield substantially improved parameter estimates: the average absolute alpha coefficient is down to 0.0041, the adjusted R^2 is up to 55.3%, and the GRS has a p-value closer to the rejection zone, consistent with the null coefficient hypothesis. These results compare favourably with their segment-resorted equivalents.

3.9.3 Testing for the Explanatory Power of Firm Returns

In the context of firm-level returns, we expect the factor models to account for only a small part of the cross-sectional variation in firm returns, because they do not incorporate any firm-specific information. The aggregation implied by computing the factors presumably aligns or reduces the estimates’ variance relative to the variance of firm-level returns.

To estimate firm-level returns, we apply a firm-level regression using the characteristics as explanatory variables in the graded model. In the segment factor model, however, we need to assign each firm a factor exposure level. Consistent with the construction of these factors, which are not graded, but segment-classifying, we assign an exposure of +1 to firms in the upper tercile of the characteristic, a zero exposure to firms in the mid tercile, and a -1 to firms in the bottom tercile.

In Table 3.10, we observe negative R^2 and adjusted R^2 with high absolute values in segment models and low absolute values in graded models. A negative R^2 means

Tab. 3.9.: Three-factor model tests for spanning and explanatory power

Panel A. Sub-portfolio Environment
(test assets: 27, periods: 113)

model (test-assets)	average $ \alpha_i $	average α_i	average R^2	average adj. R^2	GRS	p-value	residual covariance condition number	minimum residual covariance eigenvalue
segment isolated	0.01315	0.01315	0.32740	0.31093	2.08	0.00583	3055.89	2.24732E-05
segment_resorted	0.01276	0.01276	0.31752	0.30081	2.87	0.00012	1307.67	5.43809E-05
graded_univariate	0.00686	0.00662	0.28030	0.26267	2.26	0.00251	1449.77	5.49208E-05
graded_factors	0.00412	0.00085	0.56419	0.55349	1.91	0.01336	1471.87	3.43496E-05

Panel B. Firm-level Environment
(firms: min 1,047 max 2,158, 127 months)

model (test-assets)	average R^2	median R^2	average adj. R^2	share nega- tive adj. R^2	mean TSS	mean SSE	mean cor- relation actual - fitted	actual fitted variance ra- tio
segment isolated	-0.7228	-0.4122	-0.1930	0.9764	19.553	34.8554	-0.0382	0.5671
segment resorted via averages	-0.8683	-0.6357	-0.1660	0.9921	19.553	36.4604	-0.0314	0.7145
graded univariate	-0.0552	-0.0297	-0.0365	0.7795	19.553	20.7004	0.1216	0.0260
graded multivariate	-0.0282	-0.0092	-0.0304	0.5984	19.553	20.1319	0.0997	0.0226

Note: Panel A reports time-series spanning tests in the classical portfolio model. For each test asset (p), returns are regressed on the corresponding factors: $R_{p,t} = \alpha_p + \beta_p F_t + \varepsilon_{p,t}$. Average $|\alpha_p|$, and the average α_p are the average alphas resulting from the regressions for each test asset signalling pricing errors. Average R^2 and average adjusted R^2 demonstrate the average fit of the model across test assets. The GRS statistic tests the null hypothesis that all intercepts are zero. p-values for the statistic higher than $p > 0.01$ are consistent with all coefficients being zero. GRS inference is considered numerically reliable when the residual covariance matrix is well-conditioned. Reference values: condition numbers below 10^4 or 10^6 , and strictly positive minimum eigenvalues, even if very reduced. Extremely large condition numbers or non-positive eigenvalues indicate near-singularity and may render GRS statistics unreliable.

Panel B reports the results of regressing firm-level excess returns on the characteristics. The columns for R^2 and adjusted R^2 report the average values for the monthly cross-sectional regressions. The share of negative R^2 is the share of months in which R^2 is negative, indicating increased variance rather than explained. Further details are provided: total sum of the squares (TSS) as the pre-fitted variance, the sum of the squared errors (SSE), the fitted variance, the correlation between raw and fitted values, and the mean of the actual variances vs fitted variances.

that the sum of the squares of the residuals (SSE) is larger than the total sum of the squares before fitting the explanatory variables (TSS). In other words, the newly introduced variables do not help explain cross-sectional variation; instead, they amplify it. More than 90% of the months segment models have a negative R^2 , and more than 60% of the months graded factors show a negative R^2 . The correlation between observed and fitted returns (in the seventh data column) shows that, in this test, the predicted values from segment models are negatively correlated with the observed values. The correlation in the graded models is modest, but positive.

3.9.4 Retesting for Eight Factors

Given the unsatisfactory results at the firm level, we consider next a model with additional explanatory factors. Anticipating the eight factors computed in the next chapter, we examine the explanatory and spanning results under both environments.

For an eight-characteristic specification, a full three-way segmentation across all characteristics would generate $3^8 = 6,561$ portfolios. Such an approach would excessively fragment the sample, leaving many portfolios with very few firms and therefore weak diversification. The resulting portfolio return covariance matrix would become ill-conditioned or nearly singular, making multivariate time-series tests such as the GRS test numerically unstable and economically unreliable.

Following the classical authors, to consider more variables under the segment model, we generate a separate sub-model for each characteristic, excluding size. In each sub-model, the test assets are nine sub-portfolios divided by size and the selected characteristic. For example, when the additional characteristic is value, the sub-portfolios (i.e. test assets) are size-value. The remaining factors, such as greenness, are estimated by calculating the weighted returns of green and brown firms within each of the nine test assets, and then the spread between them. The resulting green factor is the average return spread across segments. The remaining factors follow the same process, and then the next sub-model is partitioned by size and the following characteristic. Each one of the nine test assets is regressed with the corresponding factor spreads.

In Table 3.10 Panel A, we observe that the resulting alpha for the segment model, 0.019, is actually higher than the three-variable alpha in Table 3.9, corresponding to the lower correspondence between test-assets, now sorted by two variables, and factors now corresponding to eight variables. However, the explanatory power increases notably to an adjusted R^2 of 48.6%, and the GRS is closer to the zero coefficient assumption. However, the numerical stability of the statistic is fragile given the elevated condition number and the presence of negative eigenvalues.

In the classical test, graded factors outperform their segment counterpart. Absolute alphas are lower: 0.010 for univariate and 0.004 for multivariate, even more notably average alpha, and the fit increases substantially for the multivariate (up to Adj $R^2 = 72.8\%$).

In the firm-level context (Table 3.10 Panel B), the inclusion of new factors increases the variation explained by the graded model, reducing the number of months with negative R^2 down to 6%, turning the negative adjusted R^2 positive and improving the fitted-to-actual correlation, only achieving modest values in-sample prediction parameters (Adj $R^2 = 4\%$, correlation actual-fitted 10%), but substantially improving the performance of the segment model.

Tab. 3.10.: Eight-factor model tests for spanning and explanatory power

Panel A. Sub-portfolio Environment (test assets: 9 size-k partitions, periods: 127)								
model (test-assets)	average $ \alpha $	average α	average R^2	average adj. R^2	GRS	p-value	residual covariance condition number	minimum residual covariance eigenvalue
segment_size_conditioned_avg	0.0192	0.0192	0.5183	0.4856	3.5380	0.0016	4.3404E+17	-2.1374E-19
graded_univariate_size_conditioned_avg	0.0100	0.0099	0.4498	0.4124	3.0068	0.0134	311.1768	5.54412E-05
graded_factors_size_conditioned_avg	0.0041	0.0004	0.7456	0.7283	5.5353	0.0009	596.2822	1.99872E-05

Panel B. Firm-level Environment (firms: min 772 max 1,610, 127 months)								
model (test-assets)	average R^2	median R^2	average adj. R^2	share nega- tive R^2	mean TSS	mean SSE	mean cor- relation actual fitted	actual fitted variance ra- tio
segment isolated	-338	-86.462	-0.7706	1.0000	11.956	4437.8078	0.0493	31.9917
segment resorted via averages	-295.95	-63.112	-0.5285	1.0000	11.956	3704.5837	0.0481	26.1369
graded univariate	-0.0545	-0.022	-0.0402	0.6850	11.956	12.7275	0.1665	0.0508
graded multivariate	0.05025	0.04484	0.0433	0.0630	11.956	11.3663	0.2197	0.0693

Note: Panel A reports time-series spanning tests in the classical portfolio model. For each test asset (p), returns are regressed on the corresponding factors: $R_{p,t} = \alpha_p + \beta_p F_t + \varepsilon_{p,t}$. Average $|\alpha_p|$, and the average α_p are the average alphas resulting from the regressions for each test asset signalling pricing errors. Average R^2 and average adjusted R^2 demonstrate the average fit of the model across test assets. The GRS statistic tests the null hypothesis that all intercepts are zero. p-values for the statistic higher than $p > 0.01$ are consistent with all coefficients being zero. GRS inference is considered numerically reliable when the residual covariance matrix is well-conditioned. Reference values: condition numbers below 10^4 or 10^6 , and strictly positive minimum eigenvalues, even if very reduced. Extremely large condition numbers or non-positive eigenvalues indicate near-singularity and may render GRS statistics unreliable.

Panel B reports the results of regressing firm-level excess returns on the characteristics. The columns for R^2 and adjusted R^2 report the average values for the monthly cross-sectional regressions. The share of negative R^2 is the share of months in which R^2 is negative, indicating increased variance rather than explained. Further details are provided: total sum of the squares (TSS) as the pre-fitted variance, the sum of the squared errors (SSE), the fitted variance, the correlation between raw and fitted values, and the mean of the actual variances vs fitted variances.

In summary, we evaluate the explanatory and spanning ability of graded factors relative to traditional segmented factors within the Fama–French testing framework and at the firm level. The comparison of the results produced under discrete portfolio segmentations and graded continuous exposures in factor construction translates into the reduced discretisation noise and improved alignment of graded factors, which exhibit higher explanatory and spanning capacities than their segmented counterparts, as shown in lower values for absolute alphas, higher R^2 , and higher correlation between predicted and realised returns. The findings demonstrate that employing graded models improves the efficiency and precision of factor models.

3.10 Discussion

The sequence of tests we have run for the newly formed factors can be summarised as follows. The first set of tests examines the characteristic itself. To start, we assess whether there is theoretical support for it as a trait that potentially anticipates risk. Then, we examine the distribution of ex-post returns. Next, we examine the correlation between size and risk in the risk factors, which is consistent with the previous two.

In the second set of tests, we examine factor returns. We start by considering univariate returns; we then test for the effects of sectoral composition, and we calculate multivariate factor returns, adhering in all cases to the call for a stricter statistical t-stat above three for full significance, but not discarding data if it is still suggestive of a pattern when the statistic does not reach full significance (Harvey et al., 2016). Lastly, we assess the time series to complement our assessment of the stability of the excess returns. This sequence, applied to size, value, and greenness, yields uneven results.

To illustrate the proposed framework, the empirical application focuses on the environmental dimension of CSR. This choice keeps the exposition centred on the methodological contribution while using the most prominent and actively debated sustainability characteristic in the asset-pricing literature; however, the framework itself is general and can be applied to any firm characteristic.

In size, we find conceptual support for a higher risk in smaller firms. The dispersion of ex-post returns is larger for the smaller third of firms than for mid-sized and larger firms, and across three risk metrics, smaller size correlates with higher risk measurements in our risk factor, which are highly significant. The three foundations examined are present: theory, realised returns, and observed risk factors perform as expected.

In the second set, univariate size-factor returns are close to the required level of significance ($t = 2.40$) and exceed it in the multivariate test ($t = 3.19$). Examining the monthly data averages, they remain stable in sign and intensity over time, and in the chart, their series matches the expected time-related behaviour, showing a regular, stable trend. The multivariate effect, simultaneously with value and greenness, yields a time premium of around 2% annually.

Value, although long supported in the literature, does not yield results similar to those obtained with the other characteristics. Conceptually, the literature has made the case for a correspondence between higher BTM and higher returns, derived from the residual-income equation by assuming the remaining variables remain constant (Fama & French, 2015). In our view, such an assumption is not useful for our purpose, and it does not conform with the reality we observe, in which lower BTM typically corresponds to 'high growth' firms. On the contrary, higher-growth firms have their future cash flows farther out, remaining more exposed to risks and more sensitive to interest rates. In the same way that the slope of the yield curve is

normally positive, we would expect growth firms, not value firms, to be the riskier subset and produce higher returns. Thus, we follow our sequence agnostically.

For this characteristic, ex post returns provide contradictory evidence. Mid-BTM firms are the least risky in the three-fold segmentation. Risk metrics also yield ambiguous results: volatility and downside volatility, as ex-post metrics, align with the high-BTM–low-risk pair we expected, but implicit volatility, an ex-ante metric, points in the opposite direction. We can conjecture that the correlation between value firms and smaller firms, and possibly investor disfavour too, may outweigh the lower realised volatility in setting options' premiums, the input into implicit volatility calculations.

Lacking a strong footing in the first set, we examine factor returns. The univariate model shows a modest outperformance of value firms relative to growth firms, well short of the required levels of significance. However, in our multivariate model, the sign turns, and significance improves. Discarding the sector as an omitted variable, the correlation of value and size ($\rho = 0.83$) absorbs the effects of value.

When considered simultaneously, both characteristics show improved explanatory power. The time-series profile of value completes the perspective. Unlike size, the value factor's time series is not compatible with a stable trend expected from a time-driven premium, but rather with a change in investor preferences away from value stocks in 2020 and 2021.

The risk profile of greenness is theoretically well supported, and, within the sector, greenness strongly correlates with lower-risk metrics, but the dispersion of realised returns does not yield the expected results. When studying the time series, we observe a strong overperformance localised to the 2019-2021 period, associated with a shift in preferences.

Our results regarding the studied characteristics are consistent with the literature, which uniformly support size as a factor with 2-3% additional yearly returns and acknowledge the vanishing effect of value (Fama & French, 2015; Hou et al., 2020; Loughran, 2025). We differ from previous studies by disproving the sectoral component of value (Kim et al., 2025), and we contribute a multivariate time-series analysis that opposes the premium-like, gradual effect of size to the shock-like, focalised effect of value and greenness.

More specifically, regarding the controversial excess returns of green stocks, green factor returns do not reach the level of significance required to indicate a stable premium ($t = 1.51$), owing to their time-series profile, which is consistent with the one-off effects associated in the literature with news flow and changes in investor preferences (DeMiguel et al., 2025; Görgen et al., 2020; Pástor et al., 2022). Importantly, the explanatory power of greenness emerges primarily after sector effects are neutralised. This finding is consistent with the construction of our greenness measure, which partly reflects industry composition because firms' environmental profiles differ systematically across sectors. Consequently, the within-sector specification provides a more informative assessment of the incremental effect of environmental characteristics beyond sector membership. Even if the resulting return premium remains unstable, the persistent relation between greenness and the risk suggests

that environmental characteristics capture economically meaningful differences in required returns. This may justify studying the return trends of greenness as a cross-sectional dimension, as some reports do (Hsu et al., 2023).

From the perspective of the model, we contribute a model that overcomes the pitfalls of the traditional segment model. The portfolio difference model may produce false positives in certain contexts because it amplifies the signal by averaging the extremes while ignoring the substantial middle portion of each characteristic. Its re-sorting distorts the weightings, altering the overall balance of cumulative returns over time (Loughran, 2025). For example, in our sample, we find that under the segment specification, the smaller size is weakly associated with lower returns. When discretionary choices are avoided, smaller size remains a statistically significant and stable factor in overperformance. Our findings strongly confirm the warning about the impact of discretionary choices on factor returns (Harvey & Liu, 2019).

When we consider the construction of the model and the mathematics underlying the analysis, for example, in cross-model spanning tests for competing models or in exclusionary tests for variables, we find two major objections that our model addresses. First, the segment model approximates the graded continuum of the dependent variables using the difference between averages calculated at two arbitrary points. These points are determined by the choice of cut-off points for the low, mid, and high segments. The return differentials of the long-minus-short segment sub-portfolios are the independent variables, formulated holistically as diversified portfolios to expose the returns to unknown variables (Fama & French, 2015). Their coefficients (s_i , h_i , r_i , and c_i , in their model) lack any specific economic meaning. They are designed as a utility to extract as much information as possible out of the average, the alpha coefficient (a_i). On the contrary, the proposed model is mathematically and economically consistent: the coefficients are the factors themselves, and the coefficients are the slopes that relate the independent variables measured in the units of the characteristic each firm possesses.

The second of our objections concerns the consideration of interactions. The segment model relates returns to the difference between the two endpoint averages that inevitably arise from univariate analyses or, alternatively, from discretionary sorting procedures that aim to clear the second variable, normally value, of its correlation with the first, normally size. The quality of the adopted independent variables in bearing the intended effects of value or other characteristics depends on the careful art of the study's authors and cannot be taken for granted (Hou et al., 2020).

Univariate slopes in a multivariate model are inherently biased. For the sake of simplicity in the argument, let's assume a bivariate size-value model. Econometrics quantifies the bias of the univariate slope of value at precisely the covariate slope of growth β_m times the covariance $Cov(m, v)$ divided by the variance of v $\sigma^2(v)$, or $\beta_m \frac{Cov(m, v)}{\sigma^2(v)}$ (Greene, 2012).

