Evaluating the impact of sustainability and financial performance:

A comparative analysis of European equity funds and global equities

Daniel Ung

A thesis submitted for the degree of Doctor of Philosophy in Finance

Department of Finance
Bayes Business School
City, University of London

March 2025

Contents

List of exhibits

1 Acknowledgements

I extend my deepest gratitude to my supervisors, Professor Andrew Clare and Professor Stephen Thomas, whose unwavering support and insightful guidance have been instrumental throughout this research journey. Their patience, encouragement, and invaluable expertise have significantly shaped the development of this thesis. Their dedication to academic excellence and their willingness to provide constructive feedback have been indispensable, and I am profoundly grateful for their mentorship.

I am also sincerely thankful to Professor Giovanni Urga for his generous support and invaluable discussions, particularly regarding the application and robustness of econometric techniques in this thesis. His expertise and thoughtful insights have greatly enriched my understanding and strengthened the methodological rigour of my research.

This work would not have been possible without their collective wisdom and guidance, and I am truly indebted to them for their contributions to my academic and professional growth.

2 Declaration

I herewith grant the powers of discretion to the University Librarian to allow this thesis to be copied, in whole or in part, without further reference to me. This permission covers only single copies made for study purposes, subject to normal conditions of acknowledgement. I declare that the two chapters included are co-authored with my PhD supervisors, Professor Andrew Clare and Professor Stephen Thomas. I independently developed the research questions, gathered and analysed the data, and carried out the research, while my supervisors provided guidance and edited the thesis.

3 Abstract

The integration of sustainability factors into investment decision-making has become a fundamental aspect of contemporary asset management. The establishment of dedicated responsible investment teams and the appointment of Chief Sustainability Officers underscore the increasing prominence of environmental, social, and governance (ESG) considerations. This trend is driven by both strategic business imperatives and regulatory mandates, with proponents arguing that ESG integration enhances risk management and long-term investment opportunities. Empirical studies suggest that firms with strong ESG practices demonstrate superior risk mitigation capabilities, leading to reduced volatility and improved risk-adjusted returns. Additionally, high ESG-rated companies tend to experience lower financial risks, reduced capital costs, and enhanced operational performance, attracting socially conscious investors.

Regulatory frameworks, particularly in Europe, play a crucial role in driving ESG integration. The European Union's Sustainable Finance Disclosure Regulation (SFDR) mandates asset managers to disclose their ESG integration practices, aligning financial markets with broader sustainability objectives. Compliance with such regulations not only ensures adherence to legal requirements but also positions investors advantageously in a market increasingly valuing sustainability.

This study investigates the relationship between ESG integration and investment performance through two key analyses. The first chapter examines whether highly-rated ESG investments generate alpha, focusing on 297 open-ended equity funds in the European market from 2014 to 2021. Results indicate no consistent relationship between sustainability levels and equity factor exposure, though governance quality and carbon scores exhibit significant correlations with alpha generation. The second chapter assesses whether sustainability factors influence financial risks across global equity markets, including the World, World ex-US, and US indices. Findings suggest that sustainability scores have limited explanatory power for financial risks, with modest effects observed in higher-risk spectrums and during crisis periods, such as the COVID-19 pandemic. Ultimately, the study concludes that ESG integration should be primarily viewed as a mechanism for corporate responsibility and ethical investment rather than a definitive tool for risk reduction or alpha generation.

4 Introduction

The integration of environmental, social, and governance (ESG) considerations into investment decision-making has become increasingly widespread, underpinned by evolving regulatory frameworks and shifting investor priorities. ESG integration is frequently posited as a means of enhancing financial performance—whether through the generation of excess returns or the mitigation of financial risk. However, the empirical evidence on its efficacy remains inconclusive, with existing research producing mixed findings. This thesis provides a structured examination of the financial materiality of ESG considerations, assessing whether sustainability metrics contribute to investment outperformance or serve as an effective risk-mitigation mechanism.

The first chapter investigates whether mutual funds with high ESG ratings generate alpha within the European equity fund universe. Employing both holdings-based and time-series analyses—placing primary emphasis on the former—the study finds no consistent relationship between ESG scores and excess returns, with performance predominantly explained by static factor exposures. Likewise, dynamic return—defined as the cumulative effect of factor timing and security selection alpha—appears largely unrelated to ESG factors. However, governance quality is identified as a statistically significant determinant of alpha, particularly among the highest-performing funds in Europe. Notably, the relationship between alpha and governance scores exhibits a dichotomous and non-linear structure, a pattern that, to the best of my knowledge, has not been documented in the literature. This finding remains robust even after accounting for an extensive set of control variables, exceeding those used in comparable studies such as Madhavan, Sobczyk, and Ang (2021). The observed relationship between superior governance scores and stock selection efficacy may be linked to the correlation between stronger governance risk management and enhanced corporate operating profitability, as discussed by Bebchuk, Cohen, and Wang (2013). Consequently, governance scores at the fund level may serve as an indirect proxy for identifying companies with superior corporate operating profitability.

The second chapter extends the analysis by shifting the focus from return generation to risk reduction. It examines whether firms with higher ESG ratings exhibit lower financial risk across the World, World ex-US, and US equity indices. Additionally, it evaluates the extent to which ESG factors mitigate downside risk—particularly during periods of market stress such as the COVID-19 pandemic—and assesses whether ESG ratings possess predictive power for future financial risk. The findings suggest that ESG scores generally exhibit a weak and inconsistent relationship with financial risk, a conclusion that contrasts with some prior studies (e.g., Dunn, Fitzgibbons, and Pomorski 2018). While there is some limited evidence to suggest that environmental and carbon metrics may offer some modest predictive insights over longer time horizons, the capacity of ESG factors to systematically reduce financial risk appears constrained.

This thesis makes several contributions to the academic literature on sustainable finance. First, it provides a dual-perspective analysis, assessing ESG's role in both return enhancement and risk mitigation—whereas much of the literature tends to examine these dimensions in isolation. Second, it employs a rigorous methodological framework that accounts for endogeneity concerns, addressing econometric limitations such as omitted variable bias and spurious correlations, which have often weakened prior empirical studies. Third, it offers a more nuanced perspective on the role of governance, demonstrating that governance quality, rather than composite ESG scores, is the primary sustainability-related driver of alpha. Fourth, it challenges the assumption that ESG integration inherently reduces investment risk, instead demonstrating that its impact on risk profiles is, at best, secondary and highly context-dependent.

By integrating these perspectives, this thesis advances the debate on ESG integration by advocating for an evidence-based approach to sustainable investing. The findings indicate that while ESG considerations may align with ethical and regulatory objectives, their financial benefits are neither uniform nor assured. This research stresses the importance of disentangling governance effects from broader ESG factors and ensuring that sustainability integration within investment strategies is supported by empirical validation rather than assumption.

5 *Chapter 1*: Evaluating the impact of sustainability and ﬁnancial performance

5.1 Introduction

From its modest origins, when religious groups established ethical standards for their investments, sustainable investing has evolved substantially. Today, it is embraced by the world's largest investors, notably some of the most influential sovereign wealth funds such as the Government Pension Investment Fund (GPIF) of Japan, the Government Pension Fund Global (GPFG) of Norway, and the Central Provident Fund (CPF) of Singapore. Its rapid growth is evident in ESG-themed investment funds, which reached US$2.7 trillion in 2021—a 53% increase from the previous year (Kishan 2022).

Early approaches to sustainable investing, often termed ethical or socially responsible investing (SRI), focused on excluding companies based on moral criteria. In contrast, contemporary ESG investing integrates environmental, social, and governance factors into analysis both to inform investment decisions and to manage risk while seeking opportunities (Bernow, Klempner, and Magnin 2017). The balance between financial and sustainability objectives, and the emphasis placed on different ESG dimensions—climate, social, or governance—varies across funds, shaping distinct investment styles. This transformation has been driven by enhanced access to ESG data, evolving public policies, and shifting investor preferences. For example, millennial investors increasingly prioritise ESG factors (IEMA 2020), while regulatory measures such as France's Article 173 mandate the disclosure of climate-related risks (Baker McKenzie, Principles for Responsible Investment 2017). Improved data access has not only spurred scholarly research into ESG's impact on asset valuation but also led to its routine use in mutual fund due diligence.

Our study makes a unique contribution to the literature in three distinct ways. First, by focusing exclusively on European equity funds and using a dual-method approach (returns-based and holdings-based analyses), we contribute a more region-specific perspective that overcomes the limitations of prior US-centric, often returns-only studies. Second, our methodology deconstructs fund returns into dynamic and security selection components, thereby contributing granular insights into how specific ESG factors—particularly governance—affect performance. Third, by disaggregating composite ESG scores, we contribute evidence of non-linear relationships that challenge the conventional view of ESG's uniform impact on fund returns. We focus on funds rather than individual stocks because funds aggregate the ESG integration efforts of professional managers, thereby providing a more robust measure of the impact of sustainability on investment performance, whereas stock-level analyses are more susceptible to idiosyncratic noise. Additionally, a purely stock-level approach might lead to different insights by emphasising each firm's specific ESG profile and higher idiosyncratic volatility, which do not necessarily reflect the net effect of active portfolio management, factor tilts, or the diversification inherent in mutual funds. While evidence from the US is mixed (e.g. Madhavan, Sobczyk, and Ang 2021; Milonas et al. 2022), this research seeks to clarify these relationships in the European context.

This study builds upon existing ESG literature by addressing key methodological gaps, particularly in the reliance on composite ESG scores in much of the research and the assumption of linearity in return dynamics. Unlike most prior research, which primarily evaluates ESG's impact on excess returns (e.g., (Nofsinger and Varma 2014)), this study disaggregates return components to separately examine dynamic return and security selection alpha. By employing a holdings-based approach and incorporating quantile regressions, it provides a more granular understanding of the asymmetric effects of sustainability factors on fund performance. Furthermore, while much of the existing literature is US-centric, this research focuses on European mutual funds, where ESG disclosure is more advanced, offering insights that are more reflective of regulatory and market realities in sustainable finance.

The remainder of the paper is structured as follows. Section 2 reviews the literature. Section 3 outlines the theoretical framework and hypotheses. Section 4 describes the data, while Section 5 presents the descriptive statistics. Section 6 details the methodology, followed by Section 7, which discusses the empirical results. Finally, Section 8 concludes with investment implications.

5.2 Literature Review

Sustainability and Risk-Return Pro/les: An Ongoing Debate

The relationship between sustainability and risk-return profiles remains a subject of extensive debate. While sustainable investing has gained prominence, empirical evidence on its financial impact remains inconclusive due to methodological disparities, regulatory fragmentation, and the evolving definition of ESG factors. The extant literature presents mixed findings: some studies argue that strong sustainability characteristics enhance returns by mitigating risk and improving long-term resilience (Madhavan, Sobczyk, and Ang 2021), while others contend that sustainability-linked stocks either underperform or exhibit no discernible financial advantage (Krüger 2015). These divergent conclusions are further complicated by the proliferation of ESG frameworks and the increasing sophistication of investment strategies.

Evolution of ESG: From Ethical Exclusions to Material Risk Integration

The conceptualisation of sustainable investing has evolved significantly. Initially, it was dominated by ethical exclusions, in which investors screened out industries such as tobacco, firearms, and alcohol based on moral imperatives rather than financial considerations (Renneboog, Horst, and Zhang 2008). By the 2000s, this approach evolved into ESG integration, with sustainability factors incorporated as material drivers of risk and return (Eccles, Ioannou, and Serafeim 2014). This shift was facilitated by improvements in ESG data availability and regulatory interventions, such as the European Union's Non-Financial Reporting Directive (NFRD) in 2014, which mandated corporate sustainability disclosures[1].

Despite these advancements, the literature frequently conflates exclusionary strategies with integrated ESG investing, leading to inconsistent empirical conclusions. Early research, such as (Statman 2000) treated socially responsible investment (SRI) funds as a homogenous category, overlooking variations in ESG implementation. More recent studies, such as (Nofsinger and Varma 2014) distinguish between exclusionary screening and ESG integration, demonstrating that while ESG funds outperform conventional counterparts during market crises, they tend to underperform in stable periods. This suggests that ESG strategies may exhibit asymmetric risk-return characteristics, warranting further investigation.

Regulatory Divergence and Its Implications

Regulatory frameworks exert a profound influence on ESG investing, particularly in Europe, where the Sustainable Finance Disclosure Regulation (SFDR) has enhanced data comparability and standardisation. In contrast, the United States lacks a unified federal ESG disclosure framework, relying instead on voluntary reporting mechanisms such as those provided by the Sustainability Accounting Standards Board (SASB) (Krueger et al. 2024). However, most published research relates to US investment funds rather than European mutual funds—where ESG disclosure and adoption are much higher—and this is the reason why European funds have been selected for analysis in this thesis. The fragmented regulatory landscape further complicates cross-border comparisons and may partially account for the heterogeneous empirical findings in the literature. European markets benefit from the transparency afforded by mandatory ESG disclosures, whereas regions with voluntary disclosure frameworks, such as the United States, may experience greater information asymmetry. As disclosure frameworks become more standardised, the potential for a clearer understanding of the relationship between sustainability and financial performance increases. However, the dynamic nature of ESG

[1] European Union (EU). (2014). Directive 2014/95/EU on Non-Financial Reporting. *Official Journal of the European Union*.

regulation suggests that empirical assessments of ESG investing require ongoing revision to account for evolving disclosure mandates and investor behaviour.

Methodological Heterogeneity and Con{ icting Evidence

The empirical literature on ESG investing is characterised by methodological heterogeneity, with studies varying in their definitions of sustainability, performance metrics, and sample periods. Many research papers simply use composite ESG scores without adequately considering the individual components that comprise them. Performance evaluation approaches also diverge: whereas some studies assess alpha generation (Nofsinger and Varma 2014), others rely on risk-adjusted measures such as the Sharpe and Treynor ratios (Hartzmark and Sussman 2019). Further complexity arises from variations in sample construction and benchmark selection. (Raghunandan and Rajgopal 2022) compare ESG funds to non-ESG funds managed by the same firm, attempting to control for fund management effects, while other studies rely on broader market indices, potentially introducing selection bias. Exhibit 1 summarises the empirical findings, illustrating the variability in conclusions—some studies report a positive correlation between ESG and financial performance, while others identify a negative or neutral relationship. These discrepancies underscore the need for methodological rigour and contextual sensitivity when interpreting ESG-related financial outcomes.

Addressing Gaps in the Literature

Despite significant progress in ESG research, several key gaps persist, thereby limiting the ability to draw definitive conclusions on its financial impact. One major issue is the reliance on composite ESG scores, which may obscure the distinct effects of environmental, social, and governance factors and therefore a disaggregated approach is necessary to isolate the specific financial impact of each ESG dimension. Additionally, much of the literature assumes a linear relationship between ESG factors and returns, typically evaluating very few dimensions of financial performance. This approach overlooks the potential for non-linearities, where ESG characteristics may exert differential effects across the return distribution. Employing granular econometric models, such as quantile regressions, could provide deeper insights into how ESG influences returns across different market environments. Another critical limitation is the geographical bias present in much of the research. The literature remains U.S.-centric, with empirical studies primarily relying on datasets that do not fully account for Europe's regulatory leadership in ESG disclosures and adoption. Given the substantial differences in regulatory frameworks, market structures, and investor behaviour across regions, findings based solely on U.S. data may lack generalisability. A more comparative, cross-jurisdictional research approach is needed to accurately assess the global financial implications of ESG investing. Furthermore, many studies employ time-series regression analysis, which, while useful for identifying broad trends, lacks the granularity provided by holdings-based approaches.

Addressing these methodological challenges is crucial for producing more precise and reliable insights into the role of sustainability in financial markets and encompasses the aims of this chapter in the thesis.

Exhibit 1 Relationship between Sustainability and Investment Fund Returns

Paper	*Key findings*
Papers documenting no relationship between sustainability and fund returns	
(Statman 2000)	Socially responsible mutual funds performed comparably to conventional mutual funds from May 1990 to September 1998, with no statistical difference in their risk-adjusted returns.
(Hartzmark and Sussman 2019)	No statistical differences in performance, as measured by alpha, Sharpe ratio, and Treynor ratio, were found between ESG funds and non-ESG funds from 2017 to 2021.
(Milonas, Rompotis, and Moutzouris 2022)	Analysis from 2017 to 2021 found no statistical differences in performance between ESG funds and non-ESG funds, using metrics such as alpha, Sharpe ratio, and Treynor ratio.
(Raghunandan, and Rajgopal (2022))	ESG funds were observed to financially underperform relative to other funds managed by the same asset managers within the same year, and they tend to charge higher fees.
Papers documenting a positive relationship between sustainability and fund returns	
(Nofsinger and Varma 2014)[2]	ESG funds outperform conventional funds during market crises but underperform during non-crisis periods, with this asymmetry in return patterns being more pronounced for ESG funds employing positive screening.
(Filbeck, Filbeck, and Zhao 2019)	The study suggests that investors are not penalised for adopting an ESG philosophy, with the market rewarding firms for good governance practices, penalising those with strong environmental credentials, and displaying ambivalence towards those with strong social track records.
(Madhavan, Sobczyk, and Ang 2021)	A statistically significant and positive correlation was found between the fund alpha and factor ESG scores, although the evidence linking ESG scores with active returns remains weak.
Papers documenting a negative relationship between sustainability and fund returns	
(Barber, Morse, and Yasuda 2021)	Venture capital funds pursuing dual objectives of financial return and social impact underperformed compared to traditional funds.
(El Ghoul and Karoui 2017)	Compared to low-CSR funds, high-CSR funds in the US exhibited poorer performance, stronger performance persistence, a weaker performance-flow relationship, and comparable persistence in flows.

Notes: The list above provides a non-exhaustive overview of recent ESG research papers. We summarise the key conclusions from these papers.

5.3 Theoretical framework and hypotheses

Superior ESG fund ratings are hypothesised to correlate with enhanced fund returns through several channels. Strong ESG performance can improve corporate governance, risk management, and strategic direction, thereby reducing capital costs, operational risks, and exposure to reputational and regulatory shocks. (Khan, Serafeim, and Yoon 2016) demonstrate that firms addressing material ESG issues achieve

[2] In light of the definition of "sustainable funds" adopted in this paper, only certain conclusions from the research results of these authors are relevant to our scope.

higher future profitability, while (Friede, Busch, and Bassen 2015) provide aggregated evidence of a positive ESG–performance relationship. Addressing gaps in the existing literature, this study examines both composite ESG scores and individual dimensions—including carbon scores—to test the relationships between sustainability and return components, which consist of excess return, dynamic return, and security selection alpha. The analysis also investigates linear and non-linear effects using a holdings-based approach for greater granularity. To ensure robustness, key control variables such as fund size and net flows are incorporated within a fixed effects regression model to account for unobserved heterogeneity.

The analysis begins by examining the relationship between excess return and sustainability. Once static return components are removed, the remaining return comprises dynamic elements: factor timing and security selection alpha. Factor timing, which reflects adjustments to passive exposures, represents a channel through which ESG integration may enhance performance. The increasing prominence of environmental and social concerns often drives regulatory changes and shifts in market sentiment. Fund managers leveraging ESG analytics may adjust factor exposures accordingly. (Capelle-Blancard and Petit 2019) find that ESG-related news—particularly negative news—provokes significant market reactions, lending support to the premise that timely portfolio adjustments can yield excess returns.