Given the strong correlation between the size and value factors and the intensity of the size effect (both affecting the numerator), we believe it is appropriate to raise a concern about the use of univariate factors in multivariate testing, even if partially mitigated by re-sorting. Our graded model addresses this limitation by consistently

considering both variables and projecting returns onto both axes, objectively and systematically.

Finally, we tested both models in their reciprocal contexts to compare the explanatory and spanning power of segment and graded factors. The new model captured a larger share of cross-sectional return variation, thereby reducing pricing errors across test assets and providing additional information beyond high-minus-low spreads. Conceptually, this suggests that graded factors approximate a more continuous representation of the stochastic discount factor, whereas the segment model may suffer from scaling persistence or fragmentation introduced by discrete sorting.

When testing for explanatory power in a regression-like setting, we observe low explanatory power for firm-level returns across both models, as most idiosyncratic information is not captured by the factors. In this setup, the graded model's additional contribution to explaining returns was modest but better than that of the segment model, which introduces additional variability rather than explaining it, as a consequence of its signal-enhancing peculiar effect. Neither model was designed to predict returns, but the graded model performs better at adjusting and delivering proportionate scaled variation metrics. In summary, the factor space becomes more parsimonious and economically interpretable: rather than relying on multiple constructed spreads, graded factors span the cross-section more effectively, while their predictive capacity remains weak without additional information.

3.11 Conclusion

Factor models play a central role in asset pricing. They provide a parsimonious framework for summarising systematic patterns across the cross-section of returns and for linking asset prices to underlying sources of risk. Their practical relevance has grown alongside the expansion of quantitative investing, where factor exposures are routinely used to explain portfolio returns and to guide allocation decisions. As a result, identifying, measuring, and interpreting factors has become a central theme in empirical finance.

However, the traditional technique for calculating factors is based on the return differential between two extreme averages, ignoring the middle section of firms. The prevailing data-based approach has also led to the proliferation of proposed factors calculated using diverse methodological choices, which, in turn, affect the outcomes. When tested under different setups, these results often fail to replicate.

To address these shortcomings, we propose a new, mathematically rigorous model for factor construction. Graded factors are calculated as the cross-sectional slope. When included in the CAPM, the new variables are fully consistent with the time-series slope (beta). Their calculation requires no discretionary cut-off points, portfolio resorting, or periodic rebalancing, and the new metric, based on the new factors, provides a measure with a more economically grounded interpretation: relative returns per unit of the characteristic. By design, in multivariate contexts, the new model projects returns onto each factor's axis, tracing each factor's effects in a

natural and systematic way. Graded factor models better adjust for and span the cross-section of firm returns, enabling more effective time-series analysis.

The new approach is not only more dependable but also offers new avenues for investigating the covariance and causality of factor returns. The graded factor, as a systematically formulated mathematical object, handles simultaneous characteristics effectively, objectively attributing performance to them and simplifying cross-model spanning tests. Under the new specification, factors can be decomposed to study the time series of their cross-sectional components.

We demonstrate the application of our model to facilitate discussion of the interaction among size, value, and greenness. We show that size is a key premium-like factor that delivers sustainable returns, and we identify how value and green factor returns respond to shocks rather than producing steady, predictable excess returns.

Our factor construction can also serve as a powerful tool for risk analysis. Applying our factor model to risk metrics, we find that relative size and greenness are strongly associated with lower risk. Which end of the value-growth line should be considered safer, and which end merits a risk premium, in our view, remains ambiguous and merits further study.

Our objective is to provide a consistent framework for constructing and analysing factors rather than a forecasting model. Accordingly, the methodology naturally accommodates the emergence, persistence, and fading of factor premia over time, treating their evolution as part of the phenomenon under study rather than as evidence of model instability. Building on this framework, future research could develop dynamic forecasting and trading models that exploit the estimated persistence of factor premia and investigate whether the observed intensification or decay of these patterns can itself be anticipated.

Considering the green factor introduces a novel characteristic that has been studied at the firm level but remains under-represented in its factor form. However, it also limits the period covered by our sample compared with classical factor studies. The design of our study has other limitations that offer opportunities for further research. First, the environmental score is known to be a metric for which different rating agencies show diverging results. Our environmental signal follows the literature in blending score and weight, but produces results that are heavily skewed towards the firm's sectoral belonging. Studies focused on this characteristic could test its robustness with alternative sources and consider different formulations for the base characteristic. Secondly, we have centred this chapter on presenting the new methodology. To illustrate its properties, we have chosen a setup with a limited number of characteristics. Our method can help interpret models with multiple variables to analyse their interactions, which we develop in the next chapter.

This analysis has immediate implications for academia and practice. Recent work on trading models that incorporate transaction costs has proven that multivariate strategies reduce trading costs and stabilise results (Li et al., 2024). Further research could investigate whether segment factors' enhanced signal may be producing excess trades relative to graded factors in multivariate contexts. In the policy domain, by better understanding the factors and eliminating discretionary choices, our model

can help challenge unjustified claims and enhance critical judgment in investment decisions. Given improvements in computational capabilities, more mathematical approaches may be better suited to algorithmic and automated investment for practitioners. Improved metrics of portfolio exposure to characteristics can yield more precise risk estimates and more efficient risk-return balances. All of these are relevant to market efficiency. From a broader theoretical perspective, we offer a new, mathematically robust approach to analysing risk premiums from ex-post returns. This path leads to improved firm valuation and, ultimately, improved overall resource allocation.

Causal Analysis of Returns and Risk

4.1 Introduction

The extensive recent literature on the determinants of returns traces back to the early development of the CAPM and its central time-series parameter, beta (Lintner, 1965; Sharpe, 1964). The model was subsequently extended to incorporate firm-specific cross-sectional characteristics to better explain realised stock returns (Fama & French, 1993). The rapid expansion of sustainable investing during the period 2015–2021 introduced an additional dimension to the already broad set of factors considered in investment analysis (Harvey & Liu, 2019; Pástor et al., 2022). This line of research has generated a wide range of concepts, models, and empirical tests, substantially advancing our understanding of both the cross-sectional and time-series behaviour of stock returns.

At the same time, the proliferation of data-driven studies has brought several concerns to the forefront. Some reported results are highly sensitive to factor construction (Hou et al., 2018), while others may reflect spurious relationships (Lewellen et al., 2010). Many proposed factors fail to achieve statistical significance or do not survive re-examination. Two influential studies estimate that roughly half of the published findings are not supported by sufficiently strong statistical evidence and argue that data-driven research should be subject to more demanding significance thresholds than studies motivated by economic theory (Harvey et al., 2016; Hou et al., 2015).

The conceptual foundations underlying return premia also remain an area of ongoing development. Factors were initially introduced to capture pricing anomalies, recognising that the characteristics used were only proxies for “unknown state variables” (Fama & French, 1993). Subsequently, some of these variables received theoretical support through interpretations of the fundamental valuation equation (e.g., book value) (Fama & French, 2015) and investment-based theories of equilibrium (e.g., the investment factor) (Hou et al., 2018). Another source of tension is the widespread use of one-period realised returns as proxies for the theoretically grounded long-term required return, despite the fact that both concepts are distinct and may even be negatively correlated (Cochrane, 2011; Hou et al., 2018). Overall, the construction, stability, theoretical rationale, and underlying drivers of factor returns remain central challenges in the literature.

We seek to contribute to the literature by developing a causal model that accounts for both time-series and cross-sectional dimensions of returns. To integrate both perspectives, we explain time variation using causal variables that are also linked

to cross-sectional characteristics, thereby capturing changes in factor returns rather than treating them as static.

In developing our model, we build on prior work that decomposes prices into a performance measure and a valuation multiple (Cochrane, 2011). While this framework was originally expressed in terms of dividends and dividend yields, we adapt it to earnings and earnings multiples, and formulate it at the factor rather than the firm level. We also draw on advances in modelling the implicit cost of capital (ICC) to address the limitations of using ex post returns as proxies for ex ante expected returns (Gebhardt et al., 2001; Hou et al., 2012).

Our results confirm the central role of changes in required returns in explaining repricing returns, while also showing that cumulative realised growth and revisions in expectations are highly significant. Although these components are only infrequently incorporated into factor return models, they are key drivers of long-term performance and, because they are closely linked to firm characteristics, help explain both the level of factor returns and their evolution over time.

These findings contribute to the ongoing discussion regarding the theoretical underpinnings of factor returns and their enduring but time-varying nature. Enhancing asset pricing models informs investment practice and extends to applications in portfolio management, valuation, corporate finance, and policy.

4.2 Foundations of the Time Series Analysis

4.2.1 The Studied Characteristics

A large body of research in asset pricing has focused on identifying firm-level attributes that account for differences in returns across firms. Initial studies concentrated on systematic exposure to market risk, particularly through beta (Fama & MacBeth, 1973), and were soon extended to include firm characteristics such as size (Banz, 1981) and book-to-market ratios (Fama & French, 1993; Lakonishok et al., 1994). Later contributions incorporated aspects of financial structure (e.g., leverage) (Bhandari, 1988), as well as variables linked to key firm characteristics, such as investment (Titman et al., 2004).

As the empirical literature expanded, a wide spectrum of additional signals was examined. These include indicators related to market behaviour and investor sentiment—such as return continuation (Carhart, 1997; Jegadeesh & Titman, 1993), trading frictions (Pástor & Stambaugh, 2003), and measures of attention or disagreement among analysts (Diether et al., 2002; Hou & Moskowitz, 2005) — alongside risk-oriented variables, including default risk (Vassalou & Xing, 2004) and firm-specific volatility (Ang et al., 2006).

In its expanded version, which adds momentum, investment, and profitability factors to the original size and value, Fama and French report that their model explains up to 94% of price variation, even though value proves increasingly redundant (Fama &

French, 2015). Similarly, other authors find support for investment-related variables in explaining a substantial share of return variation, which absorb a substantial part of the effects previously attributed to other characteristics (Hou et al., 2015). This consolidation suggests that many empirically identified characteristics share explanatory power with mainstream characteristics, are closely interconnected or may be influenced by common implicit drivers, while also highlighting that the dominant characteristics reference elements connected with firm valuation (Hou et al., 2020).

In a more recent period that most authors establish from 2007 to 2022, non-traditional attributes related to corporate social responsibility have entered the candidate dimensions of returns and risk (Estevez-Mendoza & Infante, 2025). The conceptual foundations and the effects on risk of these factors are increasingly robust (El Ghoul et al., 2018; Merladet et al., 2025; Sautner et al., 2023), but their role in return dynamics is less clear and is still being theorised (Bolton & Kacperczyk, 2023; Edmans et al., 2025; Pástor et al., 2021; Pedersen et al., 2021).

4.2.2 The Problem of Realised Returns as Proxies for Required Returns

A central issue in empirical asset pricing concerns the choice of proxy for expected returns. A large share of the literature relies on realised returns to approximate investors' required returns, an approach that has proven convenient but shows strong limitations. Evidence from ESG-related studies illustrates this tension: some contributions report higher realised performance for firms with stronger sustainability profiles (Aswani et al., 2024; Bolton & Kacperczyk, 2023; Edmans, 2012; Kräussl et al., 2023), whereas others document lower required returns for the same firms (Chava, 2014; El Ghoul et al., 2018). This divergence has encouraged the development of frameworks that jointly consider realised outcomes and expectations (Pástor et al., 2022).

To represent expected long-term returns, recent work increasingly relies on proxies for the ICC rather than realised returns. Two main approaches can be distinguished in defining the metric: the cost of capital inferred from analyst forecasts (Botosan & Plumlee, 2005; Francis et al., 2004; Gebhardt et al., 2001) and estimates of the ICC based on projected earnings (Lee et al., 2021). The latter earnings-based measures exhibit strong predictive power and closely align with long-term investment performance (Hou et al., 2012). Measures based on the ICC offer superior performance in capturing time-series dynamics (Lee et al., 2021).

Within this second approach, two modelling strategies are commonly employed: formulations based on expected earnings growth (Easton, 2004; Ohlson & Juettner-Nauroth, 2005), and residual income frameworks (Claus & Thomas, 2001; Gebhardt et al., 2001; Hou et al., 2012), which underpin the empirical design adopted in this chapter. Integrating ICC estimates with realised returns provides a more comprehensive perspective on return dynamics (Hou et al., 2012; Pástor et al., 2022), and we use them to capture both cross-sectional variation and temporal evolution

in a unified framework. The empirical analysis that follows should be interpreted as conditional on this particular ICC specification, theoretically well-founded and strongly supported by the empirical literature.

4.2.3 Models for the Cross-section and Time-series of Returns

A key contribution to understanding return dynamics is provided by Cochrane (2011), who highlights the value of factor-based approaches for summarising information relevant to investment and valuation. By shifting the focus from individual securities to underlying characteristics, the analysis becomes more stable and interpretable. At the same time, the author raises important concerns regarding the rapid expansion of proposed factors, the reliance on sorting procedures that introduce discretionary elements, and the assumption of constant expected premia, which overlooks the evolving nature of returns.

To account for price fluctuations, his framework decomposes valuation changes into components related to current cash flow generation (i.e., the current dividend level) and future expectations and discount rates (i.e., the dividend yield), building on the Campbell–Shiller approach (Campbell & Shiller, 1988), which allows for decomposing returns into a component based on ongoing results and a repricing component, captured by firm-level valuation ratios (the dividend yield). Their results indicate that fluctuations in valuation ratios are primarily driven by variation in expected returns, with no support for explanations based on changes in expected cash flows (Cochrane, 2011).

In recent times, the role of dividends as a primary indicator of performance has diminished, as several prominent companies do not pay them, while share repurchases have gained relative weight, accounting for almost half of the overall distribution of funds to shareholders (Yardeni et al., 2023). Consequently, we adopt an alternative decomposition into earnings and the price-earnings ratio and operationalise our model at the factor level rather than the firm level to benefit from enhanced data stability.

While the landmark study proxies the cost of capital with long-term realised returns as the explanatory variable, recent developments on the implicit cost of capital provide an alternative metric, conceptually closer and more adequate for improving inference (Hou et al., 2012). Nevertheless, their approach relies either on factors constructed from extreme segments and iterative sorting procedures to isolate the effects, or on firm-level regressions of returns on characteristics. While the latter offers analytical simplicity, it forgoes the benefits of aggregation and relies on parameters that are often more unstable than characteristic-based factors in analyses of cross-sectional variation (Lee et al., 2021).

The following section outlines the methodological framework and the model's construction. This is followed by a description of the data and the selection of proxy variables. The empirical results are then presented across several sections—covering the cost of capital and firm characteristics, factor returns, earnings and multiple-based

factors, and the analysis of time-series dynamics and causal relationships—before concluding with a discussion of the main findings.

4.3 Modelling Earnings, Price-Earnings, and Causal Channels

This section extends the methodology to incorporate the time dimension. We begin by outlining the construction of the factors, followed by the decomposition of returns into earnings and price–earnings (P/E) components. We then show this decomposition in terms of factor-level contributions. We present the foundations of time-series analysis and conclude with guidance on interpreting the results.

4.3.1 Base Factor Calculation

As referred in the previous chapter, the graded factor f_t is defined as the slope coefficient obtained from an ordinary least squares regression without an intercept at time t . In this specification, the dependent variable is the cross-section of firm-level returns $r_{i,t}$, while the explanatory variable is the cross-section of mean-centred characteristics from the previous period, $g_{i,t-1}$. The resulting estimator is given by:

$$f_t = \frac{\sum_i g_{i,t-1} r_{i,t}}{\sum_i g_{i,t-1}^2} \quad (4.1)$$

Extending this framework to a multivariate setting leads to a matrix representation of the regression. Let X_t denote the matrix of lagged characteristics $g_{k,i,t-1}$, where the index k identifies each of the K characteristics for firm i at time t . The fitted hyperplane yields a vector of partial slope coefficients $\tilde{F}_t = (\tilde{f}_{1,t}, \dots, \tilde{f}_{K,t})'$, capturing the marginal contribution of each characteristic. The estimator is given by (Greene, 2012):

$$\tilde{F}_t = (X_t' X_t)^{-1} X_t' r_t \quad (4.2)$$

4.3.2 Price Decomposition

To analyse long-term return dynamics, we decompose price movements into two components, following practitioner conventions and the decomposition proposed by Cochrane (2011). Rather than separate prices into dividends and dividend yields, we adopt a formulation based on earnings and price–earnings ratios. Diverging long-term earnings trends may have a substantial effect as time passes. Accordingly,

the price of firm i at time t , $P_{i,t}$, can be written as the product of earnings per share $EPS_{i,t}$ and the price–earnings multiple:

$$P_{i,t} = EPS_{i,t} \frac{P_{i,t}}{EPS_{i,t}} \quad (4.3)$$

Taking logarithms yields an additive decomposition:

$$\ln P_{i,t} = \ln EPS_{i,t} + \ln \frac{P_{i,t}}{EPS_{i,t}} \quad (4.4)$$

So price increases can be expressed as:

$$\Delta \ln P_{i,t} = \Delta \ln EPS_{i,t} + \Delta \ln \frac{P_{i,t}}{EPS_{i,t}} \quad (4.5)$$

For a firm that does not distribute dividends, total returns are fully captured by capital gains. In this case, the price ratio $P_{i,t}/P_{i,t-1}$ equals $1 + r_{i,t}$, and the log change in price can be written as $\Delta \ln P_{i,t} = \ln(P_{i,t}/P_{i,t-1}) = \ln(1 + r_{i,t})$. When dividends are paid, prices must be adjusted to ensure consistency. In a frictionless setting, the price *cum-dividend* $P_{i,t}^{\text{cum}}$ declines by the amount of the dividend $D_{i,t}$ on the ex-dividend date, resulting in the *ex-dividend* price $P_{i,t}^{\text{ex}} = P_{i,t}^{\text{cum}} - D_{i,t}$. To construct a consistent return series, dividends must therefore be reintegrated into prices, so that returns are computed as:

$$r_{i,t} = \frac{P_{i,t} + D_{i,t} - P_{i,t-1}}{P_{i,t-1}} \quad (4.6)$$

Assuming dividend-adjusted prices and total returns, we rewrite equation 4.5 by substituting $\Delta \ln P_{i,t}$ with $\ln(1 + r_{i,t})$, the equation that results is:

$$\ln(1 + r_{i,t}) = \Delta \ln EPS_{i,t} + \Delta \ln \left(\frac{P_{i,t}}{EPS_{i,t}} \right) \quad (4.7)$$

For any monthly period, we can define the earnings-increase “deflated” return $r_{i,t}^{\text{exEPS}}$ as:

$$r_{i,t}^{\text{exEPS}} = \frac{1 + r_{i,t}}{EPS_{i,t}/EPS_{i,t-1}} - 1 \quad (4.8)$$

Since $1 + r_{i,t} = EPS_{i,t}/EPS_{i,t-1} (1 + r_{i,t}^{\text{exEPS}})$, then equation 4.7 can also be formulated as

$$\ln(1 + r_{i,t}) = \Delta \ln EPS_{i,t} + \ln(1 + r_{i,t}^{\text{exEPS}}) \quad (4.9)$$

4.3.3 The Price-Earnings Factor

By substituting our return in equation 4.9 into the factor formula (equation 4.1), we calculate f_t^{log} as the factor of the logged returns:

$$\begin{aligned} f_t &= \frac{\sum_i g_{i,t-1} \ln(1 + r_{i,t})}{\sum_i g_{i,t-1}^2} \\ &= \frac{\sum_i g_{i,t-1} (\Delta \ln EPS_{i,t} + \ln(1 + r_{i,t}^{exEPS}))}{\sum_i g_{i,t-1}^2} \end{aligned} \quad (4.10)$$

The linearity of our construction allows for

$$f_t^{log} = \frac{\sum_i g_{i,t-1} \Delta \ln EPS_{i,t}}{\sum_i g_{i,t-1}^2} + \frac{\sum_i g_{i,t-1} \ln(1 + r_{i,t}^{exEPS})}{\sum_i g_{i,t-1}^2} \quad (4.11)$$

Equivalent to:

$$f_t^{log} = f_t^{logEPS} + f_t^{logPE} \quad (4.12)$$

Where f_t^{logEPS} is the factor for the growth of earnings and f_t^{logPE} is the factor of the price-earnings multiple:

$$\begin{aligned} f_t^{logEPS} &= \frac{\sum_i g_{i,t-1} \Delta \ln EPS_{i,t}}{\sum_i g_{i,t-1}^2} \\ f_t^{logPE} &= \frac{\sum_i g_{i,t-1} \ln(1 + r_{i,t}^{exEPS})}{\sum_i g_{i,t-1}^2} \end{aligned} \quad (4.13)$$

We view f_t^{log} as the coefficient linking cross-sectional log returns to the underlying characteristic. Economically, it captures the proportional change in returns associated with a unit change in that characteristic. Given that log returns provide a close approximation to arithmetic returns, *operatorname{ln}(1 + r) \approx r*, this measure is directly comparable to the return-based factor f_t (see proof in A.3).

Equation 4.12 allows for a transparent decomposition of this effect. The premium associated with the characteristic can be separated into two distinct sources: a component driven by differences in firms' underlying performance (earnings dynamics), and a component reflecting valuation adjustments (multiples or discount-rate variation). Formally, this relationship can be expressed as $f_t = f_t^{EPS} + f_t^{PE}$.

Each term admits a distinct economic meaning. The component f_t^{EPS} represents the sensitivity of earnings growth to the characteristic g , reflecting how variation in the characteristic is associated with differences in firms' underlying earnings performance at time t . The term f_t^{PE} captures the relationship between changes in valuation multiples and the same characteristic, isolating the share of returns driven

by repricing effects. When the earnings measure relies on reported figures, the corresponding valuation multiple—expressed as the price-earnings ratio—implicitly incorporates expectations of future profitability and variations in discount rates, thereby linking observed returns to forward-looking market assessments.

4.3.4 Time-Series Analysis of the Price-earnings Factor

We study the effect of repricing by regressing characteristic-based price-earnings factors on the key variables that parametrise the P/E multiple in the Gordon growth model (Gordon, 1962):

$$\frac{P}{E} = \frac{1 - b}{r_e - growth} \quad (4.14)$$

where b is the plowback ratio (i.e. dividend reinvestment), r_e , the required return on the equity, and $growth$, the perpetual growth rate. The required return is the discount rate applied to future dividends to calculate the present value of the firm's shares. In our analysis, we anticipate an inverse correlation with the price-earnings factor, in a manner similar to the inverse correlation between the internal rate of return and price in bonds. We proxy the required returns with the ICC, as defined in our next section.

Within this framework, $growth$ denotes the long-horizon growth rate, which is expected to be positively associated with valuation multiples. Market participants revise their expectations as new information becomes available, either through gradual adjustments in forecasts or through discrete updates. To capture the persistent component of this process, we define dg as the change in the 36-month earnings growth trend from its previous value.

Revisions to expectations are often triggered by firm-specific disclosures. Corporate communications—particularly periodic earnings announcements—provide information on strategic changes, product developments, and updates to business objectives, all of which may alter anticipated returns. These announcements also frequently include revisions to payout policies, corresponding to the parameter b in the model. To incorporate these effects, we define announcement returns as the abnormal returns observed around disclosure dates and include them as an additional explanatory variable. Both dg and announcement-related returns reflect forward-looking information on cash flows and are therefore expected to be positively related to realised returns, although their relative importance cannot be specified ex ante.

To analyse the determinants of valuation adjustments, we estimate a time-series model in which the multiple-related factor for characteristic k , $f_{k,t}^{PE}$, is expressed as a function of three underlying components:

$$f_{k,t}^{PE} = \alpha_k + \beta_{k,dICC} f_{k,t}^{dICC} + \beta_{k,dg} f_{k,t}^g + \beta_{k,dANN} f_{k,t}^{dANN} + u_{k,t} \quad (4.15)$$

The model can be interpreted as follows. $f_{k,t}^{PE}$ captures the portion of returns attributable to valuation adjustments associated with characteristic k . These adjustments are modelled as a function of three channels: variations in the implicit cost of capital, represented by $f_{k,t}^{dICC}$; changes in expected growth, captured by $f_{k,t}^{dg}$; and announcement-driven effects, measured by $f_{k,t}^{dANN}$, which reflect abnormal returns around earnings disclosures.

The sensitivity of valuation changes to each channel is governed by the coefficients $\beta_{k,dICC}$, $\beta_{k,dg}$, and $\beta_{k,dANN}$. The intercept α_k represents the average component of repricing not explained by these factors, while $u_{k,t}$ denotes the residual term, assumed to be orthogonal to the explanatory variables.

From a cross-sectional standpoint, returns across firms can be represented in a compact form. Let r_t denote the vector of returns for the N firms, and g_{t-1} the matrix of lagged characteristics. The factor vector f_t summarises the effect of the K characteristics, so that:

$$r_t = a_t \mathbf{1} + f_t g_{t-1} + \epsilon_t \quad (4.16)$$

Within this representation, each factor $f_{k,t}$ provides a scalar projection of the cross-section of returns along the dimension defined by characteristic k . Its evolution over time reflects changes in how the market prices that characteristic. In economic terms, $f_{k,t}$ measures the marginal return associated with a unit increase in the characteristic.

Building on the firm-level decomposition, the factor itself can be expressed as the sum of two components reflecting distinct economic mechanisms: $f_t = f_t^{EPS} + f_t^{PE}$. The series f_t^{PE} captures the portion of returns driven by valuation adjustments across firms with different exposures to the characteristic. Over extended horizons, accumulated earnings growth can dominate observed performance, as is common in studies of long-run factor behaviour. By isolating the multiple component, the proposed measure filters out the influence of realised growth and focuses exclusively on repricing effects linked to revisions in expectations.

The variables $f_{k,t}^{dICC}$, $f_{k,t}^{dg}$, and $f_{k,t}^{dANN}$ provide a structured representation of the channels through which these valuation adjustments arise. They quantify, respectively, the contribution of changes in discount rates, shifts in growth expectations, and information released through corporate announcements. Through this construction, the framework links the performance of firms defined by their characteristics—such as size or value—to underlying economic drivers. The dimensionality reduction achieved by graded factors is thus extended to the time-series domain, enabling a systematic analysis of the determinants of the time variation of returns. The following section details the data and the empirical implementation of this approach.

In summary, the methodology developed in this section combines graded factor construction with the decomposition of factor returns into earnings and valuation components, and subsequently uses the Gordon framework to relate changes in valuation to their underlying earnings-growth and required-return components. The

theoretical framework proposes a causal mechanism linking firm characteristics to risk, required returns, repricing, and ultimately realised returns; however, given the observational nature of the data, the empirical evidence should be interpreted as consistent with this causal mechanism rather than as providing unconditional causal identification. Such a causal interpretation is conditional, in particular, on the relevant characteristics and confounding factors being adequately represented in the multivariate specification, while residual endogeneity concerns, including those arising from omitted variables, measurement error, simultaneity, and reverse causality, cannot be fully excluded.

4.4 Data and Variable Transformations

As in our previous chapter, our dataset comprises 3,000 non-banking US-listed firms from Bloomberg and MSCI, possibly the least noisy ESG scores (Berg et al., 2022). We group firms into 6-digit Global Industry Classification Standard (GICS) industry groups. The sample spans from December 2014 to June 2025, constrained by earlier changes in the methodology for the same-method environmental, social, and governance scores used to study CSR factors.

4.4.1 Characteristics and Factors

The selection of characteristics is anchored in established asset pricing frameworks. We begin with the standard set of variables associated with the Fama–French–Carhart models—namely, size, valuation, momentum, profitability, and investment (Fama & French, 2015)—and augment it by incorporating sustainability-related dimensions. Specifically, we include environmental, social, and governance attributes, yielding a total of eight characteristics and their associated graded factors.

The construction of the factors follows conventions that ensure consistent economic interpretation. For certain characteristics, higher returns are associated with lower values of the underlying variable. This is the case for size (small minus big or *SMB*), where the factor captures the return differential between smaller and larger firms, and for investment, where more conservative firms (lower reinvesting firms) are contrasted with those exhibiting higher reinvestment intensity (conservative minus aggressive or *CMA*). For the remaining variables, factor exposure increases with the level of the characteristic: higher book-to-market ratios (*BTM*) proxy for value orientation (*HML*), stronger past performance captures momentum (*UMD*), and higher operating profitability reflects firm quality (robust minus weak profitability or *RMW*).

The sustainability-related dimensions are also defined in relative terms, but their scores are moderated by the weights environmental, social, and governance issues merit in the firm in the rater’s opinion, as we defined in section 3.4. We define environmental, social, or governance profiles against those with weaker attributes as green minus brown (*GMB*), social minus unsocial (*SMU*), and well-governed

minus poorly governed firms (*WMP*). Throughout the analysis, we adopt simplified labels—size, value, momentum, profitability, investment, environmental, social, and governance—.

The empirical implementation requires constructing proxies for each characteristic using transformed variables. Logarithmic scaling is applied to account for the nonlinearity of key measures, including firm size, valuation ratios, momentum indicators based on past returns, profitability metrics, and investment intensity. The contribution of each ESG dimension is adjusted through the weighting scheme assigned by the rating provider. The environmental indicator, $G_{e,i,t}$, combines the underlying score with its associated weight, as formalised in equation 3.11. An equivalent construction is applied to derive the social and governance measures.

To ensure consistency with the estimation framework, all variables are demeaned using their cross-sectional averages. In addition, extreme observations are mitigated through winsorisation at the 1st and 99th percentiles, reducing the influence of outliers on the estimated relationships (Hou et al., 2015).

4.4.2 Statistics

Table 4.1 summarises the main descriptive statistics for each characteristic, including the underlying variable, the associated factor and its logarithmic transformation, as well as the two components derived from the decomposition—earnings and valuation multiples. It also reports the factors corresponding to the three explanatory channels: variations in the cost of capital ($dICC$), changes in growth (dg), and announcement-related returns ($dANN$).

The earnings and multiple components are constructed in accordance with the methodology outlined earlier. Earnings are measured using trailing twelve-month income before extraordinary items, while the valuation component is obtained by scaling returns by earnings. The explanatory variables underlying multiple adjustments are based on three inputs: the implicit cost of capital (ICC), growth dynamics (g), and announcement effects (ANN). The estimation of ICC is described in the following section. Growth is captured through a rolling regression over a 36-month horizon, and announcement effects are measured as abnormal returns around earnings disclosures, computed over a seven-day window centred on the announcement date (Pástor et al., 2022).

4.4.3 The Estimated Cost of Capital

The estimation of the ICC follows a residual income framework (Gebhardt et al., 2001; Hou et al., 2012). Within this approach, the price per share equals the sum of the current book value and the discounted stream of expected future residual earnings per share. The discount rate that reconciles this relationship corresponds to the firm's implied cost of equity, denoted by r_e .

Tab. 4.1.: Descriptive statistics (Part A)

	n	mean	std	min	25	median	75	max
Return variables								
rit	373390	0.105214	23.99174	-0.99992	-0.06451	0.003055	0.072248	10499
rmt	285	0.008638	0.043029	-0.16795	-0.0157	0.013889	0.035882	0.128194
reit_ann	269383	3.766908	1926.981	-212.789	-0.04973	-0.01325	0.023231	999999.4
Fundamentals variables								
At	508451	8353.95	325846.3	0	174.3295	962.603	4310.2	1.34E+08
Et	490562	411.272	2630.896	-33008	-9.71425	21.476	180.116	127161
Dt	475084	183.7831	882.86	0	0	0	45.9506	36099.64
ACt	487559	-211.964	1846.833	-123316	-94.026	-4.185	22.128	31895
Bt	508529	2781.354	32634.16	-23562	68.621	385.1	1548.7	12697311
BPS	500418	1.65E+08	2.57E+10	-2.2E+12	2.8023	8.7929	19.31428	8.23E+12
EPS	484258	-1.2E+08	1.09E+10	-1.5E+12	-0.4563	0.616	2.2	10000000
DPS	483896	0.874876	12.38432	0	0	0	0.6635	1050
PAYOUT	444239	91.90266	3857.38	0	0	0	36.3412	1199989
PX_LAST	499268	2.65E+10	4.43E+12	0.000001	9.68	23.92	53.35	1.12E+15
ICC	226196	0.111684	0.150906	-0.49773	0.061534	0.080806	0.116962	0.999962
m — size-market-cap — CUR_MKT_CAP								
Characteristic: size-market-cap	312767	12629.76	79885.6	0	236.0751	1269.135	5502.578	4340028
factor	129	0.001894	0.00763	-0.01647	-0.00238	0.00142	0.006131	0.046878
log factor	129	-0.00071	0.006656	-0.01946	-0.00444	-0.00111	0.002724	0.032791
earnings	129	-0.00203	0.00492	-0.02094	-0.00249	-0.00053	-0.0001	0.018386
multiple	129	0.002423	0.0079	-0.01269	-0.00236	0.001633	0.006846	0.031681
dICC	129	-0.0018	0.005679	-0.02187	-0.00425	-0.00142	0.001863	0.009411
dg	129	3.25E-05	0.000124	-0.00021	-5.3E-05	1.87E-05	0.00011	0.000373
dANN	129	-0.0001	0.001705	-0.00811	-0.00088	0.000111	0.000899	0.003852
v — value — BTM								
Characteristic: value	303082	0.768314	29.61607	2.77E-06	0.169088	0.368589	0.669703	10000
factor	129	0.000314	0.008386	-0.02294	-0.00528	-0.0003	0.00481	0.025283
log factor	129	0.000724	0.008402	-0.02712	-0.00504	-4.8E-05	0.005215	0.023664
earnings	129	-0.00705	0.012352	-0.07347	-0.01089	-0.00112	-0.00019	0.011934
multiple	129	0.002272	0.011195	-0.03373	-0.00437	0.001391	0.007749	0.039742
dICC	129	-0.00395	0.022576	-0.0604	-0.01613	-0.00258	0.010585	0.071322
dg	129	-0.00015	0.000154	-0.00039	-0.00026	-0.00017	-7.6E-05	0.000311
dANN	129	0.000203	0.002622	-0.01061	-0.00127	0.000127	0.001466	0.00875
u — momentum — reit_12_2								
Characteristic: momentum	236257	-2.4E+18	1.16E+21	-5.6E+23	-0.29435	-0.08062	0.135043	4.99E+21
factor	116	0.003214	0.010396	-0.02275	-0.00235	0.002776	0.008938	0.045655
log factor	116	0.001976	0.009172	-0.02635	-0.00295	0.001904	0.007316	0.030536
earnings	116	0.003946	0.010863	-0.02703	-0.00017	0.000539	0.004703	0.052263
multiple	116	0.001591	0.013545	-0.0502	-0.00439	0.001234	0.008641	0.035909
dICC	116	-2.4E-06	0.006222	-0.01821	-0.00255	-0.00015	0.002713	0.02838
dg	116	0.000136	0.000163	-0.00027	3.49E-05	0.000135	0.000215	0.000571
dANN	116	0.000749	0.003568	-0.00777	-0.002	0.000895	0.002746	0.010297
p — profitability — OPERATING_ROA								
Characteristic: profitability	303449	-126.74	5261.051	-923729	-8.053	4.0894	9.7741	2280.904
factor	129	0.002484	0.006825	-0.01468	-0.00197	0.002181	0.007241	0.023654
log factor	129	0.002853	0.006982	-0.01447	-0.00151	0.00247	0.00736	0.030195
earnings	129	-0.00824	0.019554	-0.10892	-0.01071	-0.00046	0.000476	0.071086
multiple	129	0.013404	0.023269	-0.05634	0.002215	0.006856	0.015781	0.121787
dICC	129	-0.00034	0.008165	-0.02789	-0.00528	-0.00133	0.00435	0.024566
dg	129	0.000367	0.000331	-0.00057	0.000197	0.000326	0.000561	0.00113
dANN	129	0.000896	0.003143	-0.00654	-0.001	0.00041	0.00259	0.011144