Security selection captures the alpha generated through stock-picking. ESG integration may enable fund managers to identify firms with sustainable competitive advantages and robust operational performance. (Eccles, Ioannou, and Serafeim 2014) argue that a corporate culture committed to sustainability fosters long-term value creation through strategic planning, stakeholder engagement, and enhanced transparency in non-financial disclosures. This supports the proposition that ESG-driven security selection can improve fund performance. Although strict ESG screening may constrain the investment universe, when applied judiciously, it is expected to enhance security selection returns.

The transmission mechanism thus suggests that funds with superior ESG ratings should, on average, generate higher excess returns relative to their benchmarks. Accordingly, the following hypotheses are proposed for empirical analysis:

1. Overall Excess Return Hypothesis: *Funds with higher ESG ratings generate superior excess returns due to improved risk management and strategic positioning.*
2. Dynamic Return Hypothesis: *Funds with higher ESG ratings achieve superior dynamic returns—encompassing both factor timing and security selection alpha—by adjusting exposures in response to ESG-related market shifts.*

3. Security Selection Return Hypothesis: *Funds with higher ESG ratings generate greater security selection returns by identifying firms with sustainable competitive advantages and strong financial fundamentals.*

5.4 Data used in the analysis

The primary objective of this analysis is to assess the return drivers and alpha potential of sustainable funds. We make use of the underlying company ESG scores to calculate the final score, which reflects the weighted-average ESG score of the investment fund at a specific point in time.

5.4.1 Investment fund data

Our primary data sources are Morningstar Direct and FactSet. Our dataset initially covers 297[3] mutual funds with approximately US$689 million in assets, representing the entirety of the European equity-focused fund universe. This study includes all equity funds, regardless of fund size, domicile, investment style, or the level of activity in the investment strategy. We utilise quarterly holdings from March 2014 to September 2021 at the master fund class level, rather than sub-fund class levels, to prevent double counting. Additionally, the analysis universe has been adjusted for survivorship bias. Although the time span is relatively short, the dataset is extensive and details the portfolio constituents of these mutual funds during this period.

5.4.2 Stock-level and fund-level sustainability ratings

MSCI's sustainability data covers 8,500 companies and over 680,000 equity and fixed-income securities globally, rated across environmental, social, and governance pillars.[4] These pillars encompass 10 sustainability themes and 35 key ESG issues, evaluating a company's resilience to long-term, financially relevant ESG risks and opportunities. Within the environmental pillar, the focus is on themes such as climate change, carbon emissions, natural capital, pollution and waste, and environmental opportunities. The social pillar covers themes like human capital, product liability, stakeholder opposition, and social opportunities. The governance pillar focuses on corporate governance and behaviour.

A company's final ESG rating[5] is derived from the weighted average of individual scores for environmental and social key issues, combined with the governance pillar score, and then normalised relative to industry peers. This final rating, termed the Industry-Adjusted Score (IAS), ranges from 0 to 10, with 0 representing the lowest sustainability rating and 10 the highest. These assessments are intended for comparative analysis against industry peers rather than as absolute measures. MSCI applies a similar methodology to compute its carbon scores and the individual ESG dimensions.

The methodology for computing fund-level ESG scores in this study follows a holdings-based approach. Fund holdings are obtained from Morningstar Direct on a quarterly basis from 2014. Each fund's holdings are then mapped to MSCI's stock-level ESG scores, and an overall fund ESG score is computed

---

[3] The constituent coverage for the funds under investigation is around 95%.

[4] Source: MSCI ESG Ratings, MSCI

[5] For further details, see Appendix 4-A.

using a weighted-average aggregation based on portfolio weights. Since MSCI's aggregated fund-level scores are only freely available for the most recent date, they cannot be used for historical analysis. To construct historical fund-level ESG scores, we apply MSCI's aggregate fund scoring methodology to the computed stock-level data at each time point. A fund is assigned a score only if at least 65% of its constituents have available ESG data. Funds without a score are typically new to the market or have relatively low assets under management (AUM). Overall, our analysis covers 90.3% of the fund universe by AUM.

Potential drawbacks of this approach include mapping inconsistencies between fund holdings and stock-level ESG data, coverage bias due to incomplete data, and potential timing mismatches between quarterly holdings data and MSCI ESG scores. Additionally, the minimum coverage threshold could introduce selection bias by excluding funds with lower ESG data availability. While these limitations are acknowledged, they are not expected to substantially affect the overall results.

5.4.3 Definition of sustainable investment funds

As discussed by (Raghunandan and Rajgopal (2022)), defining the ultimate goal of ESG funds poses significant challenges, particularly in establishing a causal relation between ESG factors and explicit financial outcomes due to disclosure and data limitations. The primary definition of sustainability we employ is based on the sustainability score of the fund, independent of the fund's stated objective. It calculates the sustainability score quantitatively by determining the weighted-average score of all constituents on a quarterly basis. This approach implicitly assumes that funds incorporating sustainability considerations into their investment strategies are fully reflected in these scores. Additionally, in our regressions to establish the relationship between return components and returns, we also consider the Morningstar Sustainability Label, which categorises a fund as "sustainable" if it is described in its official documentation as focusing on sustainability, impact, or ESG factors, though the effectiveness of the fund's strategy is not rated by Morningstar.

5.5 Descriptive Statistics

5.5.1 Description of data and summary statistics

Exhibit 2 presents various descriptive statistics for the most recent Morningstar fund universe utilised in the analysis. These statistics encompass all funds invested in European equities, irrespective of domicile, style, AUM, and the degree of active stock picking involved in the strategy implementation. The values reported represent average point-in-time estimates, except for financial metrics, which are presented as median figures.

The exhibit reveals that the largest number of funds falls within the large-cap categories, with the most substantial assets under management (AUM) and the highest number of funds located in the general large-cap and large-cap blend categories. Additionally, these categories typically feature the lowest expense ratios. There appears to be little variation in sustainability characteristics across different categories, with the exception of small caps, where ESG scores are marginally lower. According to Gupta, Lodh, Harris (2021)[6], smaller companies have historically lagged their large-cap counterparts in terms of ESG metrics, likely due to the sparser availability of ESG information among small caps.

Regarding the point-in-time returns, the annualised excess returns of the various fund categories vary significantly, ranging from -11.1% in the European equity income category to 38.3% in the European small-cap category, while fund volatility remains relatively stable, ranging from approximately 19-23%. Tracking errors vary between 3.1% and 7.4%. Moreover, Exhibit 3 indicates that the majority of samples in the analysis predominantly belong to the large-cap fund group, specifically the large-cap blend category. It is also evident that small-cap funds often rank in the lower ESG deciles, whereas larger-cap funds, particularly those in the large-cap blend category, are more prevalent in the highest ESG deciles.

When evaluating the benchmark-excess returns of investment funds organised into sustainability deciles from 2014 to 2021, Exhibit 4 demonstrates that the lowest sustainability decile generally exhibits the highest average return, while the highest sustainability decile shows the lowest return. The relationship is not monotonic and appears to be "kinked" towards the most sustainable deciles. This pattern holds across all sustainability measures, except for governance, where the highest governance decile generates an excess return roughly equivalent to that of the lowest governance decile.

[6] https://www.msci.com/research-and-insights/global-investing-trends/esg-credentials-how-have-small-caps-stacked-up

Exhibit 2 Descriptive Statistics of the Morningstar European Equity Universe in Scope

	General Fund Characteristics			Financial metrics			
Category	No. in each category	Average Expense Ratio	Average AUM (USD million)	Average ESG Score	Median Monthly Excess Return (Annual.)	Median Fund Vol (Annual.)	Median Tracking Error (Annual.)
Europe Large-Cap Blend Equity	130	1.174	768.323	7.146	-3.781	20.320	3.100
Europe Large-Cap Growth Equity	40	1.614	1326.004	7.265	-3.093	18.520	5.645
Europe Large-Cap Value Equity	28	1.699	442.518	7.006	8.168	25.730	4.350
Europe Flex-Cap Equity	40	1.582	382.521	6.207	14.598	21.100	7.395
Europe Equity Income	27	1.597	428.369	7.113	-11.097	21.472	3.980
Europe Mid-Cap Equity	19	1.363	712.737	6.213	18.194	20.601	4.850
Europe Small-Cap Equity	7	1.551	249.161	5.494	38.264	23.432	4.590

Source: Morningstar, author's estimates. Descriptive statistics cover the period of September 2021.

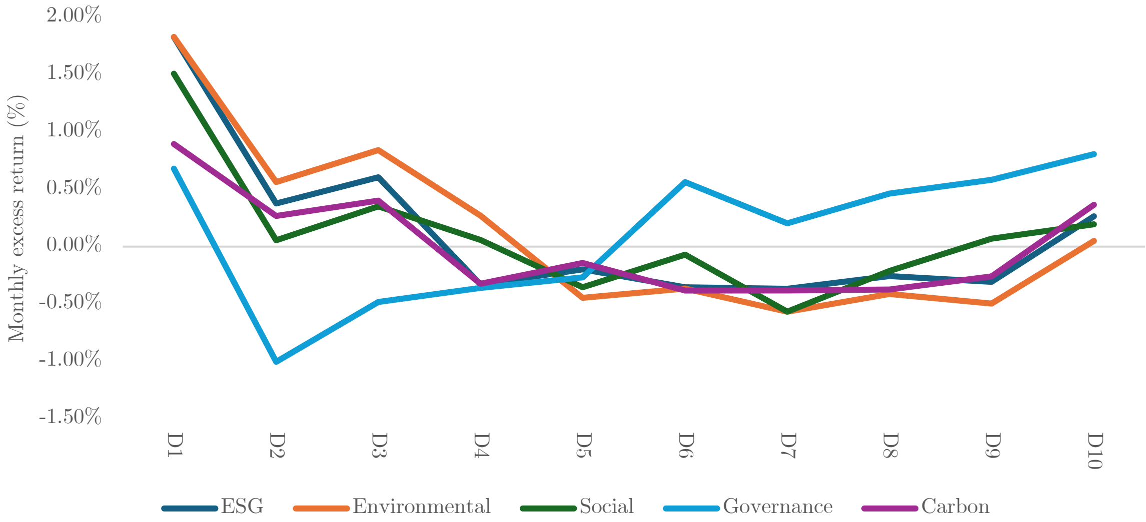
Notes: Figures for the number of funds, expense ratio and average AUM are taken as point-in-time figures as of September 2021. Sustainability metrics represent the mean for the category and are calculated as weighted averages of the constituents as of September 2021. Financial metrics represent the median for the category and are calculated as of September 2021. Past performance does not guarantee future results.

Exhibit 3 Distribution of Funds Across ESG Deciles Within Various Fund Categories

	Portfolios arranged by ESG deciles *(higher deciles represent stronger ESG credentials)*										
Categories	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	*D10-D1*
Europe Large-Cap Blend Equity	1.26%	1.96%	3.31%	4.73%	5.28%	6.31%	6.13%	4.99%	5.26%	5.81%	*4.55%*
Europe Large-Cap Growth Equity	0.15%	0.49%	1.25%	1.35%	1.37%	1.40%	1.32%	2.32%	1.88%	2.29%	*2.14%*
Europe Large-Cap Value Equity	0.07%	0.91%	1.37%	1.40%	1.15%	0.92%	0.76%	1.22%	1.15%	0.42%	*0.35%*
Europe Flex-Cap Equity	4.18%	3.70%	2.08%	1.07%	0.76%	0.47%	0.55%	0.38%	0.48%	0.19%	*-3.99%*
Europe Equity Income	0.20%	0.61%	1.00%	1.12%	1.02%	0.63%	0.91%	0.93%	1.25%	1.47%	*1.27%*
Europe Mid-Cap Equity	2.57%	1.86%	0.88%	0.32%	0.21%	0.11%	0.15%	0.22%	0.11%	0.01%	*-2.56%*
Europe Small-Cap Equity	1.65%	0.62%	0.08%	0.02%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	*-1.65%*

Source: Morningstar, author's estimates. Statistics cover the period of March 2014 to September 2021.

Exhibit 4 Benchmark-Excess Return Across Various Sustainability Deciles, with D1 Representing the Lowest Scoring Decile and D10 the Highest

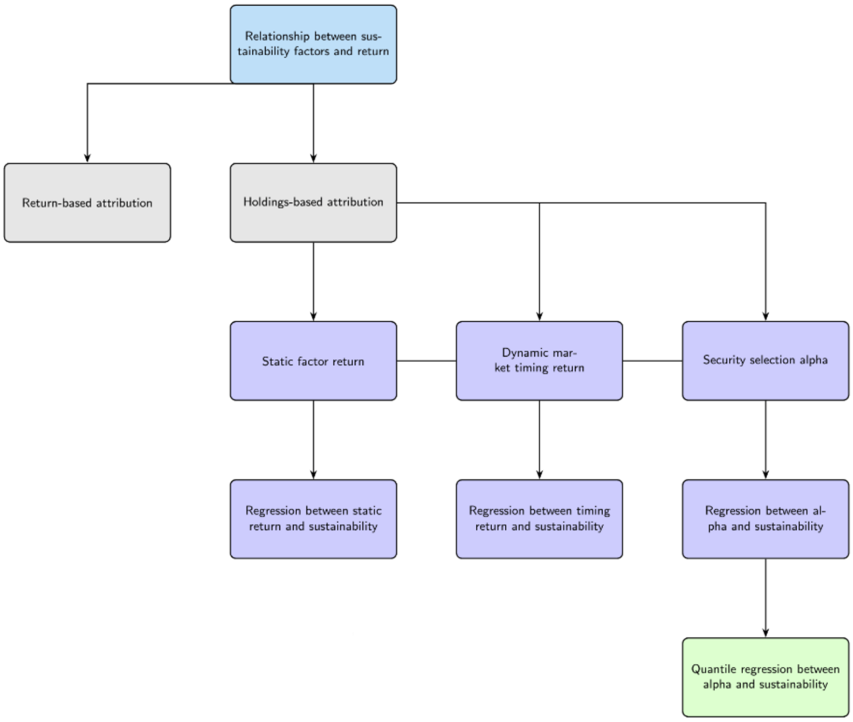


Source: Authors' estimates. Monthly returns from March 2014 to September 2021.

5.6 Analysis Methodology

To elucidate and quantify any associations between sustainability factors and portfolio returns, the following methodology, summarised in the diagram below, has been adopted (Exhibit 5).

Exhibit 5 The Analysis Methodology Adopted in This Study



Source: Authors' depiction

The investigation begins by classifying investment funds into deciles based on their sustainability factors, followed by conducting both a returns-based attribution analysis and a holdings-based analysis. Initially, a time-series analysis entails regressions of the returns of these investment funds—equally weighted and categorised according to their corresponding sustainability factors—against traditional factor models such as those developed by Fama-French and AQR. Moreover, a holdings-based approach, which leverages information on stock-level characteristics for a more robust analysis, forms the central premise of the analysis. Here, the returns are disaggregated into static factor return (risk premia), factor timing return, and alpha (security selection). To ascertain whether these return components are influenced by sustainability factors, fixed-effects regressions are employed, incorporating fund-related independent variables. Furthermore, to validate the robustness of the results concerning alpha across different segments of the return distribution, quantile regressions are undertaken.

5.7 Time-Series-based attribution analysis

This method involves estimating factor loadings through rolling regressions of portfolio returns on factor returns, noted for its straightforward implementation. However, its granularity is limited, and it does not provide insights at the security level, potentially obscuring the true drivers of performance. Moreover, assuming a constant beta throughout the estimation window renders this approach less suitable for managers who engage in factor timing, as highlighted by (Ang, Madhavan, and Sobczyk 2017).

To estimate the cross-sectional exposure (β_j) of portfolio returns (PR_j), are typically conducted between the returns and long-short factors, with beta assumed constant throughout the estimation period. Following (Treynor and Mazuy 1966), an additional term—the square of the market premium—is incorporated into each regression model to capture the non-linear effects of market timing and to examine whether portfolio returns sorted by sustainability characteristics also relate to the market timing abilities of portfolio managers. The analysis utilises three model specifications in the time-series regression analysis[7]: the Fama-French 3-factor model with Carhart momentum, the Fama-French 6-factor model, and the AQR factor model.

Model 1: Fama French 3 factor model with Carhart momentum

$$\mathrm{PR}_j(t) = \alpha_j + \beta_{j1}MKT(t) + \beta_{j2}SMB(t) + \beta_{j3}HML(t) + \beta_{j4}MOM(t) + +\beta_{j5}MKT^2(t) + \epsilon_j(t)$$

Model 2: Fama French 6 factor model

$$\mathrm{PR}_j(t) = \alpha_j + \beta_{j1}MKT(t) + \beta_{j2}SMB(t) + \beta_{j3}HML(t) + \beta_{j4}RMW(t) + \beta_{j4}MOM(t) + \beta_{j6}CMA(t) \\ + \beta_{j7}MKT^2(t) + \epsilon_j(t)$$

Model 3: AQR factor model

$$\mathrm{PR}_j(t) = \alpha_j + \beta_{j1}MKT(t) + \beta_{j2}HML(t) + \beta_{j3}SMB(t) + \beta_{j4}UMD(t) + \beta_{j5}QMJ(t) + \beta_{j6}MKT^2(t) + \epsilon_j(t);$$

where MKT represents the market premium, SMB the size premium, HML the value premium, MOM the Carhart momentum premium, RMW the profitability premium, CMA the investment premium, UMD the up-minus-down momentum premium, QMJ the quality-minus-junk premium and MKT^2 the square of the market premium (market timing).

5.8 Holdings-based attribution analysis

This analysis, as proposed by (Madhavan, Sobczyk, and Ang 2018), provides a nuanced examination at the security level, crucial for understanding the influence of asset selection on portfolio performance. The approach utilises (Lo 2008)'s active-passive (AP) decomposition for analysing portfolio returns.

[7] For details, see the footnotes of Exhibit 6.

Under certain simplifying assumptions[8], the expected benchmark-relative portfolio return ($R_{j,t}$) of a fund j at time t is redefined into three distinct components: a passive exposure to systematic market-wide factors, a factor timing return influenced by the covariance between portfolio betas and these factors, and a security selection component. Thus, the portfolio return can be articulated as follows:

$$\mathrm{R}_{\mathrm{j,t}} = \mathrm{SFR}_{\mathrm{j,t}} + \mathrm{FTR}_{\mathrm{j,t}} + \alpha_{\mathrm{j,t}}$$

where: $SFR_{j,t}$ represents the static factor return (also known as the risk premia), the $FTR_{j,t}$ represents the factor timing return and $\alpha_{j,t}$ represents the expected security selection return.

Typically, static factor return reflects the expected return from passive exposure to factor risks, whereas factor timing return, achieved through strategic adjustment of factor exposures, and alpha, derived from security selection, are sources of excess return.

The comprehensive approach adopted not only facilitates an understanding of the contributions of various return components to overall portfolio performance but also examines the potential influence of sustainability factors on these components, thus offering a robust framework for assessing the efficacy of sustainability-focused investment strategies.

5.8.1 Static factor return (risk premia)

The computation of static factor return (risk premia) aims to elucidate the component of portfolio return attributable to systematic risk factors. Employing quarterly holdings data, the time-varying factor loadings across diverse fund portfolios is estimated, aligning the stock-level characteristics of factor-mimicking portfolios with those of the individual investment funds. The characteristics of the stocks used in this analysis are derived from normalised style scores, based on the factors specified in the Axioma Equity Factor Risk Model[9]. For each designated fund j, a factor-mimicking portfolio is defined.