Tab. 4.1.: Descriptive statistics (Part B)

	n	mean	std	min	25	median	75	max
c — investment — CAPCFO								
Characteristic: investment	204565	1.350043	24.38919	1.57E-05	0.123249	0.297219	0.70836	4909.5
factor	129	0.003433	0.004618	-0.00878	2.71E-05	0.002966	0.007111	0.013995
log factor	129	0.003147	0.004584	-0.00771	-0.0003	0.002331	0.006988	0.015828
earnings	129	0.003389	0.008623	-0.03493	4.63E-05	0.000689	0.003805	0.041645
multiple	129	0.001771	0.009254	-0.0404	-0.00152	0.002136	0.006497	0.04388
dICC	129	-0.00449	0.005073	-0.02057	-0.00701	-0.00444	-0.00104	0.005147
dg	129	6.28E-05	0.000113	-0.00021	-1.9E-05	6.66E-05	0.000159	0.000277
dANN	129	0.001889	0.002466	-0.00394	0.000483	0.001548	0.00314	0.009749
e — environmental — ENVIRONMENTAL_PILLAR_SCORE ENVIRONMENTAL_PILLAR_WEIGHT								
Characteristic: environmental	197347	4.933423	2.140743	0	3.4	4.8	6.4	10
ENVIRONMENTAL_PILLAR_WEIGHT	197347	25.5773	17.20943	5	10	22	38	84
factor	127	-0.00028	0.011485	-0.03644	-0.00736	0.001125	0.007663	0.031945
log factor	127	-0.00033	0.01118	-0.03483	-0.00747	0.000568	0.007005	0.031932
earnings	127	0.001371	0.015832	-0.06536	-0.00045	0.000147	0.001367	0.04869
multiple	127	-0.00125	0.015698	-0.04417	-0.01011	-0.00036	0.008976	0.048796
dICC	127	1.71E-05	0.013618	-0.06886	-0.00692	8.81E-05	0.006423	0.036505
dg	127	8.17E-05	0.00034	-0.00053	-0.00012	4.73E-05	0.000208	0.00104
dANN	127	0.000611	0.005455	-0.01684	-0.00201	0.000329	0.002691	0.020396
s — social — SOCIAL_PILLAR_SCORE SOCIAL_PILLAR_WEIGHT								
Characteristic: social	197326	4.471561	1.572174	0	3.5	4.5	5.5	10
SOCIAL_PILLAR_WEIGHT	197347	39.96102	15.0181	5	27	42	53	84
factor	127	9.23E-05	0.010425	-0.02514	-0.00627	-0.00023	0.006914	0.029512
log factor	127	0.001211	0.010225	-0.02296	-0.00551	0.000731	0.007285	0.028824
earnings	127	-0.00034	0.012732	-0.02814	-0.00237	-0.00012	0.000777	0.067329
multiple	127	0.000459	0.013337	-0.03995	-0.00709	0.000495	0.007614	0.035902
dICC	127	-0.00026	0.012269	-0.03254	-0.00782	-0.00025	0.006616	0.056423
dg	127	-7.8E-05	0.000288	-0.00081	-0.00019	-4.3E-05	8.93E-05	0.000439
dANN	127	-0.00012	0.004078	-0.0151	-0.00202	-0.00038	0.001227	0.014306
g — governance — GOVERNANCE_PILLAR_SCORE GOVERNANCE_PILLAR_WEIGHT								
Characteristic: governance	197326	5.409867	1.317968	0	4.6	5.5	6.4	10
GOVERNANCE_PILLAR_WEIGHT	197347	34.46243	11.39687	5	29	35	41	73
factor	127	-0.00072	0.009015	-0.02397	-0.00612	-0.00013	0.004943	0.028756
log factor	127	-0.00027	0.008683	-0.02093	-0.00593	0.000361	0.00521	0.028207
earnings	127	0.000187	0.013219	-0.052	-0.00191	1.28E-05	0.002286	0.050248
multiple	127	-0.00056	0.01424	-0.04975	-0.00832	-0.00105	0.007185	0.054442
dICC	127	0.000699	0.008754	-0.02316	-0.00511	0.000319	0.00638	0.028781
dg	127	-4E-05	0.00022	-0.00065	-0.00011	-3.3E-05	6.76E-05	0.000541
dANN	127	1.95E-05	0.004817	-0.02209	-0.00171	0.000412	0.002266	0.013756

Note: $r_{i,t}$ denotes the total monthly return of firm i , and $r_{m,t}$ represents the corresponding market return, proxied by the S&P 500 total return index. Announcement-related returns, $re_{i,t}^{ann}$, are computed as abnormal returns over a seven-day window centred on the disclosure date, obtained by subtracting the beta-adjusted market return from the cumulative stock return over that interval.

A_t corresponds to total assets, E_t to trailing twelve-month earnings before extraordinary items, D_t to dividends paid, AC_t to accruals, and B_t to total book equity. BPS, EPS, and DPS denote per-share book value, earnings, and dividends, respectively. PAYOUT measures the dividend payout ratio, and PX_LAST indicates the share price. ICC refers to the estimated ICC, as defined in the main text.

Each factor k is associated with a specific economic characteristic, indicated in the block heading. Within each group, the reported variables include: the graded return factor; the log factor, constructed from log excess returns; an earnings-based component derived from changes in earnings; a valuation component based on non-earnings returns; and three explanatory factors capturing discount-rate variation ($dICC$), growth dynamics (dg), and announcement-driven effects ($dANN$).

Formally, residual income in each future period τ is defined as the difference between expected earnings per share at time $t + \tau$, conditional on information available at t , and the opportunity cost of capital applied to the opening book value of equity. That is, it is given by expected earnings $E_t[EPS_{i,t+\tau}]$ less r_e times $BPS_{i,t+\tau-1}$:

$$P_{i,t} = BPS_{i,t} + \sum_{\tau=1}^{\infty} \frac{E_t[EPS_{i,t+\tau} - r_e BPS_{i,t+\tau-1}]}{(1 + r_e)^\tau} \quad (4.17)$$

Rewriting equation 4.17 as a function of the return on equity, we obtain:

$$P_t = B_t + \sum_{\tau=1}^{11} \frac{E_t[(ROE_{t+\tau} - r_e) B_{t+\tau-1}]}{(1 + r_e)^\tau} + \frac{E_t[(ROE_{t+12} - r_e) B_{t+11}]}{r_e(1 + r_e)^{11}} \quad (4.18)$$

Forward-looking earnings are obtained by estimating predictive models for one-, two-, and three-year horizons, denoted by $\hat{E}_{1,i,t}$, $\hat{E}_{2,i,t}$, and $\hat{E}_{3,i,t}$. Each forecast is derived from rolling pooled regressions using a 120-month estimation window. The specification relates future earnings to contemporaneous firm characteristics, including current earnings, asset base, dividend payments, book equity, and accruals, as well as two binary variables capturing loss-making status and dividend-paying status.

These earnings forecasts are then used to construct forward accounting variables via a recursive mechanism that links profitability, payouts, and reinvestment. The expected return on equity for the next period is obtained by multiplying forecasted earnings by the expected return on equity. This measure is combined with book value per share to derive projected earnings per share, which, in turn, feeds into the evolution of book value. Specifically, future book value per share is updated by adding projected earnings and subtracting expected dividends:

$$\widehat{BPS}_{1,i,t} = BPS_{0,i,t} + \widehat{EPS}_{1,i,t} - \widehat{DPS}_{1,i,t} \quad (4.19)$$

The estimation of return on equity incorporates a set of constraints designed to stabilise the projections, as the authors cite. The payout ratio is restricted to the interval 10%-95%, while the equity base is bounded below at 6% of total assets to prevent inflated ratios arising from small denominators. To further mitigate volatility, the initial ROE estimate blends the model-implied value with the most recent realised figure, assigning weights of 70% and 30%, respectively.

This recursive structure is extended to subsequent periods. For the second horizon, the projected ROE is derived from forecasted earnings and the updated book value, and is then used to obtain forward earnings, dividends, and book value per share. The same mechanism applies to the third year, ensuring internal consistency across the projected financial statements.

Beyond the explicit forecast window, the trajectory of ROE is determined through a convergence scheme. Values for years four through eleven are obtained by interpolating between the third-period estimate and a long-run benchmark. This terminal level reflects a combination of industry-specific conditions and a steady-state assumption, defined as a weighted average of the sector median ROE (70%) and a long-term equilibrium return of 10% (30%).

The valuation equation is inverted numerically to recover the implied cost of equity r_e , using the Newton–Raphson method to obtain firm-level estimates at a monthly frequency. The resulting ICC measures are summarised in Table 4.2. Panel A reports their time-series distribution, while Panel B presents the average coefficients from annually estimated pooled regressions, along with Newey–West adjusted t-statistics.

Our estimate of future earnings confirms documented earnings persistence, enabling reliable predictions (Fama & French, 2006; Hou et al., 2012). As shown in the last column of Table 4.2 Panel A, the average adjusted R^2 for one-, two-, and three-year-ahead forecasts are 0.86, 0.76, and 0.72, respectively, and the coefficients for the regressors are all highly statistically significant, as shown in their respective columns. Across the full sample, the implied cost of capital exhibits a mean of 11.1% and a median of 8.1%, with variation across periods reflected in mean values between 9.4% and 13.1%, and median values between 7.6% and 9.1% (Table 4.2 Panel B).

With the data construction complete, the following sections of this chapter turn to the empirical results.

4.5 The Cost of Capital Relative to the Characteristics

An initial step in the analysis is to examine whether the implied cost of capital varies systematically with firm characteristics. Figure 4.1 indicates that smaller firms, the long leg of the SMB factor (*icc_long* in the figure), are consistently associated with higher discount rates than larger firms, the short leg in the figure (*icc_short*). Although the magnitude of the gap declines over time, it remains economically meaningful across the sample. Comparable patterns are observed for firms with higher valuation ratios, stronger past returns, and lower reinvestment intensity, all of which exhibit relatively elevated ICC levels. In contrast, firms characterised by higher profitability and stronger environmental profiles tend to face lower implied costs of capital, with weaker but directionally similar evidence for social and governance attributes.

With the exception of momentum—which reflects market dynamics rather than firm fundamentals—these relationships are broadly aligned with theoretical priors linking risk to required returns. Importantly, since these characteristics do not directly enter the ICC estimation procedure, the observed associations support the internal consistency of the cross-sectional variation in the inferred discount rates.

Tab. 4.2.: ICC. Regression model for earnings estimates and descriptive statistics

PANEL A. Average coefficients in the forward earnings regression estimate								
	intercept	coef_At	coef_Dt	coef_DDt	coef_Et	coef_NegEt	coef_AcT	Adj_R2
Et1	11.2448	0.0113	0.3013	-17.6702	0.8584	-7.7469	0.2751	0.8014
(t-stat)	(4.76)	(77.76)	(66.96)	(-6.85)	(219.72)	(-1.92)	(61.15)	
Et2	17.5875	0.0171	0.3677	-23.2476	0.7576	0.2581	0.2633	0.7385
(t-stat)	(6.53)	(97.36)	(66.94)	(-7.51)	(159.24)	(0.84)	(48.27)	
Et3	26.9661	0.0198	0.3491	-26.1241	0.7215	5.5375	0.1931	0.7081
(t-stat)	(9.26)	(99.63)	(55.55)	(-7.64)	(133.39)	(1.97)	(31.16)	

PANEL B. Summary statistics in the time series of ICC						
	N	Mean	Std	25%	Median	75%
2011	2,414	0.13076	0.15494	0.06985	0.09074	0.12783
2012	14,501	0.12506	0.15445	0.06712	0.08687	0.12307
2013	13,787	0.11613	0.15693	0.06180	0.07787	0.10838
2014	13,920	0.11535	0.15717	0.05958	0.07389	0.10633
2015	14,285	0.11913	0.16390	0.05957	0.07605	0.11523
2016	15,147	0.12625	0.17116	0.06092	0.07859	0.12318
2017	15,888	0.12292	0.17555	0.05978	0.07616	0.11446
2018	16,879	0.11583	0.14921	0.06255	0.08215	0.11872
2019	17,208	0.11665	0.15523	0.06275	0.08417	0.12241
2020	16,766	0.11824	0.14960	0.06317	0.08568	0.12847
2021	16,327	0.09553	0.11678	0.05893	0.07750	0.11007
2022	18,962	0.10101	0.11407	0.06242	0.08336	0.11952
2023	18,946	0.10065	0.11504	0.06222	0.08408	0.11832
2024	18,481	0.09354	0.11375	0.06083	0.08124	0.11007
2025	12,685	0.09356	0.11164	0.06102	0.08138	0.11443
Full Sample	226,196	0.11117	0.14441	0.06153	0.08081	0.11696

Note: As described in the main text, the ICC is estimated as the long-term implicit rate of return that equates the market price of a firm's shares to the present value of expected future residual incomes from year one onward to infinity. Residual income is estimated using forecasts of future earnings obtained from pooled regressions on A_t (assets), D_t (dividends), DD_t (an indicator for dividend-paying firms), E_t (most recently reported earnings), $NegE_t$ (an indicator for negative earnings), and AC_t (accruals), as reported in Panel A. Newey–West t-statistics are reported beneath each coefficient. Panel B presents descriptive statistics for the resulting ICC estimates by year.

Extending the analysis to factor construction, replacing realised returns with ICC preserves the interpretation of the factors as marginal effects of characteristics. The resulting estimates suggest that firms with larger size, growth orientation, stronger profitability, and higher environmental scores are associated with lower required returns. However, the evidence for social and governance dimensions points in the opposite direction, while the patterns for investment intensity and momentum remain inconclusive over time.

4.6 Factor Returns

Table 4.3 provides evidence from univariate factor estimates, highlighting a pronounced and highly significant return premium associated with lower investment intensity ($t = 9.2$) - in Panel A, in the 'investment' column. The economic magnitude is considerable, amounting to 0.0034, that is 34 basis points per month, or approximately 4.2% on an annualised basis. Firms with higher profitability and momentous firms also display stronger performance, with a more moderate effect observed for smaller firms.

Anticipating the subsequent decomposition, Panel B reports factors computed using log returns. In general, the two specifications yield comparable results in terms of direction and scale. Notable differences arise, however, from the transformation: the use of logarithms attenuates return dispersion, leading to a reversal in the size effect and a reduction in its statistical significance, while modestly amplifying the magnitude and significance of the social factor.

At the firm level, the cross-sectional relationships among characteristics are generally weak, as reported in Table 4.4 Panel A. Across the 129-month sample, only one pair exhibits a pronounced association: environmental and social attributes display a substantial negative correlation ($\rho = -0.52$). A more moderate inverse relationship is observed between environmental and governance measures ($\rho = -0.38$), while size shows a positive but limited association with momentum ($\rho = 0.26$).

In contrast to the firm-level results, correlations among factors are more pronounced, reflecting the aggregation inherent in their construction (Table 4.4 Panel B). With eight explanatory dimensions condensed into a smaller set of signals, stronger comovement is both expected and observed. In addition to the relationships inherited from the underlying characteristics—such as those linking ESG dimensions and the size–momentum pair—the value factor exhibits substantial negative associations with higher profitability ($\rho = -0.55$), lower investment intensity ($\rho = -0.54$), and environmental exposure ($\rho = -0.57$).