[8] For details, refer to the original paper by Lo (2008).

[9] The Axioma Fundamental Equity Risk Model is one of the most well-adopted model used in the financial industry to evaluate and manage risks in equity portfolios. It integrates fundamental financial data - such as earnings and book values - to identify and quantify systematic and idiosyncratic risk factors. Systematic risks include market exposure, sector/industry exposure, and style factors like value, growth, size, and momentum. Idiosyncratic risks are specific to individual stocks.

The model employs advanced statistical techniques, namely principal component analysis and regression analysis, to estimate factor exposures and construct a covariance matrix that captures the relationships between different risk factors and assets. This allows for comprehensive risk decomposition, attributing total portfolio risk to various sources.

In practice, investment managers use the Axioma model for portfolio construction and optimisation, aligning portfolios with risk-return objectives while managing downside risks. It also assists in risk attribution and performance analysis, This portfolio comprises a range of investible factor indices, each optimised to best represent the specific characteristics of the fund under analysis. Initially, the aggregated factor loadings for fund j and each index m in the factor-mimicking portfolio are calculated at the stock level i and can be defined as $\beta_{jk} = \sum_{i=1}^{N} w_{ij} \cdot FL_{ik}$ and Index $_{mk} = \sum_{i=1}^{P} w_{im} \cdot FL_{ik}$, where FL_{ik} represents the respective factor loadings.

This portfolio is fully invested and adheres to a long-only strategy, ensuring the number of investible factor indices (M) in the portfolio cannot surpass the number of risk factors being replicated. Mathematically, the formulation is expressed as follows:

$$\min_{\widehat{w_{jm}}} \sum_{k=1}^{K} \left(\widehat{\hat{\beta}_{jk}} - \sum_{m=1}^{M} \widehat{w_{jm}} \cdot \text{Index}_{mk} \right)^2 \quad \text{s.t.} \;\; \widehat{w_{jm}} \geq 0 \quad \forall m, \; \sum_{m=1}^{M} \widehat{w_{jm}} = 1, \; M \leq K$$

where j represents a particular fund, $k = 1 \ldots K$ denotes the individual risk factors, $m = 1 \ldots M$ refers to individual investible factor indices.

Employing the method set out above, the combination of active weights (or exposures) in the factor-mimicking portfolio is ascertained and subsequently utilised to estimate the static factor return ($\widehat{SFR_j}$) (or risk premia) of the fund, devoid of any alpha component by design. The estimation procedure follows a root mean-square minimisation, applied to each of the investment funds under scrutiny. The static factor return is calculated as:

$$\widehat{\text{SFR}_j} = \sum_{k=1}^{K} \widehat{\beta_{jk}} \cdot \mathbf{E}(\text{F}_k)$$

where $(\hat{\beta}_{jk})$ denotes the estimated loading of the fund on each factor k in the Axioma model and the expected returns of these factors $\text{E}(F_k)$. This approach enhances the understanding of how static risk factors contribute to the overall return landscape of investment funds.

5.8.2 Dynamic return and factor timing return

Dynamic return comprises both factor timing return and security selection alpha, reflecting a portfolio manager's ability to generate returns through dynamic adjustments.

The factor timing return specifically measures the manager's proficiency in modifying market exposure at strategically favourable moments to capitalise on anticipated market fluctuations. This sub-component depends on the covariance between the fund's portfolio betas and the returns of various

providing insights into the effectiveness of investment strategies. Overall, the Axioma model is essential for understanding, managing, and mitigating equity portfolio risks.

factors, denoted by K for the factors previously mentioned. In mathematical terms, the estimated factor timing return is expressed as:

$$\widehat{\mathrm{FTR}_{\mathrm{J}}} = \sum_{k=1}^{K} \mathrm{Cov}\left[\widehat{\beta_{jk}},\, \mathrm{F}_k\right]$$

where $\left(\widehat{FTR_J}\right)$ denotes the estimated factor timing return of fund j.

5.8.3 Security selection (or alpha) and sustainability information as a "signal"

Security selection, or alpha, is computed by aggregating the stock-specific alphas across the fund, each weighted by its average active weight. This metric is viewed as an integral, active component that reflects the efficacy of the fund managers' predictive insights at the security level:

$$\widehat{\alpha_{\mathrm{j}}} = \sum_{i=1}^{N} \alpha_i \mathbf{E}[w_i]$$

where $\left(\widehat{\alpha_J}\right)$ denotes the estimated fund alpha and $\mathrm{E}[w_i]$ denotes the expected active weight of stock i in the portfolio

Following the methodology articulated by (Clarke, de Silva, and Thorley 2005), the residuals $(\widehat{\alpha_J})$ of a fund j can be regressed against the forecasted signal $(\mathrm{S_j})$ and its payoff $(\widehat{\gamma_{J,t}})$. Note that $\widehat{\varepsilon_{J,t}}$ is the regression disturbance term.

$$\widehat{\alpha_{\mathrm{j}}} = \widehat{\gamma_J}\mathrm{S_j} + \widehat{\varepsilon_{\mathrm{j}}}$$

where: $\begin{cases} \mathrm{S_j} \subset \{\mathrm{S_{Sustainability}}, \mathrm{S_{EQ}}\} \\ \mathrm{S_{Sustainability}} \perp \mathrm{S_{EQ}} \end{cases}$

In this formulation, the signal forecast integrates both sustainability data and other financially pertinent information regarding expected returns, with an assumption that sustainability information is orthogonal to other expected return information (S_{EQ}). Similar to the approach taken by (Pedersen, Fitzgibbons, and Pomorski 2021), ESG scores are employed to refine overall perspectives on expected returns.

5.9 Analysing the sources of return while controlling for unobserved heterogeneity

The objective of this segment is to ascertain whether sustainability signals have influenced various aspects of return, including excess return, dynamic return, and security selection alpha.

5.9.1 Excess return and sustainability information

The initial series of regressions investigate the relationship between excess return (ER) and sustainability information, utilising a fixed effects regression model that includes fund-specific variables such as expense ratio, fund flows, size, age, volatility, and static factor return, supplemented by additional control variables like Morningstar categories and ratings. Our analysis assesses both the linear and non-linear effects of sustainability scores as independent variables. This is achieved through two sets of regressions: one focusing purely on sustainability scores, and another that incorporates sustainability scores alongside an indicator variable representing whether scores are above or below the median, thereby capturing non-linear effects.

$$ER_{j,t} = \beta \mathrm{S}_{\mathrm{j,t}} + \gamma_1 \mathrm{EX}_{j,t} + \gamma_2 \mathrm{FL}_{j,t} + \gamma_3 \mathrm{SZ}_{j,t} + \gamma_4 \mathrm{AGE}_{j,t} + \gamma_5 \mathrm{VOL}_{j,t} + \gamma_6 \mathrm{SFR}_{j,t} + \left(\theta_\tau I(\mathrm{S}_{j,t} > \widetilde{\mathrm{S}_{j,t}}\right) + \delta_1 \mathrm{MCAT}_{j,t} + \delta_2 \mathrm{MAR}_j + \delta_3 \mathrm{MSR}_j + \delta_4 \mathrm{Index}_j + \lambda_t + \epsilon_{j,t}$$

where independent variables include S_j (ESG scores, Environmental scores, Social scores, Governance scores, or Carbon scores), control variables where EX is the total expense ratio, FL is the fund flows, SZ is fund size, AGE is the fund age, VOL is the fund volatility, SFR is the static factor return, θ is the coefficient for the binary indicator $\left(I(\mathrm{S}_j > \widetilde{\mathrm{S}_j})\right)$ which captures the additional non-linear effect on excess returns when a fund's sustainability score is above the median $(\widetilde{\mathrm{S}_j})$ compared to being below it. Fixed effects variables include MCAT is the fund Morningstar category, MAR is Morningstar analyst rating, MSR is Morningstar sustainability rating and Index is whether a fund is an active or index fund. λ_t represents the time fixed effects. Endogeneity is not a concern in this analysis. A robustness check was conducted by incorporating lagged returns as an explanatory variable using the instrumental variable approach to assess whether past returns influence current returns. The results indicate that lagged returns are not statistically significant in the fixed effects model, confirming that omitted past returns do not bias the estimation. This outcome aligns with the well-documented characteristic of financial return series, which generally exhibit no memory, unlike risk-related variables such as volatility, which tend to display persistence.

5.9.2 Other return components and sustainability information

The subsequent set of regressions delves into the interplay between additional return components, specifically dynamic return and security selection alpha, and sustainability information. This analysis adopts the methodology previously detailed in section 5.3.1, with a notable adjustment: the static factor return variable is excluded from the regression model as an independent variable. This refinement ensures that the focus remains sharply on the dynamic components of return, isolating their relationships with sustainability inputs more precisely. Consistent with the previous approach, two sets of regressions are employed: one exclusively examining the level of sustainability, and another that combines sustainability scores with an indicator variable denoting whether scores are above or below the median, thus facilitating the examination of non-linear effects.

$$R_{j,t} = \beta \mathrm{S}_{\mathrm{j,t}} + \gamma_1 \mathrm{EX}_{j,t} + \gamma_2 \mathrm{FL}_{j,t} + \gamma_3 \mathrm{SZ}_{j,t} + \gamma_4 \mathrm{AGE}_{j,t} + \gamma_5 \mathrm{VOL}_{j,t} + \left(\theta_\tau I(\mathrm{S}_{j,t} > \widetilde{\mathrm{S}_{j,t}})\right) + \delta_1 \mathrm{MCAT}_{j,t} + \delta_2 \mathrm{MAR}_j + \delta_3 \mathrm{MSR}_j + \delta_4 \mathrm{Index}_j + \lambda_t + \epsilon_{j,t}$$