These relationships are consistent with an interpretation of value firms as more mature, less profitable, and more capital-intensive entities, often tied to legacy technologies with higher environmental impact, as documented in prior work (Jagannathan et al., 2025). However, two patterns deviate from this intuition. First, value shows a positive association with social metrics ($\rho = 0.50$). Second, profitability and lower investment intensity are positively related ($\rho = 0.41$), which

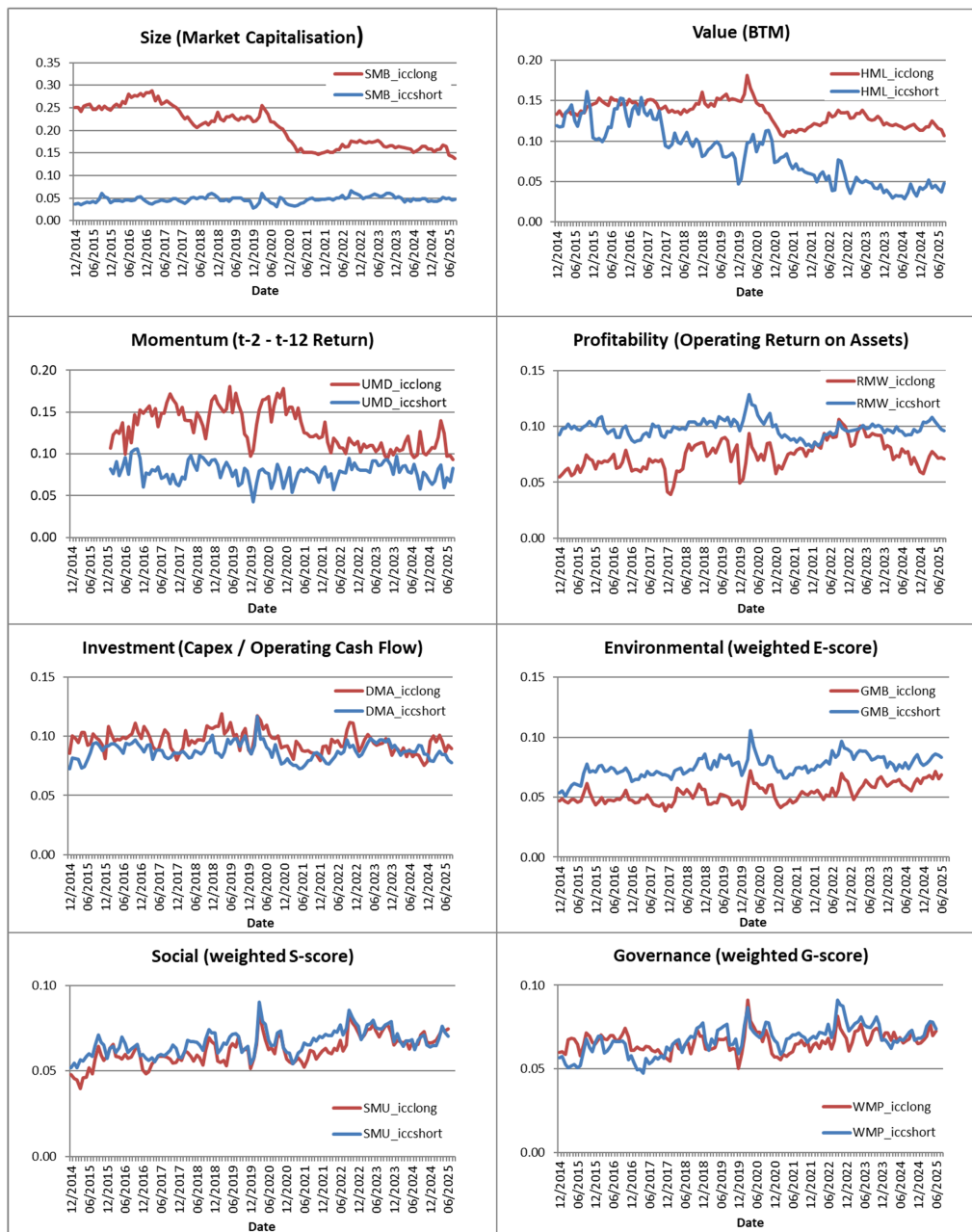


Fig. 4.1.: ICC of the upper and bottom sample terciles

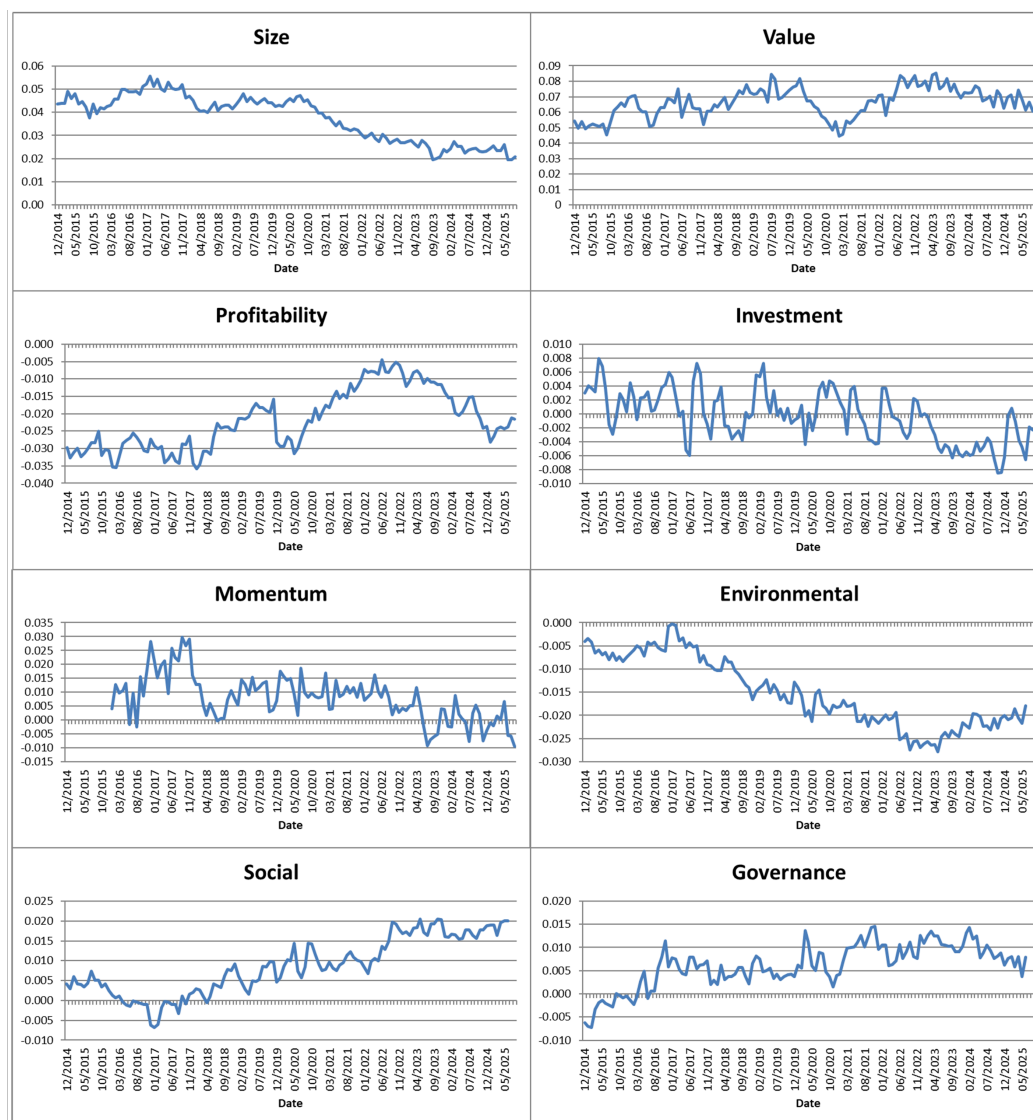


Fig. 4.2.: ICC factors (additional percentage points cost of capital per unit of the characteristic)

may reflect structural shifts in the sample period, potentially linked to phases of innovation and technological transition (Table 4.4 Panel B).

The presence of strong interdependencies among factors points to the need to consider joint effects, motivating the multivariate framework employed in the subsequent analysis. Evidence from Table 4.3, Panel C, shows that the investment factor loses a substantial portion of its explanatory content once other characteristics are introduced, largely reflecting its overlap with profitability. Importantly, this adjustment does not materially weaken the contribution of the remaining factors, despite their mutual correlations.

The temporal behaviour of the value factor warrants particular attention (Table 4.3, Panel E). With the exception of the 2016–2020 interval — corresponding to the rolling windows ending in 2019 and 2020 — the series suggests a pattern of moderate yet persistent outperformance. This evidence contrasts with the widely held view of a sustained underperformance of value strategies over the sample period.

The behaviour of ESG-related factors further illustrates the multidimensional nature of firm characteristics. The social dimension retains a positive, economically meaningful effect even after controlling for value, despite the strong association between the two. The environmental factor also contributes positively, although its statistical significance is confined to within-sector variation (Table 4.3, Panel D).

Including all eight characteristics simultaneously does not indicate overparameterisation. Diagnostic measures indicate that multicollinearity remains limited. The variance inflation factors (VIF) remain low across the sample, with average values between 0.69 and 2.04 and a maximum of 2.9, well below conventional thresholds (i.e. 5 for 'moderate' and 10 for 'severe' variance inflation). Similarly, the condition number of the cross-sectional moment matrix remains moderate, averaging 30 and peaking at 50, far from levels typically associated with collinearity (100 for limited, and 10,000 for severe collinearity). These results support the stability of the multivariate specification.

4.7 Earnings and the Price-Earnings Factor

Decomposing returns into realised earnings and valuation components within a multivariate setting reveals that factor performance reflects the interaction of these two forces. Evidence from Panels A and B of Table 4.5 shows that firms exhibiting stronger earnings trends — typically larger, growth-oriented, lower-profitability, low-investment, and environmentally weaker firms — tend to experience offsetting effects through contraction in valuation multiples.

At the aggregate level (Table 4.5, Panel C), the relative outperformance of smaller firms (second column in the table, row marked as 'Returns'), amounting to approximately 10% over the full sample, is driven by a substantial divergence between components: cumulative earnings contribute negatively (-58%), marked as 'Earnings'

Tab. 4.3.: Significance and stability of graded factors - excess returns per unit of the underlying characteristic

PANEL A - Univariate factors								
3-year to	size	value	momentum	profitability	investment	environmental	social	governance
2015-2025 (t-stat)	0.0019 (2.40)	0.0003 (0.33)	0.0032 (2.98)	0.0025 (4.09)	0.0034 (9.23)	-0.0003 (-0.26)	0.0001 (0.12)	-0.0007 (-0.96)
PANEL B - Univariate factors (logged returns)								
3-year to	size	value	momentum	profitability	investment	environmental	social	governance
2015-2025 (t-stat)	-0.0007 (-1.06)	0.0007 (0.81)	0.0020 (2.07)	0.0029 (4.56)	0.0032 (8.25)	-0.0004 (-0.32)	0.0012 (1.24)	-0.0003 (-0.40)
PANEL C - Multivariate factors (logged returns)								
3-year to	size	value	momentum	profitability	investment	environmental	social	governance
2015-2025 (t-stat)	0.0009 (1.63)	0.0009 (1.07)	0.0019 (1.43)	0.0005 (0.57)	0.0026 (5.06)	0.0006 (0.43)	0.0017 (2.47)	0.0012 (1.32)
PANEL D - Multivariate factors - within characteristic								
3-year to	size	value	momentum	profitability	investment	environmental	social	governance
2015-2025 (t-stat)	0.0007 (1.15)	0.0015 (1.73)	0.0022 (1.55)	0.0008 (0.95)	0.0029 (6.63)	0.0015 (1.64)	0.0008 (1.00)	0.0018 (1.76)
PANEL E - Multivariate factors (logged returns) - three-year rolling periods								
3-year to	size	value	momentum	profitability	investment	environmental	social	governance
2017 (t-stat)	0.0005 (0.81)	0.0014 (1.05)	-0.0009 (-1.58)	0.0014 (1.17)	0.0028 (2.56)	-0.0001 (-0.05)	0.0016 (1.51)	0.0014 (1.01)
2018 (t-stat)	0.0005 (0.78)	0.0006 (0.55)	0.0012 (0.58)	-0.0004 (-0.32)	0.0029 (3.35)	0.0018 (1.12)	0.0018 (1.76)	0.0033 (1.65)
2019 (t-stat)	0.0003 (0.45)	-0.0002 (-0.21)	0.0035 (1.29)	-0.0003 (-0.20)	0.0018 (1.76)	0.0017 (1.05)	0.0018 (1.69)	0.0033 (1.68)
2020 (t-stat)	0.0009 (1.13)	-0.0017 (-1.19)	0.0035 (1.10)	-0.0015 (-0.96)	0.0022 (1.96)	0.0020 (1.07)	0.0014 (0.95)	0.0025 (1.19)
2021 (t-stat)	0.0018 (2.28)	-0.0008 (-0.49)	0.0010 (0.42)	0.0000 (0.02)	0.0013 (1.24)	0.0010 (0.56)	0.0019 (1.19)	-0.0006 (-0.40)
2022 (t-stat)	0.0004 (0.29)	0.0010 (0.46)	0.0024 (0.84)	-0.0005 (-0.35)	0.0031 (3.56)	-0.0024 (-0.73)	0.0012 (0.82)	0.0002 (0.13)
2023 (t-stat)	0.0007 (0.53)	0.0036 (2.17)	0.0022 (0.81)	0.0011 (0.97)	0.0031 (3.96)	-0.0021 (-0.63)	0.0018 (1.87)	0.0008 (0.59)
2024 (t-stat)	0.0005 (0.37)	0.0026 (1.51)	0.0036 (1.34)	0.0004 (0.28)	0.0035 (5.47)	-0.0007 (-0.20)	0.0018 (1.85)	0.0019 (1.65)
2025 (t-stat)	0.0021 (2.57)	0.0014 (1.05)	0.0006 (0.55)	0.0021 (1.20)	0.0030 (4.19)	0.0033 (1.88)	0.0013 (1.16)	-0.0003 (-0.20)
2015-2025 (t-stat)	0.0009 (1.63)	0.0009 (1.07)	0.0019 (1.43)	0.0005 (0.57)	0.0026 (5.06)	0.0006 (0.43)	0.0017 (2.47)	0.0012 (1.32)

Note: The table exhibits average graded factor returns for each of the characteristics under different assumptions in each of the Panels. Panels A and B calculate univariate factors with raw returns and returns proxied by $\log(1 + \text{returns})$, respectively; Panels C and D calculate multivariate and multivariate within-sector returns, that is, relative to the average in the sector to which the firm belongs under the GICS classification; Panel E shows the factors for different sub-periods in the sample.

The size and investment factors are measured on a low-to-high scale, with higher values indicating over-performance by smaller, low-reinvestment firms. Under each return figure, the table shows the t-statistic with Newey-West standard errors. In Panel E, the years indicate the ending year of the 3-year calendar period for which the average excess returns per unit of the characteristic are shown. Under each average factor value is its t-stat.

Tab. 4.4.: Correlations

	size	value	momentum	profitability	investment	environmental	social	governance
size-market-cap								
value	0.173							
momentum	0.263	-0.108						
profitability	-0.111	-0.388	0.078					
investment	0.065	-0.149	0.056	0.243				
environmental	-0.105	-0.217	-0.008	0.021	0.179			
social	-0.101	0.157	-0.084	-0.055	-0.156	-0.521		
governance	-0.021	0.014	-0.016	0.053	-0.075	-0.379	-0.083	

	size	value	momentum	profitability	investment	environmental	social	governance
size-market-cap								
value	0.064							
momentum	0.489	-0.264						
profitability	-0.237	-0.548	0.092					
investment	-0.034	-0.540	0.147	0.405				
environmental	-0.125	-0.568	0.026	0.102	0.541			
social	-0.252	0.498	-0.241	-0.038	-0.494	-0.807		
governance	-0.125	0.145	-0.049	0.135	-0.275	-0.446	0.203	

Note: Firm-level correlations are the average of cross-sectional monthly correlations during the period. Market-level factor correlations are the correlations of the time series.

in the table, while valuation effects contribute positively (134%), marked as 'Multiple'. Similar patterns emerge for other characteristics. In particular, firms with high profitability and strong environmental profiles benefit from sizeable valuation-driven gains, whereas firms with lower investment intensity exhibit negative contributions from multiple adjustments.

Both components display strong statistical significance and temporal stability. Once realised earnings are accounted for, variation in the multiple captures shifts in expectations, either through anticipated cash flows or discount-rate adjustments. This makes the price-earnings component central to the subsequent analysis. Overall, the evidence indicates that, during the sample period, valuation expansion is associated with smaller firms, value orientation, high profitability, intensive investment, and stronger ESG profiles.

4.8 The Time Series and the Causal Channels

4.8.1 Explanatory Variables and Characteristics

Variations in valuation multiples can be attributed to shifts in expected cash flows or to changes in discount rates. The latter are proxied by the implied cost of capital (ICC), which serves as a forward-looking measure of required returns. To capture the evolution of cash flow expectations, the analysis incorporates two

Tab. 4.5.: Factor returns: earnings and price-earnings components

PANEL A - Multivariate earning factors								
	size	value	momentum	profitability	investment	environmental	social	governance
2015-2025	-0.0076	-0.0084	0.0067	-0.0206	0.0068	-0.0090	-0.0012	-0.0012
(t-stat)	(-6.54)	(-5.60)	(6.24)	(-5.48)	(5.81)	(-4.13)	(-0.92)	(-0.66)

PANEL B - Multivariate price-earnings factors								
	size	value	momentum	profitability	investment	environmental	social	governance
2015-2025	0.0076	0.0071	-0.0047	0.0139	-0.0035	0.0079	0.0019	0.0025
(t-stat)	(6.22)	(3.88)	(-2.75)	(3.66)	(-2.61)	(3.57)	(1.25)	(1.26)

PANEL C - Cumulative factors of returns, earnings and price-earnings multiple (multivariate)								
2015-2025	size	value	momentum	profitability	investment	environmental	social	governance
Returns	0.1011	0.1077	0.2294	0.0489	0.3398	0.0571	0.2059	0.1386
Earnings	-0.5829	-0.6282	1.1119	-0.9170	1.1532	-0.6519	-0.1330	-0.1533
Multiple	1.3449	1.1861	-0.4260	3.4251	-0.3331	1.3706	0.2253	0.2949

PANEL D - Multivariate price-earnings multiple factors (time series)								
3-year to	size	value	momentum	profitability	investment	environmental	social	governance
2017	0.0061	0.0077	-0.0091	0.0183	-0.0023	0.0069	0.0017	0.0044
(t-stat)	(3.94)	(3.12)	(-4.68)	(2.78)	(-0.83)	(2.09)	(1.08)	(0.83)
2018	0.0057	0.0045	-0.0036	0.0081	-0.0038	0.0070	0.0031	0.0026
(t-stat)	(4.16)	(1.82)	(-1.15)	(1.09)	(-1.70)	(2.34)	(1.95)	(0.68)
2019	0.0053	0.0026	-0.0021	0.0080	-0.0027	0.0043	0.0023	0.0043
(t-stat)	(3.65)	(0.99)	(-0.60)	(1.01)	(-1.20)	(1.11)	(1.31)	(1.12)
2020	0.0043	0.0022	-0.0016	-0.0006	-0.0044	0.0029	-0.0007	-0.0001
(t-stat)	(2.90)	(0.86)	(-0.39)	(-0.09)	(-2.14)	(0.80)	(-0.23)	(-0.02)
2021	0.0092	0.0085	-0.0068	0.0135	-0.0065	0.0098	0.0006	-0.0023
(t-stat)	(3.02)	(2.74)	(-2.15)	(2.56)	(-2.69)	(1.71)	(0.16)	(-0.78)
2022	0.0084	0.0094	-0.0058	0.0110	-0.0049	0.0135	-0.0005	-0.0004
(t-stat)	(2.72)	(3.19)	(-1.58)	(1.93)	(-1.96)	(2.88)	(-0.12)	(-0.12)
2023	0.0095	0.0149	-0.0049	0.0192	-0.0033	0.0127	0.0024	0.0028
(t-stat)	(3.33)	(4.49)	(-1.62)	(3.17)	(-1.14)	(2.60)	(0.77)	(0.67)
2024	0.0070	0.0109	-0.0038	0.0180	-0.0005	0.0074	0.0009	0.0058
(t-stat)	(3.99)	(3.34)	(-1.17)	(2.46)	(-0.23)	(2.18)	(0.39)	(1.86)
2025	0.0104	0.0077	-0.0056	0.0257	-0.0017	0.0076	0.0041	0.0053
(t-stat)	(7.78)	(1.71)	(-3.28)	(3.72)	(-0.69)	(3.06)	(1.76)	(1.68)
2015-2025	0.0076	0.0071	-0.0047	0.0139	-0.0035	0.0079	0.0019	0.0025
(t-stat)	(6.22)	(3.88)	(-2.75)	(3.66)	(-2.61)	(3.57)	(1.25)	(1.26)

Note: The table shows average and cumulative graded factor returns and their t-statistics by characteristic for different components of returns. Panel A shows the average factor returns for realised earnings growth of each characteristic in a multivariate analysis; Panel B shows the average factor returns for the price-earnings multiple component in a multivariate analysis; Panel C shows the cumulative factor returns for the full period of the sample and their decomposition into realised earnings growth and multiple changes, which proxies repricing; Panel D details the time series of the multiple component in the three-year subperiods within the sample for enhanced reliability of the estimated averages. The corresponding t-statistics are displayed beneath.

additional variables: changes in earnings trajectories and announcement-related returns, reflecting the immediate market response to new information.

The evidence indicates that, on average, firms characterised by smaller size, value orientation, lower investment intensity, and stronger ESG profiles experience declines in their implied cost of capital relative to the cross-sectional mean (Table 4.6, Panel A). In terms of size, the estimated reduction amounts to approximately 19 basis points per month, translating into an annualised decrease of 2.3%. This effect is statistically significant at conventional levels ($t = -2.90$).

Relative to the cross-section, changes in growth expectations are more pronounced for firms characterised by higher BTM (value), stronger past performance (momentum), and greater profitability, whereas no comparable acceleration is observed for smaller firms or for those with stronger ESG attributes. Market reactions to corporate disclosures, captured through announcement returns, are generally positive across characteristics, although statistically robust effects are concentrated among smaller firms and, to a lesser extent, among momentum, low-investment, and well-governed firms.

To assess the relative importance of the three channels, their cumulative contributions are constructed by aggregating monthly effects over the sample horizon. Each contribution is obtained by combining the estimated time-series sensitivity of the multiple with the realised value of the corresponding variable in each period. Independent of statistical significance at the monthly frequency, the overall variation associated with discount-rate changes ($dICC$) and announcement effects ($dANN$) tends to exceed that of growth dynamics (dg), with the exception of value and profitability (Table 4.6, Panel B).

Tab. 4.6.: Multiple factor and factors for the explanatory variables

PANEL A. Factor averages - size of the effect and statistical significance 2015-2025								
	size	value	momentum	profitability	investment	environmental	social	governance
Multiple	0.0076	0.0071	-0.0047	0.0139	-0.0035	0.0079	0.0019	0.0025
(t-stat)	(6.22)	(3.88)	(-2.75)	(3.66)	(-2.61)	(3.57)	(1.25)	(1.26)
dICC factor	-0.0019	-0.0089	0.0015	-0.0008	-0.0052	-0.0040	-0.0028	-0.0031
(t-stat)	(-2.90)	(-3.37)	(2.34)	(-0.49)	(-8.99)	(-3.59)	(-2.84)	(-2.61)
dg factor	0.0000	0.0002	0.0001	0.0005	0.0000	0.0000	0.0000	0.0000
(t-stat)	(-0.92)	(2.54)	(7.13)	(4.33)	(-1.05)	(0.47)	(0.06)	(-0.10)
dANN factor	0.0035	0.0002	0.0028	-0.0007	0.0011	0.0012	0.0008	0.0017
(t-stat)	(3.47)	(0.42)	(2.57)	(-1.22)	(2.28)	(1.27)	(2.15)	(2.32)

PANEL B. Compounded cumulative contribution to the multiple's monthly variations 2015-2025								
	size	value	momentum	profitability	investment	environmental	social	governance
Multiple effect	1.3449	1.1861	-0.4260	3.4251	-0.3331	1.3706	0.2253	0.2949
dICC effect	0.2471	0.1603	-0.1924	0.0660	0.3526	0.5552	0.2500	0.2680
dg effect	0.0462	-0.1620	-0.1077	-0.4173	0.0205	-0.0246	-0.0011	0.0031
dANN effect	0.3389	0.0129	0.3308	-0.1214	0.0949	0.0946	0.0945	0.0959

Note: This table shows the average repricing factor returns (i.e. the price-earnings multiple factor returns) and the factor returns of their explanatory variables during the sample period. Panel A shows the average factor returns for the multiple components and the three explanatory variables. Statistical significance is represented by the t-statistics computed with Newey–West adjusted standard errors. Panel B provides the cumulative effect of each variable on the multiple during the full period. These cumulative contributions are constructed by compounding period-by-period effects, where each monthly contribution is approximated by combining the estimated time-series factor with the realised value of the corresponding variable.

Tab. 4.7.: Regression model summary by characteristic — multivariate factors

	(1) size	(2) value	(3) momentum	(4) profitability	(5) investment	(6) environmental	(7) social	(8) governance
Dep. variable	multiple	multiple	multiple	multiple	multiple	multiple	multiple	multiple
Intercept	0.0026	0.0072	-0.0044	0.0191	-0.0071	0.0033	-0.0009	-0.0005
(t-stat)_const	(2.33)	(4.03)	(-2.38)	(3.96)	(-4.50)	(2.22)	(-0.71)	(-0.28)
dICC	-1.0278	-0.1477	-1.2195	-0.7930	-0.5160	-0.9935	-0.7020	-0.6945
(t-stat)_dICC	(-6.48)	(-1.61)	(-6.43)	(-4.01)	(-2.22)	(-3.72)	(-4.61)	(-2.72)
dg	-13.5727	-8.6547	-6.7860	-9.8322	-9.7575	-6.6815	-5.5027	-6.3844
(t-stat)_dg	(-2.94)	(-1.80)	(-0.66)	(-2.01)	(-1.38)	(-1.50)	(-0.88)	(-0.86)
dANN	0.7414	0.5237	0.9278	1.4611	0.7155	0.6703	0.9427	0.4826
(t-stat)_dANN	(5.88)	(1.62)	(8.35)	(3.69)	(2.90)	(3.84)	(2.86)	(2.46)
N	114.0000	114.0000	114.0000	114.0000	114.0000	114.0000	114.0000	114.0000
Adj. R ²	0.4196	0.0491	0.5031	0.1643	0.1189	0.3169	0.2988	0.2023
F-stat	15.5112	2.6437	50.2655	10.9141	6.7046	8.7444	16.1819	8.7537
df(F)	(3, 110)	(3, 110)	(3, 110)	(3, 110)	(3, 110)	(3, 110)	(3, 110)	(3, 110)

Note: The table shows the regressions of each characteristic-based repricing return on the explanatory variables: changes in the cost of capital *dICC*, changes in the growth trends *dg*, and announcement returns *dANN*. Each column corresponds to a separate regression estimated for the valuation component associated with a given characteristic. The reported values include the constant term and the estimated sensitivities to the explanatory variables. Measures of statistical significance, based on t-statistics, are shown in parentheses beneath each estimate.

4.8.2 ICC's and Growth's Explanatory Power

Focusing first on the role of discount-rate variations, the estimates reported in Table 4.7 exhibit the anticipated negative relationship between changes in the cost of capital and valuation multiples. The coefficients are strongly significant for most characteristics—including size, momentum, profitability, and ESG dimensions ($|t| > 3$) — while remaining moderately significant for investment ($t = -2.2$) and governance ($t = -2.7$). The effect associated with value is comparatively weaker and does not reach conventional levels of statistical significance ($t = -1.6$). Economically, this pattern indicates that reductions in required returns contribute to valuation gains, particularly for smaller firms.

Regarding announcement-driven effects, these variables correspond directly to realised abnormal returns and are therefore expected to load positively on valuation changes, with coefficients approaching one. The empirical results are consistent with this intuition, showing robust and statistically significant relationships across the same set of characteristics identified for discount-rate effects. This confirms that announcement-related returns play a meaningful role in explaining variation in multiples.

The behaviour of the growth channel differs from prior expectations. An acceleration in earnings dynamics ($dg > 1$) would normally be associated with an expansion in valuation multiples. However, the estimated coefficients are predominantly negative and are less statistically significant than those for the other explanatory variables. This pattern suggests that improvements in growth prospects are, on average, offset through adjustments in valuation, with markets incorporating stronger earnings trajectories by compressing relative multiples rather than allowing them to translate directly into higher returns. In contrast, valuation responses are strongly positive

only in the presence of new information, as captured by announcement-related returns.

To ensure that this result is not driven by interaction effects between the two growth-related variables, the explanatory variables are introduced sequentially. The estimates for the growth component remain largely unchanged in terms of sign, magnitude, and statistical significance when considered in isolation, indicating that its limited explanatory power is not subsumed by announcement effects (see B).

4.9 Discussion

The empirical analysis focuses on five firm characteristics widely studied in asset pricing, supplemented by ESG dimensions as proxies for corporate social responsibility. At the firm level, correlations among these variables are limited, yet their aggregation into factors generates substantially stronger co-movement. To capture their joint influence, our model adopts a multivariate framework based on cross-sectional slopes, enabling the marginal contribution of each characteristic to be systematically and internally consistently identified. This contrasts with traditional sorting-based methodologies, where variables are introduced sequentially through portfolio partitions and averages (Fama & French, 2015; Hou et al., 2018). The availability of modern computational resources makes it simple to implement this approach on large datasets, offering a more integrated representation of the full cross-section, rather than partition-based averages.

In the univariate model, when characteristics are considered individually, the results align with established findings. Profitability and investment emerge as key drivers of performance, with higher profitability and lower reinvestment intensity associated with stronger returns. These patterns are typically interpreted within valuation frameworks in which such variables proxy for underlying state variables governing expected cash flows and discount rates (Harvey et al., 2016; Hou et al., 2018).

However, as the analysis advances to a multivariate framework, the role of profitability differs from that reported in prior studies (Fama & French, 2015). Its explanatory contribution diminishes once other characteristics are jointly considered, likely reflecting its close association with investment. Setting aside momentum — which reflects past price behaviour rather than underlying risk — both size and value continue to exert a limited but persistent influence on returns.

The inclusion of ESG-related dimensions yields results that are comparable in terms of stability and statistical significance. Although existing research has primarily focused on environmental factors (Bolton & Kacperczyk, 2023; Pástor et al., 2022) or on the ESG consideration by long-term investors Starks et al., 2026, we have not found a prior analysis that encompasses all three environmental, social, and governance factors. Our tests indicate that the environmental dimension operates largely through sector-specific effects and contributes meaningfully when evaluated within industries. More broadly, all three ESG dimensions are associated with

positive returns at the factor level, corroborating earlier firm-level findings (Krueger et al., 2020; Vasenin et al., 2026).

Consistent with prior evidence, realised short-term returns provide a weak and often inversely related signal of long-term required returns. This relationship was first documented through the negative association between short- and long-horizon realised returns (Cochrane, 2011), and later by the also negative correlation between short-term realised returns and ICC, which proved to be a more reliable forward-looking measure of the required returns (Hou et al., 2012). Our analysis extends this validation by linking factor-based return patterns to variations in the implied discount rate, showing that characteristics associated with lower risk systematically align with lower ICC estimates and that these estimates carry explanatory power for return dynamics.

Building on the insight that fluctuations in required returns dominate changes in expected growth in driving asset prices (Cochrane, 2011; Golez & Koudijs, 2025), the proposed framework adopts a more direct approach to the explanatory variable by incorporating the ICC into the analysis of valuation multiples rather than relying on forward realised returns. Second, we base our analysis on the price-earnings multiple, which is a more broadly applicable proxy than the traditional dividend yield, given the increasing proportion of non-dividend-paying firms and the growing importance of share buybacks (DeAngelo et al., 2025; Golez & Koudijs, 2025). Third, our model replaces long-term analyst forecasts as proxies for changes in expected growth with earnings trend changes, a slow-moving channel, and announcement-related returns, which capture the market's immediate response to new information and have previously been used in the literature in firm-level analyses (Pástor et al., 2022). And, lastly, benefiting from the greater stability of aggregated returns, relative to noisier firm-level returns, we conduct our analysis at the factor level.

Our findings are consistent with the prior literature in highlighting the dominance of required returns as the main causal channel. At the same time, unlike previous work, our results show that expected growth is a statistically and economically meaningful source of time variation in prices through the immediate channel of announcement returns. These effects also have a lasting, meaningful influence on long-term returns. Finally, our study relates repricing returns to firm characteristics, linking shifts in investor preferences to changes in the cross-section of returns over time.

In summary, the graded factor framework provides a coherent solution to the multidimensional nature of cross-sectional asset pricing, allowing the sources of excess returns associated with specific firm attributes to be identified and interpreted (Cochrane, 2011). By integrating these cross-sectional insights with a structured analysis of time-series drivers, the approach establishes a unified link between characteristics and the mechanisms that govern return dynamics.

4.10 Conclusion

The analysis of five established factors alongside three ESG dimensions reveals that their effects are highly interdependent, making an objective, jointly estimated framework essential for reliable inference. Within this setting, investment intensity — captured by lower reinvestment — emerges as a key determinant of performance during the 2015–2025 period, exceeding the explanatory power traditionally attributed to profitability. At the same time, characteristics such as size, valuation, and ESG attributes continue to exert a meaningful, albeit more moderate, influence on return variation.

Decomposing returns into realised earnings and valuation adjustments highlights the central role of repricing in shaping observed performance. Once the contribution of earnings growth is removed, changes in valuation multiples provide a direct measure of expectation-driven effects. The results indicate that shifts in required returns are the dominant force behind these adjustments, while revisions in growth expectations primarily affect them through discrete information events. In particular, announcement-related shocks generate immediate and persistent valuation changes, whereas gradual modifications in growth trajectories are largely internalised within pricing and do not translate into distinct return effects.

From a conceptual standpoint, the information-reducing properties of factors make them efficient metrics of underlying economic mechanisms. Despite their evolving nature, their empirical stability and explanatory power justify their continued use in asset pricing. The framework proposed in this study extends existing approaches by providing a systematic, internally consistent method for estimating multiple interacting factors while consistently linking cross-sectional patterns to their time-series drivers. This integration allows for a more comprehensive understanding of the origins of return variation.