5.9.3 Security selection alpha and sustainability information in quantile regressions

Subsequently, quantile regressions are utilised to examine the relationship between alpha and sustainability information using the fixed effects quantile regression methodology developed by (Machado and Santos Silva 2019)[10]. This approach is particularly suitable for capturing the impacts of independent variables across different segments of the return distribution, offering robustness against outliers and non-normal error distributions. As in previous analyses, two sets of regressions are conducted: one focusing exclusively on the level of sustainability, and another that integrates the sustainability scores with an indicator variable to denote whether scores are above or below the median. This dual approach allows for a nuanced exploration of both linear and non-linear effects.

$$Q_\tau(R_{j.t}) = \beta_\tau \mathrm{S}_{j,t} + \sum_{k=1}^{5} \gamma_{k,\tau} \mathrm{X}_{k,jt} + \left(\theta_\tau I(\mathrm{S}_{j,t} > \widetilde{\mathrm{S}_{j,t}})\right) + \sum_{l=1}^{4} \delta_{l,\tau} \mathrm{Z}_{l,j} + \lambda_{t,\tau} + \epsilon_{jt,\tau}$$

Here $Q_\tau(R_{j,t})$ denotes the quantile conditional regression at quantile τ, independent variables include S_j (ESG scores, Environmental scores, Social scores, Governance scores, or Carbon scores), $\widetilde{\mathrm{S}_j}$ is the median of the sustainability score in question, $X_{k,jt}$ includes EXP_{jt}, FL_{jt}, SZ_{jt}, AGE_{jt}, VOL_{jt}, θ_τ is the

[10] The paper by Machado and Silva (2019) develops an approach to quantile regression by employing quantile fixed effects, which allows for the estimation of quantiles within a panel data framework. It introduces a method that uses moment conditions to estimate the fixed effects, enhancing the model's flexibility and efficiency. This approach is particularly useful in settings where the impact of covariates varies across different points of the conditional distribution of the outcome.

coefficient for the binary indicator $\left(I(\mathrm{S}_{\mathrm{j,t}} > \widetilde{S_{j,t}}\right)$ which captures the additional non-linear effect of returns at the quantile level and $Z_{l,j}$ includes MCAT_j, MAR_j, MSR_j, Index_j.

5.10 Empirical results

5.10.1 Drivers of systematic (static) return for funds with strong sustainability performance

A more direct linkage between sustainability and factor investing is documented by (Madhavan, Sobczyk, and Ang 2021). They find that style factors explain approximately 75% of the variation in environmental (E) scores, whereas factors have markedly lower explanatory power for social (S) and governance (G) scores. Moreover, funds with particularly high E scores exhibit near-monotonic increases in both momentum and quality exposures, underscoring the importance of environmental considerations in driving factor tilts.

As delineated in the Analysis Methodology section, the initial phase of the study involves conducting a time series analysis of portfolios categorised into deciles based on increasing sustainability metrics, encompassing composite and component ESG scores, and carbon scores. Subsequently, these portfolios undergo separate analysis via cross-sectional regressions employing traditional factor models, specifically the Fama-French 3-factor model with Carhart momentum, the Fama-French 6-factor model, and the AQR model. To assess potential market timing effects, a term proxied by the square of market beta is incorporated into each regression. The objective is to analyse whether there is an association between higher or lower sustainability investment funds and specific equity factor loadings.

Exhibit 6 presents the outcomes for portfolios classified according to ESG scores, with additional results detailed in Appendix 4-B. Notably, the factor loading of market beta is significant across all deciles, which is unsurprising for long-only portfolios, while market timing—proxied by the square of market beta—remains largely extraneous. However, the emergence of market beta as the sole significant factor across all deciles indicates that there is no conclusive evidence that portfolios with higher sustainability ratings correspond with materially lower beta or elevated momentum and/or quality factor loadings.

Lower deciles (D1, lowest ESG scores) exhibit high sensitivity to market returns, while higher deciles (D10, highest ESG scores) maintain significant but slightly lower sensitivity—though the difference is modest and thus, inconclusive. The value factor (HML) reveals a nuanced relationship, with value stocks more prevalent in lower ESG score deciles and growth stocks in higher deciles, even if the trend is not unequivocal. The absence of a discernible trend persists across portfolios organised by individual ESG dimensions, as well as those categorised by carbon scores. In the latter case, while some portfolios with higher carbon scores frequently display a tendency towards growth (or negative value) loadings, these results lack consistency, and the relationship between carbon scores and returns is not monotonic. Similarly, a preference for growth stocks is also apparent in the highest governance deciles, whereas tilts towards size (SMB) gain significance in the lower social deciles.

One possible explanation for the lack of a clear relationship between sustainability and factor loadings derived from time-series regressions may lie in the granularity of the analysis. The reliance on returns data over the entire period, rather than on holdings data, may restrict the depth and specificity of the insights obtained. Additionally, factor loadings generally evolve gradually over time, leading to coefficients that are smoothed and predominantly influenced by the market factor. These elements collectively result in diluted interpretability and minimal variation in factor loadings across deciles, thereby diminishing their economic and financial relevance. For these reasons, we now transition to a holdings-based analysis, which forms the cornerstone of our investigation. This method is designed to address some of the limitations identified in earlier returns-based assessments.

This approach utilises quarterly holdings information from each of the investment funds under analysis. The aim is to replicate the performance of each fund through three components: static factor return, based on systematic time-varying exposure to factors that can be obtained using investible indices; dynamic timing return, which pertains to the timing of these factors; and a security selection alpha return. For this analysis, seven systematic factors are employed[11], including low volatility, quality, value, momentum, size (small caps), risk-weighted, and large cap multifactor[12]. The subsequent step involves calculating, on a quarterly basis, the time-varying exposure to these factors by determining the combination of weights into these factors such that their stock characteristics closely align with those of the investment fund under review, facilitated by the Axioma Equity Risk Model.

An examination of Exhibit 7, alongside the supplementary data presented in Appendix 4-C, reveals the absence of a consistent linear progression in the allocation to specific factors within funds that achieve higher scores. This pattern persists regardless of whether the portfolios are sorted by individual ESG dimensions, overall ESG metrics, or carbon scores, mirroring the findings of prior analyses. Across all evaluations, the allocation to low volatility remains notably modest. Notably, portfolios categorised under the overall ESG criteria exhibit a pronounced reduction in allocation to the value factor and an increase in allocation to the risk-weighted factor, particularly at the highest extreme of the portfolio groupings. Despite the quality factor commanding the highest allocation across all deciles, its

[11] Other factors and combinations have been analysed; however, they do not significantly enhance the explanatory power of the performance of the funds in scope.

[12] These systematic factors are represented by MSCI Europe Minimum Volatility Index, MSCI Europe Enhanced Value Index, MSCI Europe Momentum Index, MSCI Europe Small Caps, MSCI Europe Risk Weighted Index and MSCI Europe Multi-factor index.

distribution exhibits significant fluctuations between the highest and lowest scores, lacking any discernible pattern.

Conversely, portfolios sorted by environmental and social scores demonstrate a marked increase in the allocation to the momentum factor, which overwhelmingly dominates in portfolios with the highest scores. Intriguingly, the momentum factor's allocation follows a non-linear trajectory across deciles, initially increasing, then decreasing, and ultimately rising again towards the highest-scoring environmental ventiles, partly at the expense of allocation to value (or in favour of growth).

In portfolios organised by governance scores, a reduction in momentum allocation is observed in the highest governance portfolios, though this reduction is more modest than that in portfolios sorted by environmental and social scores, particularly at the uppermost end of the spectrum as scores increase. Regarding carbon scores, there is a strategic reallocation towards small caps and a shift away from value at the highest terminal sections of the grouping.

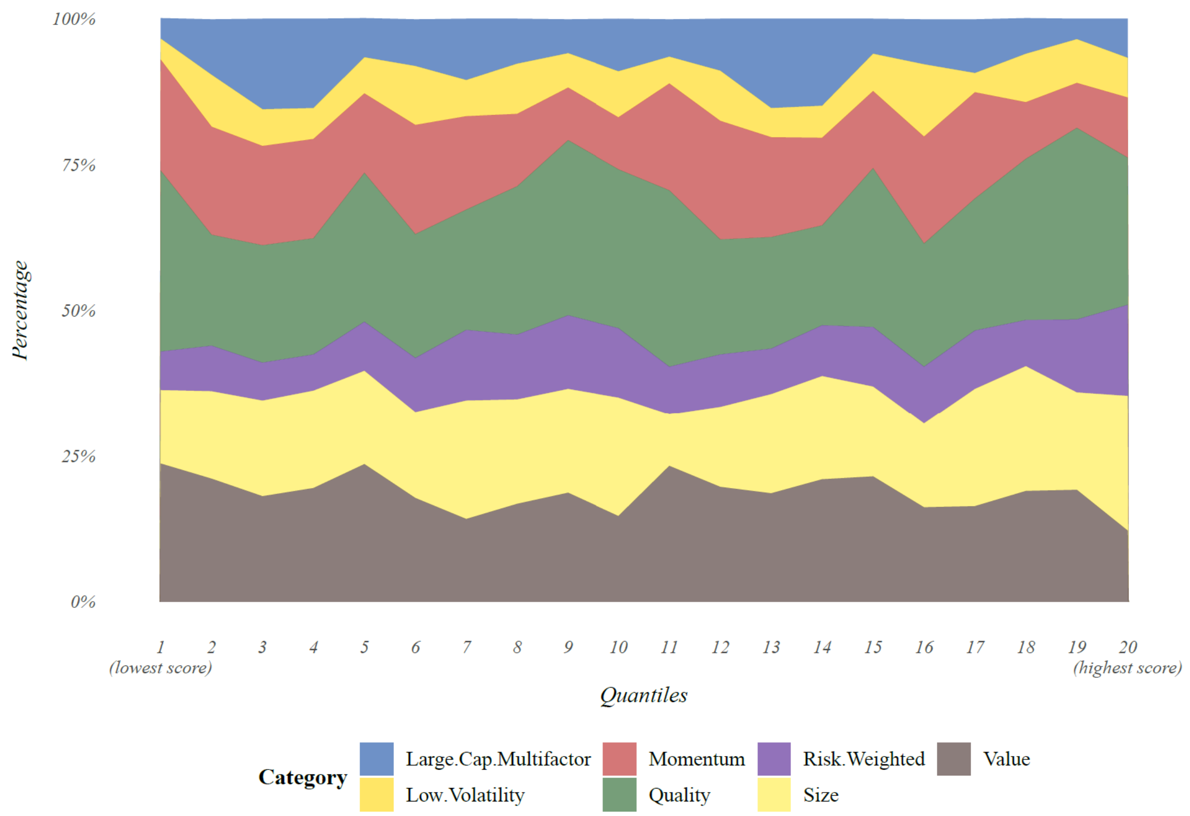
These patterns observed in the analysis of European funds share certain similarities with the findings by (Madhavan, Sobczyk, and Ang 2021) regarding US funds, though notable differences persist. According to their research, portfolios with robust environmental scores exhibit high factor loadings in quality and momentum, while the highest-rated governance funds demonstrate low momentum loadings. Furthermore, funds with high social and governance scores frequently invest in growth companies, as indicated by their negative loadings in value.

Exhibit 6 Factor loadings from cross-sectional regressions for portfolios sorted by ESG scores using three attribution methods

Decile	Model	α	MKT	MKT^2	SMB	HML	MOM	RMW	CMA	UMD	BAB	QMJ	R^2
1 (Lowest Score)	FF3M	0.001	1.020***	-0.717	-0.162	0.347.	0.006						69%
	FF6F	0.000	1.011***	-0.334	-0.084	0.554	0.039	0.550	0.183				70%
	AQ6F	0.000	1.002***	-0.855	0.175	0.573				0.146	-0.175	0.196	68%
2	FF3M	-0.007	1.248***	1.675	-0.095	-0.456*	0.047						66%
	FF6F	-0.007	1.255***	1.496	-0.131	-0.562	0.026	-0.259	-0.048				66%
	AQ6F	-0.007	1.251***	1.713	-0.109	-0.435				0.110	-0.129	-0.072	66%
3	FF3M	-0.007	1.089***	0.791	-0.275	0.224	0.015						67%
	FF6F	-0.005	1.161***	0.530	-0.178	-0.368	-0.095	-0.572	0.686				68%
	AQ6F	-0.003	0.924***	-0.004	-0.482	-0.484				-0.453	0.299	-0.621	68%
4	FF3M	0.004	1.012***	-1.791	-0.396	-0.171	-0.083						55%
	FF6F	0.002	0.967***	-1.374	-0.430	0.338	-0.002	0.734	-0.241				57%
	AQ6F	0.004	1.008***	-1.777	0.043	0.355				0.099	-0.265	0.434	56%
5	FF3M	-0.011*	1.087***	1.166	-0.130	-0.097	-0.048						68%
	FF6F	-0.012*	1.034***	1.158	-0.283	0.303	0.019	0.174	-0.666				69%
	AQ6F	-0.011*	1.088***	1.152	-0.137	0.057				0.081	-0.078	0.031	68%
6	FF3M	-0.004	0.995***	-1.536	0.069.	-0.438*	-0.392.						64%
	FF6F	-0.005	1.005***	-1.291	0.161	-0.426	-0.387.	0.297	0.303				64%
	AQ6F	-0.004	0.990***	-1.428	0.140	-0.446				-0.516	0.047	0.158	63%
7	FF3M	0.002	0.989***	-1.345	-0.626**	0.094.	0.015						63%
	FF6F	0.003	0.997***	-1.426	-0.642*	0.032	-0.012	-0.119	0.074				63%
	AQ6F	0.004	0.872***	-1.815	-0.635*	-0.392				-0.449	0.270	-0.227	62%
8	FF3M	-0.004	1.035***	-0.943	-0.723**	0.279	0.311.						64%
	FF6F	-0.001	1.116***	-1.151	-0.586*	-0.354	0.182	-0.527	0.877.				67%
	AQ6F	-0.002	0.892***	-1.378	-0.911**	-0.135				0.095	0.215	-0.589	63%
9	FF3M	-0.003	1.105***	0.945	0.021	-0.289	0.200						59%
	FF6F	-0.001	1.117***	0.267	-0.120	-0.624	0.140	-0.960*	-0.353				62%
	AQ6F	-0.001	1.011***	0.801	-0.247	-0.998**				-0.146	0.244	-0.645	63%
10 (Highest Score)	FF3M	-0.008	1.028***	1.863	-0.003	-0.236	-0.038						59%
	FF6F	-0.006	1.107***	1.637	0.122	-0.876.	-0.149	-0.553	0.782				60%
	AQ6F	-0.005	0.968***	1.546	0.065	-0.323				0.011	-0.155	-0.305	60%

Source: Authors' estimates. The FF3M model includes the market risk premium (Mkt-Rf), which measures the excess return of the market over the risk-free rate, size (SMB) reflecting the outperformance of small-cap stocks over large-cap ones, and value (HML), capturing the higher returns of value stocks over growth stocks, with an additional momentum (MOM) factor accounting for the persistence of stock performance trends. The FF6F model builds on FF3M by adding profitability (RMW), which measures the return difference between highly profitable and less profitable firms, and investment (CMA), which captures returns based on firms' investment behaviours. The AQ6F model by AQR includes the market risk premium, size, value, and momentum factors from traditional models, but also incorporates quality (focusing on profitable and stable companies) and defensive (low-risk, high-return stocks) factors for a broader investment strategy. *** represents statistical significance at 0.1%, ** represents statistical significance at 1%, * represents statistical significance at 5% and . represents statistical significance at 10% levels. MKT represents the market beta exposure, MKT^2 represents the square of the market beta exposure which seeks to proxy the non-linear market timing ability, SMB represents the size factor, HML represents the value factor, MOM represents the Carhart momentum factor, RMW represents the operating profitability factor, CMA represents the investment conservatism, UMD represents the AQR momentum factor, BAB represents the betting against beta factor and QMJ represents the quality factor.

Exhibit 7 Allocations to Investible Factors Across Investment Funds Grouped by Their ESG Scores



Source: Authors' estimates.

5.10.2 Relationship between components of return and sustainability information

In this final section, we aim to quantify the relationship between different components of return—specifically, excess return, dynamic timing return, and security selection alpha—and sustainability information, as detailed in Section 5.3.1. Unlike previous sections, where funds were aggregated into deciles and ventiles to analyse their behaviour based on sustainability groupings, the following analyses are conducted using data and estimations on individual funds. This involves regressing these return components against key fund-specific variables, including expense ratio, fund age, flows, size, and volatility, utilising both ordinary least squares (OLS) and fixed effects panel regressions, with a particular focus on the latter. Fixed effects regressions address unobserved heterogeneity by assigning a unique intercept to each entity (or grouping within the data) in the fixed effects model. This approach effectively eliminates biases from time-invariant unobserved variables. The primary advantage of this method over OLS regressions is that it reduces omitted variable bias, controls for time-invariant characteristics, and provides insights into the effects of intragroup changes on the dependent variable, while also being robust to autocorrelation within entities over time. The fixed effects included in the model comprise Morningstar categories, Morningstar analyst ratings, the Morningstar Fund Sustainability Label[13], and whether the fund is an index fund. To ensure the validity of the estimates, errors are clustered by investment fund and date.

[13] The Morningstar Fund Sustainable Label relates to whether, in the view of Morningstar, a fund includes any sustainability objective in its fund prospectus and is not related to the ESG performance of any given fund.

5.10.3 Relationship between excess return and sustainability

As delineated in Section 5.3.1, the objective of this section is to quantify the general relationship between excess return—defined as the return of investment funds relative to their prospectus benchmarks—and sustainability information, while incorporating a range of independent and additional control variables in the fixed effects specifications.

We commence by reviewing the regression findings detailed in Exhibit 8, which investigate the relationship between excess return and ESG scores. Across all specifications, the static return is both positive and highly significant, emphasising its pivotal role in explaining excess return. This strong result stems from broad market factor exposures that consistently drive fund performance ((Fama and French 1993), (Carhart 1997)). In essence, static return captures systematic (passive) factors that dominate the variability in returns, overshadowing smaller, active contributions such as ESG-related tilts. This result aligns with expectations, as factors are presumed to largely dictate the performance of the investment funds under review. A critical insight is the reduction in the t-statistics associated with the static return coefficients from the OLS (132.4) to the fixed effects specifications (22.5), although they remain substantially high, offering robust evidence against the null hypothesis. Moreover, while the ESG score is initially significant in the OLS regressions, it becomes insignificant or markedly less significant (-0.556) in the fixed effects regressions, which include both the raw score and the median as explanatory variables. This shift suggests that the initial findings may be skewed by omitted variables that vary between groups but not within them, potentially compromising the reliability of these results. Intriguingly, where the ESG score is significant, it negatively influences the excess return, suggesting that lower ESG scores correlate with higher returns. Other notable variables that modestly affect excess return include fund flows, fund age, both of which are positively correlated with excess return. Notably, the analysis reveals that newer funds tend to achieve higher excess returns. This implies that although active management decisions and sustainability-related strategies may contribute to performance, they do not outweigh the dominant influence of passive factor exposures encapsulated by the static return component.