From a practical perspective, the proposed framework has several implications for investment analysis. By decomposing returns into earnings- and valuation-driven components linked to firm characteristics, it enables a more nuanced assessment of investment opportunities, particularly when realised performance diverges from the expected returns implied by underlying risk exposures. It also supports more coherent multifactor risk attribution and provides a foundation for extending characteristic-based approaches to hedging strategies in a cross-sectional setting.

In this context, prior research has cautioned that reported *alpha* may in fact reflect unobserved factor exposures that can be identified with more structured models and enhanced computational methods (Cochrane, 2011). Building on the evidence that short-horizon realised returns are unreliable proxies for required returns, the findings further suggest that standard mean–variance frameworks may require reconsideration.

Beyond asset pricing, the proposed framework has direct implications for corporate finance and managerial decision-making, particularly in the valuation of projects, assets, and firms. By reinforcing the empirical credibility of the implicit cost of capital

as a measure of required returns, the analysis in this chapter calls for more accurate estimation of discount rates. Extending this approach to incorporate characteristic-based variations in ICC can enhance the precision of valuation practices, supporting investment appraisal, the fair-value assessment of illiquid assets, and firm-level valuation exercises.

In accounting applications, especially those involving fair-value adjustments, distinguishing the underlying sources of valuation changes becomes critical. Decomposing asset revaluations into components driven by expected cash flows, aggregate shifts in discount rates, or characteristic-specific risk adjustments can lead to materially different managerial responses. At a broader level, improved identification and interpretation of firm attributes can contribute to more coherent assessments of emerging factors, informing both regulatory perspectives and the evolution of investor preferences.

The analysis draws on a rich dataset that combines detailed accounting information with ESG indicators for US firms, sourced from reputable data providers. Nonetheless, several limitations should be acknowledged. The relatively recent and evolving nature of ESG metrics constrains the length of the available time series, and differences in rating methodologies across providers introduce an additional source of measurement variation (Berg et al., 2022). Moreover, the focus on firms within a single institutional setting limits the generalisability of the results, as alternative regulatory and cultural environments may yield different patterns. Future research extending the analysis to other jurisdictions would provide a useful test of the robustness of the findings (Breuer et al., 2018). Finally, although the sample period exceeds a decade and supports several structural conclusions, certain results—particularly those related to factor performance—are likely sensitive to shifts in market conditions and investor sentiment.

Taken together, the evidence presented advances the understanding of asset pricing by integrating cross-sectional and time-series perspectives. In doing so, it contributes to the development of a more unified and economically grounded framework for investment analysis and valuation.

Conclusion

This thesis set out to address a central question in asset pricing: whether corporate social responsibility (CSR) drives asset risk and returns, and how CSR and other risk-bearing firm-defining characteristics can be modelled consistently across the cross-section of firms and over time.

5.1 The Challenges

These questions arise in a context where the literature remains fragmented. CSR has been studied extensively in relation to both risk and returns, yet conclusions regarding returns are conflicting, while those regarding risk are often conditional on specific metrics or particular settings.

More broadly, the link between the wider set of firm characteristics and realised risk and returns remains highly dependent on modelling choices. Factor investing provides a framework for consolidating returns, benefiting from information reduction and greater stability, but it remains contested. Model choices, disrupted weightings, selective reporting, and the disconnect between time-series and cross-sectional approaches have been widely documented. We add to these concerns the need for a more appropriate treatment of interactions. Taken together, these concerns signal a fragile model construction and limit the ability to provide a unified interpretation of asset pricing mechanisms consistent with the theory.

5.2 Results and Contributions

The empirical results of this thesis respond to these challenges. First, the analysis of CSR and risk establishes a robust relationship between CSR and risk measures across model specifications and periods. Simple, model-free metrics, such as partial lower momentum or idiosyncratic volatility, are parsimonious and effective approaches to risk measurement. However, this robustness does not extend to realised returns, more volatile and context-dependent.

Second, the thesis proposes a new framework for factor construction based on graded factors defined as cross-sectional slopes. This approach departs from traditional portfolio sorting, avoiding the arbitrariness of segment definitions and the amplification of extreme portfolios. The results show that segment-based methods tend to overstate effects and are highly sensitive to modelling choices. In contrast, the graded framework provides a more stable and objective representation of factor returns and incorporates interactions structurally. These interactions prove critical:

size exhibits a stable premium-like behaviour, while value and green factors reflect episodic preference shifts rather than persistent premia.

Third, it develops a causal time-series analysis by decomposing returns into earnings and price–earnings multiple components within the graded framework. Under the proposed model and its identifying assumptions, the decomposition enables a clearer analysis of return drivers. The results are consistent with a central role for required returns, proxied by the implicit cost of capital, in explaining variations in valuation multiples. Announcement-related returns serve as a key channel for incorporating new information, while gradual changes in growth trends are largely reflected in valuation. Accordingly, within our model specification, returns appear to be driven primarily by changes in the discount rate and discrete information shocks rather than by predictable growth patterns, although this interpretation remains conditional on the adequacy of the factor specification and the absence of material residual endogeneity.

Bringing these findings together, the thesis proposes a consistent causal chain linking firm characteristics to asset returns and risk. Corporate traits — both conventional and ESG-related — shape firms' risk profiles, which influence required returns. Changes in required returns drive repricing through valuation multiples, while realised returns reflect the combined effect of repricing and earnings dynamics. This framework reconciles the apparent disconnect between characteristics and returns by showing that the relationship operates through risk and expectations.

In revisiting the causal sequence, this thesis makes several conceptual, methodological, and theoretical contributions:

- It demonstrates the robust risk-reduction benefits of better CSR and proposes instrumental metrics for downside and idiosyncratic risks.
- It introduces a graded-factor model based on cross-sectional slopes, thereby avoiding the arbitrariness of portfolio sorting.
- It provides a systematic approach to the joint effects of conventional and ESG characteristics.
- It decomposes returns into earnings and multiple components, explaining repricing and announcement effects.
- It validates the implicit cost of capital as a key driver of return dynamics within a unified framework.
- It follows a causal chain linking characteristics to risk, required returns, repricing, and realised returns to empirically observe the effects of corporate traits.

In summary, this thesis contributes to a more coherent understanding of asset pricing by integrating firm characteristics, risk, and return dynamics within a unified framework. By combining a graded factor approach with a causal decomposition of returns, it shows how cross-sectional attributes translate into time-series variation through changes in required returns and information shocks.

5.3 Implications

In asset pricing, our findings highlight the need for models that are inherently multivariate and consistent across time. We show strong interactions, so factor effects cannot be reliably interpreted in isolation; their dynamics are better understood within a unified framework that links cross-sectional characteristics and time-series variation. These challenges are insufficiently considered in the currently used segment portfolio approaches.

In investment practice, the results suggest that observed performance often reflects exposure to underlying factors rather than true abnormal returns. Beyond returns, graded factors can also be used to compute consistent characteristic-based risk metrics, thereby producing better risk analyses. For sustainability-oriented investors, this provides a framework for distinguishing between temporary preference-driven valuation effects and persistent changes in the underlying risk profile associated with environmental and social characteristics.

Developing new models that integrate cross-sections with time series to assess risk and returns could yield more consistent investment proposals. At any given price, investment (divestment) opportunities may arise from the divergence between the implicit returns embedded in asset prices and their risk profiles relative to alternative assets and their implicit risk-return balance, which can be tracked by the factors associated with each characteristic.

Practitioners already distinguish between earnings-driven and multiple-driven (repricing) returns. Extending this practice to the factor level provides a consistent framework for developing quantitative and fundamental models. Analysts could compute their expectations for future results and required returns, both in absolute terms and for specific characteristics.

In corporate finance, our tests demonstrate the usefulness of the implicit cost of capital as a metric for required returns that reflect the investment's risk. More refined estimates of the cost of capital can better structure real asset valuations, capital allocation decisions, and firm valuations. From a managerial perspective, this suggests that sustainability initiatives should not be assessed solely through their potential effects on short-term market valuations, but also through their influence on the firm's long-term risk profile and, consequently, on its required return. If CSR characteristics contribute to lower required returns, part of their value arises through a lower cost of capital rather than through immediate improvements in expected cash flows.

More broadly, the findings contribute to the growing view that responsibility can be analysed within mainstream financial economics rather than as a separate investment paradigm. By relating CSR characteristics to risk, required returns, and valuation, the framework provides an economic rationale through which sustainable corporate behaviour may create value. In this sense, the methodology offers a bridge between financial decision-making and broader sustainability objectives by enabling sustainability characteristics to be incorporated into investment analysis

and corporate valuation using the same analytical framework as traditional financial factors.

5.4 Limitations and Future Research

This study is subject to several limitations that suggest directions for future research. First, measuring characteristics remains imperfect. Different authors may consider different metrics for the same essential characteristic. For example, we chose to represent investment intensity by the ratio of capital expenditures to operating cash flow, while other authors may relate it to capital expenditures relative to the pre-existing level of assets. In particular, ESG measurements remain controversial. Differences in data collection and processing among raters yield divergent metrics for equivalent concepts across firms. Our chosen definition of greenness, which combines the pillar score and the weight of environmental issues within the firm, shows an over-reliance on the firm's sector, calling for further consideration of the construction of ESG metrics for factor investing.

Second, although the multivariate framework simultaneously controls for the characteristics included in the model, the causal interpretation of the results remains conditional on the adequacy of the factor specification. Omission of a relevant characteristic that is correlated with the included factors may bias their estimated effects and, consequently, the causal interpretation attributed to them. Future research may therefore benefit from progressively richer factor specifications and from further analysis of the sensitivity of the results to alternative sets of characteristics.

Third, the analysis focuses on non-financial US firms, which limits the generalizability of the findings. Institutional, cultural, and regulatory differences across countries may lead to different relationships between characteristics, risk, and returns. Testing industry-specific metrics across sectors such as banking, insurance, and real estate, or in alternative regulatory and cultural settings, could provide valuable new insights in future research.

Fourth, although the sample period spans more than a decade, some results — particularly those related to factor performance — may be sensitive to specific technological changes, market conditions and shifts in investor preferences. Graded factors are a useful tool for examining their trends and causes. Future research could develop additional tests that relate factor time variation to structural changes, macroeconomic factors, or dynamic adjustments in market conditions, such as market volatility.

Finally, the framework could be extended to incorporate a broader set of characteristics and to explore more complex interactions among them. Eight characteristics considered simultaneously do not lead to collinearity, nor variance inflation in our model, even if some of the characteristics are strongly interrelated. Which sets of characteristics have the highest explanatory power, how far the predictive power of returns extends, and how behavioural variables can be modelled profiting from the graded-model framework remain open fields for research.

By extending established frameworks, leveraging broader CSR metrics, new concepts, and models, and drawing on enhanced computational capacity, we build on the contributions of our predecessors. This study aims to contribute to existing research on the advancement of asset pricing, investment, and financial economics during a transformative era of promising innovations.

Appendix - Model Development

A.1 Proof of the Additivity of Factors

Let $G_{i,t}$ be the measurement of any of the characteristics for firm i at time t and $\bar{G}_t$ its weighted average, with weights $w_{i,t}$ and $\sum_i w_{i,t} = 1$. Then, the centred characteristic around the average $g_{i,t}$ is $g_{i,t} = G_{i,t} - \bar{G}_t$.

With it, we define the graded factor return at time t as the slope of the cross-sectional ordinary least squares linear fit of the returns at time t as $r_{i,t}$ on the centred characteristic $g_{i,t}$:

$$f_t = \frac{\sum_i g_{i,t-1} r_{i,t}}{\sum_i g_{i,t-1}^2} \quad (\text{A.1})$$

Suppose that the signal $G_{i,t}$, and correspondingly $g_{i,t}$, admits an additive decomposition into C components $G_{i,t}^{(c)}$. The paired mean-centred components will be $g_{i,t}^{(c)}$, and $g_{i,t} = \sum_{c=1}^C g_{i,t}^{(c)}$. A factor defined on a component would have the same formula as A.1, but referred to the component c :

$$f_t^{(c)} = \frac{\sum_i g_{i,t-1}^{(c)} r_{i,t}}{\sum_i (g_{i,t-1}^{(c)})^2} \quad (\text{A.2})$$

The factor as a linear combination of component factors

Our factor f_t can be expressed as the combination of its additive characteristics as:

$$f_t = \frac{\sum_i \left(\sum_c g_{i,t-1}^{(c)} \right) r_{i,t}}{\sum_i g_{i,t-1}^2} \quad (\text{A.3})$$

The numerator is always additive and can be simplified and rewritten to:

$$\begin{aligned}
f_t &= \frac{\sum_c \sum_i g_{i,t-1}^{(c)} r_{i,t}}{\sum_i g_{i,t-1}^2} \\
&= \frac{\sum_c N_{c,t}}{D_t}
\end{aligned} \tag{A.4}$$

where each numerator $N_{c,t}$ is equal to $\sum_i g_{i,t-1}^{(c)} r_{i,t}$, and the common denominator D_t is $\sum_i g_{i,t-1}^2$. The denominator $D_{c,t}$ in each one of the C component factors is similar, just referred to the characteristic c : $D_{c,t} = \sum_i (g_{i,t-1}^{(c)})^2$.

The denominator in A.4 is invariant to c , so we can rearrange for our factor f_t bringing the denominator inside the sum for c , and multiply all numerators and denominators by the corresponding c -based term $\sum_i (g_{i,t-1}^{(c)})^2$ without altering the result:

$$\begin{aligned}
f_t &= \sum_c \frac{\sum_i g_{i,t-1}^{(c)} r_{i,t}}{\sum_i g_{i,t-1}^2} \\
&= \sum_c \frac{\left(\sum_i g_{i,t-1}^{(c)} r_{i,t} \right) \left(\sum_i (g_{i,t-1}^{(c)})^2 \right)}{\sum_i g_{i,t-1}^2 \sum_i (g_{i,t-1}^{(c)})^2} \\
&= \sum_c \frac{\left(\sum_i (g_{i,t-1}^{(c)})^2 \right) \left(\sum_i g_{i,t-1}^{(c)} r_{i,t} \right)}{\sum_i g_{i,t-1}^2 \sum_i (g_{i,t-1}^{(c)})^2} \\
&= \sum_{c=1}^C \frac{D_{c,t}}{D_t} f_t^{(c)}
\end{aligned} \tag{A.5}$$

The contribution of each component factor to the main factor is related by the proportion of the denominators $D_{c,t}/D_t$. Therefore, the addition of component factors is a linear function of the main factor, with components weighted by their respective denominator contributions.

Interpreting the weightings as a variance share

When expanding the denominator, squaring the sum of characteristics, which is the composite $g_{i,t-1}^2 = (\sum_c g_{i,t-1}^{(c)})^2$, generates not only the individual squared terms $(g_{i,t-1}^{(c)})^2$, but also interaction terms $2g_{i,t-1}^{(l)}g_{i,t-1}^{(m)}$ for every pair of distinct characteristics l and m , where $l \neq m$:

$$\begin{aligned}
D_t &= \sum_i \left(\sum_c g_{i,t-1}^{(c)} \right)^2 \\
&= \sum_i \left(\sum_c (g_{i,t-1}^{(c)})^2 + 2 \sum_{1 < l < m < c} g_{i,t-1}^{(l)} g_{i,t-1}^{(m)} \right)
\end{aligned} \tag{A.6}$$

Being $g_{i,t}^{(c)} = G_{i,t}^{(c)} - \bar{G}_{c,t}$, a difference to the mean, the component terms of A.4 sum the squares, so the N -terms resemble the sum of the squares in covariances between $r_{i,t}$ and $g_{i,t-1}$ and D -terms resemble the sum of the squares in variances of $g_{i,t-1}$, except that they are centred on different means. Each centred characteristic is centred on its weighted average $\bar{G}_{c,t}$, while a second moment is centred on the simple mean $\mu_{c,t}$. Such a difference of means $\mu_{c,t} - \bar{G}_{c,t}$ creates an adjustment.

In detail, the precise expansion of $D_{c,t} = \sum_i (g_{i,t-1}^{(c)})^2$ in terms of the raw component characteristic $\bar{G}_{c,t}$ is $\sum_i (G_{i,t}^{(c)} - \bar{G}_{c,t})^2$. This expression is similar to the number of observations, N , times the cross-sectional variance of $G_{i,t}^{(c)}$, except that is centred around the weighted mean $\bar{G}_{c,t}$ rather than the simple mean $\mu_{c,t}$. The variance is invariant to translation, and for every t the mean is cross-sectionally constant, so $\sigma(G_{i,t}^{(c)})^2 = \sigma(g_{i,t}^{(c)})^2$, and $\sigma(g_{i,t}^{(c)})^2 = 1/N \sum_i ((G_{i,t}^{(c)}) - \mu_{c,t})^2$. Therefore,

$$\begin{aligned} D_{c,t} &= \sum_i (G_{i,t}^{(c)} - \bar{G}_{c,t})^2 \\ &= \sum_i (G_{i,t}^{(c)} - \mu_{c,t})^2 + N(\mu_{c,t} - \bar{G}_{c,t})^2 \\ &= N\sigma(G_{i,t}^{(c)})^2 + N(\mu_{c,t} - \bar{G}_{c,t})^2 \end{aligned} \quad (\text{A.7})$$

In formula A.7, we can interpret each $D_{c,t}$ as N times the adjusted variance for the de-centring effect of the weights. $(\mu_{c,t} - \bar{G}_{c,t})^2$ is the correction factor. When calculating the ratio $D_{c,t}/D_t$, N , present in the numerator and denominator, cancels out, so effectively $D_{c,t}/D_t$ is the adjusted variance share of each factor in the composite factor. To better represent this fact, we rename $D_{c,t}$ as $\sigma_{c,t}^2$ for our formula:

$$f_t = \sum_{c=1}^C \frac{\sigma_{c,t}^2}{\sigma_t^2} f_t^{(c)} \quad (\text{A.8})$$

In conclusion, the composite factor can be decomposed into the addition of its component factors, weighted by the component factor's variance share relative to the main factor's variance (A.8). This variance needs to be corrected by the squared mean of the decentration, a measure of the distortion introduced by the weighted mean. This correction factor will be zero for equally weighted and standardised factors, because in both cases the simple mean of the characteristics equals the weighted mean. The model accounts for interactions among factors and their covariances. Should the components be orthogonal, the cross-factor term would be zero, and $\sigma_t^2 = \sum_c (\sigma_{t,c})^2$.

A.2 The Effects of Simultaneously Interacting Factors

The general form of the model

To cover the most general case of interacting factors, in this appendix we develop the case of a value-weighted characteristic and a value-weighted slope. Dropping the weights at either level allows us to observe the unweighted cases of the characteristic and/or the slope. Consider the cross-sectional regression of firm returns r_t regressed on the matrix of characteristics X_t at time t . Without an intercept, the model is:

$$r_t = X_t F_t + \epsilon_t \quad (\text{A.9})$$

The vector of slopes F_t , which defines the fitted hyperplane, is obtained from the weighted least squares estimator as (Greene, 2012):

$$F_t = (X_t' W_t X_t)^{-1} X_t' W_t r_t \quad (\text{A.10})$$

In a multivariate model of K variables, the elements in the matrix X_t are the k de-meaned characteristics for each time t and firm i : $g_{k,i,t}$. Similarly, W_t and r_t are the vectors for the weights and the returns with firm and time dimensions. F_t is the $1 \times K$ dimension vector of factors for every time t and its components are $\tilde{f}_{k,t}$ factors, the first of which $\tilde{f}_{1,t}$ refers to the first characteristic $g_{(1,i,t)}$.

$$X_t = \begin{bmatrix} g_{1,1,t} & \cdots & g_{K,1,t} \\ \vdots & \ddots & \vdots \\ g_{1,N,t} & \cdots & g_{K,N,t} \end{bmatrix}, \quad W_t = \begin{bmatrix} w_{1,t} \\ \vdots \\ w_{N,t} \end{bmatrix}, \quad r_t = \begin{bmatrix} r_{1,t} \\ \vdots \\ r_{N,t} \end{bmatrix}, \quad F_t = \begin{bmatrix} \tilde{f}_{1,t} \\ \vdots \\ \tilde{f}_{K,t} \end{bmatrix}$$

Two-Factor Expanded Form

To prove equation 3.10 in our text, we apply the matrix formulae for the case of two factors: $\tilde{f}_{m,t}$ and $\tilde{f}_{v,t}$, the partial effects of size and value. The five possible weighted second moments among the two explanatory variables and the dependent variable will be

$$\begin{aligned}
S_{mm,t} &= \sum_i w_{i,t} g_{m,i,t}^2, \\
S_{vv,t} &= \sum_i w_{i,t} g_{v,i,t}^2, \\
S_{mv,t} &= \sum_i w_{i,t} g_{m,i,t} g_{v,i,t}, \\
S_{mr,t} &= \sum_i w_{i,t} g_{m,i,t} r_{i,t}, \\
S_{vr,t} &= \sum_i w_{i,t} g_{v,i,t} r_{i,t}.
\end{aligned} \tag{A.11}$$

The vector of factors is $F_t = (X_t' W_t X_t)^{-1} X_t' W_t r_t$, that can be expanded to:

$$\begin{aligned}
\tilde{f}_{m,t} &= \frac{S_{mr,t} S_{vv,t} - S_{vr,t} S_{mv,t}}{S_{mm,t} S_{vv,t} - S_{mv,t}^2}, \\
\tilde{f}_{v,t} &= \frac{S_{vr,t} S_{mm,t} - S_{mr,t} S_{mv,t}}{S_{mm,t} S_{vv,t} - S_{mv,t}^2}.
\end{aligned} \tag{A.12}$$

Each moment can be expressed in terms of variances and covariances, for example: $(1/N) S_{mr,t} = \text{Cov}(g_{m,t}, r_t) = (1/N) \sum_i g_{m,i,t} r_{i,t}$. By reformulating in terms of variance with N cancelling out in numerator and denominator, we derive the formula with direct interpretation:

$$\begin{aligned}
\tilde{f}_{m,t} &= \frac{\sigma_{v,t}^2 \text{Cov}(g_{m,t}, r_t) - \text{Cov}(g_{m,t}, g_{v,t}) \text{Cov}(g_{v,t}, r_t)}{\sigma_{m,t}^2 \sigma_{v,t}^2 - \text{Cov}(g_{m,t}, g_{v,t})^2}, \\
\tilde{f}_{v,t} &= \frac{\sigma_{m,t}^2 \text{Cov}(g_{v,t}, r_t) - \text{Cov}(g_{m,t}, g_{v,t}) \text{Cov}(g_{m,t}, r_t)}{\sigma_{m,t}^2 \sigma_{v,t}^2 - \text{Cov}(g_{m,t}, g_{v,t})^2}.
\end{aligned} \tag{A.13}$$

And the model equation is:

$$r_{i,t} = \tilde{f}_{m,t} g_{m,i,t} + \tilde{f}_{v,t} g_{v,i,t} + \epsilon_{i,t} \tag{A.14}$$

The Three-Factor Model in our Tests

In the unweighted case for the three factors that we apply in our paper, the subscripts for size, value, and greenness are m , v , and e , and our model equation is:

$$r_{i,t} = \tilde{f}_{m,t} g_{m,i,t} + \tilde{f}_{v,t} g_{v,i,t} + \tilde{f}_{e,t} g_{e,i,t} + \epsilon_{i,t} \tag{A.15}$$

In this case, our matrix of second moments $X'X$ and the vector of covariances $X'r$ for every time t result in

$$X_t'X_t = \begin{bmatrix} S_{mm,t} & S_{mv,t} & S_{me,t} \\ S_{mv,t} & S_{vv,t} & S_{ve,t} \\ S_{me,t} & S_{vg,t} & S_{ee,t} \end{bmatrix}, \quad X_t'r_t = \begin{bmatrix} S_{mr,t} \\ S_{vr,t} \\ S_{er,t} \end{bmatrix}$$

Because all weights are equal to 1, our vector of partial factors is $F_t = (X_t'X_t)^{-1}X_t'r_t$, so we effectively calculate each of the factors $\tilde{f}_{k,t}$ in F_t as

$$\begin{bmatrix} f_{m,t} \\ f_{v,t} \\ f_{g,t} \end{bmatrix} = \begin{bmatrix} S_{mm,t} & S_{mv,t} & S_{mg,t} \\ S_{mv,t} & S_{vv,t} & S_{vg,t} \\ S_{mg,t} & S_{vg,t} & S_{gg,t} \end{bmatrix}^{-1} \begin{bmatrix} S_{mr,t} \\ S_{vr,t} \\ S_{gr,t} \end{bmatrix}$$

For the multiplication, the determinant of matrix $X'X$ and its expanded form are

$$\begin{aligned} \Delta_t &= \begin{vmatrix} S_{mm,t} & S_{mv,t} & S_{me,t} \\ S_{mv,t} & S_{vv,t} & S_{ve,t} \\ S_{me,t} & S_{ve,t} & S_{ee,t} \end{vmatrix} \\ &= S_{mm,t}(S_{vv,t}S_{ee,t} - S_{ve,t}^2) - S_{mv,t}(S_{mv,t}S_{ee,t} - S_{me,t}S_{ve,t}) \\ &\quad + S_{me,t}(S_{mv,t}S_{ve,t} - S_{me,t}S_{vv,t}). \end{aligned} \tag{A.16}$$

The Cramer numerator for size (subscript m) is $\Delta_{m,t}$:

$$\begin{aligned} \Delta_{m,t} &= \begin{vmatrix} S_{mr,t} & S_{mv,t} & S_{me,t} \\ S_{vr,t} & S_{vv,t} & S_{ve,t} \\ S_{er,t} & S_{ve,t} & S_{ee,t} \end{vmatrix} \\ &= S_{mr,t}(S_{vv,t}S_{ee,t} - S_{ve,t}^2) - S_{mv,t}(S_{vr,t}S_{ee,t} - S_{er,t}S_{ve,t}) \\ &\quad + S_{me,t}(S_{vr,t}S_{ve,t} - S_{er,t}S_{vv,t}). \end{aligned} \tag{A.17}$$

The partial factor for m in the three-way model is $\tilde{f}_{m,t} = \frac{\Delta_{m,t}}{\Delta_t}$. Similarly, the partial value factor for t is $\tilde{f}_{v,t} = \frac{\Delta_{v,t}}{\Delta_t}$, and the partial green factor is $\tilde{f}_{e,t} = \frac{\Delta_{e,t}}{\Delta_t}$, in which $\Delta_{v,t}$ and $\Delta_{e,t}$ are the corresponding Cramer determinants that substitute their respective columns in Δ_t for the components of vector $X_t'r_t$.

A.3 Proof of the return proxy for price decomposition

In our paper, we use log returns $\ln(1 + r_{i,t})$, which exactly match changes in log total return indices as a close approximation of simple returns at monthly frequency.

As a starting point, we are interested in total gross returns, which include price appreciation and dividends. We assume that the latter is reinvested in the shares of the firm on the same day, in such a way that the total return index $TR_{i,t}$ for firm i in month t , and the return of the firm is:

$$1 + r_{i,t} = \frac{TR_{i,t}}{TR_{i,t-1}} \quad (\text{A.18})$$

So, taking logs

$$\ln(1 + r_{i,t}) = \ln TR_{i,t} - \ln TR_{i,t-1} \quad (\text{A.19})$$

And

$$\ln(1 + r_{i,t}) \approx r_{i,t} \quad (\text{A.20})$$

Using the Taylor expansion around $r=0$,

$$\ln(1 + r) = r - \frac{r^2}{2} + \frac{r^3}{3} - \dots \quad (\text{A.21})$$

So, for small monthly returns, since the squared and cubed second- and third-order terms are very small, log returns and simple returns are very close.

Appendix - Causal Model Regressions.

Factor k = m (size-market-cap)					
Dep.	(1)	(2)	(3)	(4)	(5)
const	fMmsl_t 0.0068*** (0.0010)	fMmsl_t 0.0072*** (0.0011)	fMmsl_t 0.0069*** (0.0012)	fMmsl_t 0.0065*** (0.0010)	fMmsl_t 0.0026** (0.0011)
dICC	-0.4277*** (0.1368)			-0.4050*** (0.1249)	-1.0278*** (0.1587)
dg		-11.6864 (8.3750)		-8.6383 (7.5197)	-13.5727*** (4.6130)
dANN			0.1829* (0.1029)		0.7414*** (0.1261)
Adj. R ²	0.110	0.029	0.034	0.125	0.435
N	114	114	114	114	114

Factor k = c (investment)					
Dep.	(1)	(2)	(3)	(4)	(5)
const	fMcsl_t -0.0060*** (0.0015)	fMcsl_t -0.0036*** (0.0013)	fMcsl_t -0.0042*** (0.0013)	fMcsl_t -0.0062*** (0.0016)	fMcsl_t -0.0071*** (0.0016)
dICC	-0.5021** (0.2240)			-0.4991** (0.2229)	-0.5160** (0.2329)
dg		-10.0731 (7.5734)		-9.5917 (7.5921)	-9.7575 (7.0812)
dANN			0.6867*** (0.2308)		0.7155*** (0.2467)
Adj. R ²	0.070	0.009	0.059	0.078	0.142
N	114	114	114	114	114

Factor k = v (value)					
Dep.	(1)	(2)	(3)	(4)	(5)
const	fMvsl_t 0.0057*** (0.0017)	fMvsl_t 0.0085*** (0.0020)	fMvsl_t 0.0071*** (0.0019)	fMvsl_t 0.0070*** (0.0018)	fMvsl_t 0.0072*** (0.0018)
dICC	-0.1562 (0.1008)			-0.1461 (0.0965)	-0.1477 (0.0920)
dg		-7.8634 (5.0682)		-6.6039 (4.5532)	-8.6547* (4.8198)
dANN			0.2752 (0.3345)		0.5237 (0.3226)
Adj. R ²	0.046	0.021	0.004	0.060	0.074
N	114	114	114	114	114

Factor k = e (environmental)					
Dep.	(1)	(2)	(3)	(4)	(5)
const	fMesl_t 0.0044*** (0.0015)	fMesl_t 0.0081*** (0.0022)	fMesl_t 0.0074*** (0.0022)	fMesl_t 0.0046*** (0.0016)	fMesl_t 0.0033** (0.0015)
dICC	-0.8695*** (0.2666)			-0.8578*** (0.2645)	-0.9935*** (0.2668)
dg		-7.3024 (5.7444)		-4.4824 (4.1597)	-6.6815 (4.4674)
dANN			0.4029 (0.2720)		0.6703*** (0.1744)
Adj. R ²	0.223	0.012	0.041	0.228	0.335
N	114	114	114	114	114

Factor k = u (momentum)					
Dep.	(1)	(2)	(3)	(4)	(5)
const	fMusl_t -0.0027* (0.0015)	fMusl_t -0.0005 (0.0027)	fMusl_t -0.0073*** (0.0013)	fMusl_t -0.0001 (0.0026)	fMusl_t -0.0044** (0.0018)
dICC	-1.2892*** (0.1959)			-1.2320*** (0.1902)	-1.2195*** (0.1898)
dg		-28.0357* (14.4562)		-18.4179 (12.9434)	-6.7860 (10.2861)
dANN			0.9722*** (0.1298)		0.9278*** (0.1111)
Adj. R ²	0.236	0.044	0.296	0.255	0.516
N	114	114	114	114	114

Factor k = s (social)					
Dep.	(1)	(2)	(3)	(4)	(5)
const	fMssl_t -0.0001 (0.0012)	fMssl_t 0.0019 (0.0015)	fMssl_t 0.0011 (0.0015)	fMssl_t -0.0001 (0.0012)	fMssl_t -0.0009 (0.0012)
dICC	-0.7217*** (0.1782)			-0.7003*** (0.1760)	-0.7020*** (0.1523)
dg		-14.4630 (9.3994)		-5.8203 (6.7344)	-5.5027 (6.2759)
dANN			0.9434*** (0.3071)		0.9427*** (0.3293)
Adj. R ²	0.242	0.029	0.071	0.246	0.317
N	114	114	114	114	114

Factor k = p (profitability)					
Dep.	(1)	(2)	(3)	(4)	(5)
const	fMpssl_t 0.0133*** (0.0033)	fMpssl_t 0.0202*** (0.0057)	fMpssl_t 0.0147*** (0.0038)	fMpssl_t 0.0177*** (0.0050)	fMpssl_t 0.0191*** (0.0048)
dICC	-0.7674*** (0.2665)			-0.6984*** (0.2446)	-0.7930*** (0.1979)
dg		-12.9823** (6.4456)		-9.1587* (5.2919)	-9.8322** (4.8981)
dANN			1.0594*** (0.2993)		1.4611*** (0.3955)
Adj. R ²	0.106	0.042	0.033	0.126	0.187
N	114	114	114	114	114

Factor k = g (governance)					
Dep.	(1)	(2)	(3)	(4)	(5)
const	fMgsl_t 0.0004 (0.0017)	fMgsl_t 0.0025 (0.0020)	fMgsl_t 0.0018 (0.0020)	fMgsl_t 0.0004 (0.0017)	fMgsl_t -0.0005 (0.0017)
dICC	-0.6832** (0.2657)			-0.6667** (0.2710)	-0.6945*** (0.2556)
dg		-11.1099 (7.4962)		-8.0952 (7.4316)	-6.3844 (7.4062)
dANN			0.4085** (0.1688)		0.4826** (0.1964)
Adj. R ²	0.181	0.022	0.022	0.193	0.223
N	114	114	114	114	114

Note: The table shows five regression models for all characteristics studied. The dependent variable is the multivariate multiple factor. The first three are univariate regressions on each of the three explanatory variables, and the last two are multivariate analyses. In parentheses under each coefficient is the t-statistic. *** denotes the significance of the coefficient to the 0.001, ** to the 0.01, and * to the 0.05.

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” *Grant me a penetrating mind to understand, a retentive memory, method and ease in learning, the lucidity to comprehend, and abundant grace in expressing myself. Guide the beginning of my work, direct its progress, and bring it to successful completion.*

— **St. Thomas Aquinas**
Patron Saint of Students