Regarding the regression findings for other sustainability variables—such as the individual dimensions of ESG and carbon scores—these are elaborated upon in Appendix 4-D. Irrespective of the sustainability metrics considered, the static return consistently emerges as a highly significant and influential factor across all regression models, as demonstrated by its substantial coefficients. Fund flows and fund age, while statistically significant, exert a much smaller impact. As for the relevance of sustainability variables within the regressions, their significance has decreased from the OLS to the fixed effects regressions, to the point where the environmental score is no longer significant, whilst the social score retains mild significance in the latter models. Concerning carbon scores, although the absolute level of carbon scores has lost its significance, the binary variable indicating whether the carbon score is above or below the median (0.704) retains its relevance, suggesting a potential non-linear relationship between excess return and carbon scores. A similar outcome is observed with the governance variable, where only the binary variable indicating whether governance scores are above or below the median has maintained significance, albeit reduced. This underscores the non-linear response of excess returns to governance scores, as highlighted by the positive coefficient (1.126) for the median governance indicator variable.

Exhibit 8 Regressions Analysing the Relationship Between Excess Return, Dynamic Return, and ESG Using Various Specifications

Dependent Variables / Independent Variables	EXCESS RETURN: Scores only		EXCESS RETURN: Scores and median		DYNAMIC RETURN: Scores only		DYNAMIC RETURN: Scores and median	
	OLS Regression (1)	**FE regression (2)**	**OLS Regression (3)**	**FE Regression (4)**	**OLS Regression (5)**	**FE Regression (6)**	**OLS Regression (7)**	**FE Regression (8)**
ESG Score	**-0.941***** *(-6.079)*	-0.354 *(-1.512)*	**-1.003***** *(-4.704)*	**-0.556*** *(-2.265)*	**-0.163*** *(-2.056)*	-0.145 *(-1.571)*	**-0.323**** *(-2.955)*	-0.228 *(-1.586)*
Median ESG Score			0.120 *(0.420)*	0.372 *(1.591)*			**0.312*** *(2.125)*	0.153 *(1.014)*
Expense Ratio	0.147 *(0.943)*	0.184 *(1.081)*	0.151 *(0.968)*	0.188 *(1.108)*	-0.111 *(-1.389)*	-0.073 *(-0.620)*	-0.101 *(-1.255)*	-0.071 *(-0.604)*
Fund Age	-0.025 *(-0.413)*	**-0.235*** *(-2.142)*	-0.016 *(-0.254)*	**-0.253*** *(-2.400)*	**0.169***** *(5.493)*	**0.130*** *(2.090)*	**0.191***** *(5.886)*	**0.122.** *(1.955)*
Flows	0.051 *(0.707)*	**0.173*** *(2.314)*	0.052 *(0.717)*	**0.176*** *(2.359)*	**0.109**** *(2.923)*	**0.089*** *(2.288)*	**0.111**** *(2.970)*	**0.090*** *(2.303)*
Fund Size	0.009 *(0.128)*	0.058 *(0.543)*	0.010 *(0.148)*	0.066 *(0.640)*	-0.017 *(-0.483)*	-0.051 *(-1.122)*	-0.014 *(-0.382)*	-0.048 *(-1.061)*
Fund Volatility	**-0.043.** *(-1.912)*	0.120 *(0.684)*	**-0.042.** *(-1.875)*	0.123 *(0.696)*	**0.065***** *(5.645)*	-0.008 *(-0.230)*	**0.066***** *(5.787)*	-0.007 *(-0.204)*
Static Return	**1.479***** *(132.400)*	**1.461***** *(22.540)*	**1.479***** *(132.400)*	**1.461***** *(22.530)*				
R^2	66.328%	67.110%	66.328%	67.116%	1.611%	4.590%	1.660%	4.601%
Adj. R^2	66.302%	66.933%	66.299%	66.935%	1.547%	4.087%	1.585%	4.087%
Year Fixed Effect	No	Yes	No	Yes	No	Yes	No	Yes
Other fixed effects (Morningstar rating, Morningstar Category, Sustainability Rating, Index Fund)	No	Yes	No	Yes	No	Yes	No	Yes

Source: Authors' estimates.

5.10.4 Relationship between dynamic return and sustainability

We now examine the regression findings that evaluate the general average relationship between dynamic timing return and ESG scores, as presented in Exhibit 8. Overall, sustainability information—whether the actual level of the ESG score or the indicator for median ESG score—is statistically insignificant. Depending on the regression specification, fund age is mildly statistically significant; unlike excess return, dynamic timing return positively correlates with it, indicating that dynamic timing return is associated with funds possessing longer track records. Fund flows also emerge as a statistically significant explanatory variable, albeit with a very minimal impact on dynamic return, particularly since its coefficient has decreased from 0.176 in the fixed effects regression for excess return to 0.090 for dynamic return.

The regression results for the remaining sustainability variables are presented in Appendix 4-D. Consistent with the ESG findings, fund flows and fund age are statistically significant across all regression specifications. However, the magnitude of their impact remains modest, as reflected by the relatively small coefficient sizes, especially in the case of fund flows. Interestingly, sustainability information is largely not germane to explaining dynamic return, with the exception of one regression specification related to environmental scores, where dynamic return is negatively correlated with the level of environmental scores (-0.185).

5.10.5 Relationship between alpha and sustainability

We now turn our attention to the regression findings that evaluate the relationship between security selection alpha and sustainability information, as detailed in Exhibit 9 and Appendix 4-E. Concerning ESG scores, sustainability information—whether represented by the level of the ESG score or the associated binary variable—generally lacks relevance. Notably, alpha is associated with more recently established funds, as indicated by the negative coefficients for fund age (ranging from -0.449 to -0.462) and demonstrates a positive correlation with fund flows (approximately 0.25), both of which are statistically highly significant.

Concerning regressions that involve other sustainability variables, both stronger fund flows and newer fund launches are associated with higher alpha, although the impact of these variables, while statistically significant, is relatively modest. Regarding the relationship between other sustainability metrics (namely, environmental, social, governance, and carbon scores) and alpha, the actual level of this information proves to be irrelevant. However, alpha is positively correlated with the indicator variables that denote whether a fund has higher than median carbon and governance scores. Specifically, funds with higher-than-median carbon and governance scores exhibit higher alpha than those with lower-than-median scores, as demonstrated by the positive coefficients for these indicators, which are 1.393 and 1.284, respectively in Specification (4) of the regressions.

Exhibit 9 Regressions Examining the Relationship Between Alpha and ESG Across Various Specifications for Linear and Quantile Regressions

Dependent Variables	ALPHA Scores Only		ALPHA Scores and Median		ALPHA 25%, 50%, 75% Quantiles		
Independent Variables	**OLS Regression (1)**	**FE Regression (2)**	**OLS Regression (3)**	**FE Regression (4)**	**25% Quantile FE Regression (5)**	**50% Quantile FE Regression (6)**	**75% Quantile FE Regression (7)**
ESG Score	**-1.443***** *(-7.524)*	-0.309 *(-0.782)*	**-1.433***** *(-5.417)*	-0.447 *(-1.099)*	0.169 *(0.44)*	0.003 *(0.01)*	-0.207 *(-0.37)*
Median ESG Score			-0.020 *(-0.055)*	0.254 *(0.625)*	-0.128 *(-0.46)*	-0.230 *(-0.62)*	-0.358 *(-0.66)*
Expense Ratio	0.304 *(1.572)*	0.348 *(1.380)*	0.303 *(1.566)*	0.352 *(1.387)*	-0.282 *(-1.36)*	0.192 *(0.84)*	**0.792**** *(2.63)*
Fund Age	-0.050 *(-0.674)*	**-0.449***** *(-3.733)*	-0.051 *(-0.655)*	**-0.462***** *(-4.144)*	**-0.570***** *(-4.12)*	**-0.323.** *(-1.92)*	-0.010 *(-0.05)*
Flows	0.032 *(0.358)*	**0.248***** *(4.163)*	0.032 *(0.357)*	**0.250***** *(4.234)*	0.054 *(0.78)*	0.073 *(1.11)*	0.096 *(1.34)*
Fund Size	0.069 *(0.800)*	0.128 *(0.897)*	0.069 *(0.796)*	0.134 *(0.978)*	0.072 *(0.72)*	0.078 *(0.62)*	0.085 *(0.49)*
Fund Volatility	**-0.0596*** *(-2.157)*	0.244 *(0.804)*	**-0.0597*** *(-2.157)*	0.246 *(0.810)*	-0.101 *(-1.25)*	-0.067 *(-0.69)*	-0.023 *(-0.19)*
R^2	1.196%	5.606%	1.196%	5.611%	-	-	-
Adj. R^2	1.132%	5.109%	1.121%	5.103%	-	-	-
Fixed Effects (Year)	No	Yes	No	Yes	Yes	Yes	Yes
Other fixed effects	No	Yes	No	Yes	Yes	Yes	Yes

Source: Authors' estimates

5.10.6 Quantile relationship between alpha and sustainability information

In this final section, we evaluate the relationship between security selection alpha and sustainability information through the use of quantile regressions. Quantile fixed effects panel regression analyses the influence of explanatory variables—here, alpha—on various quantiles of the dependent variable, including median and extreme values, while controlling for unobserved individual characteristics that are consistent over time. This method goes beyond traditional linear fixed effects models, which only determine average effects, by revealing the diversity in impacts across the distribution of the outcome. For example, it can distinguish the differential impacts on various subgroups within a population, such as lower versus higher performers. This technique is especially beneficial for a deeper understanding of distributional effects, offering a nuanced and comprehensive perspective.

The quantile regression results detailed in Exhibit 9 reveal that ESG information does not notably influence the variation in alpha across different quantiles. At the lower quantiles, newer funds are positively associated with higher alpha values, whereas at the higher quantiles, increased expense ratios correspond to elevated alpha. Regarding other sustainability dimensions (i.e., environmental, social, governance, and carbon scores), newer funds consistently demonstrate a positive correlation with alpha at lower quantiles, and similarly, a positive relationship with higher expense ratios at the upper quantiles across all assessed sustainability variables. Beyond carbon and governance, sustainability information generally does not serve as a significant explanatory variable in these regressions. Regarding carbon scores, the binary indicator variable shows significance both on average and at the median level, indicating that funds with above-median carbon scores generally achieve higher alpha than those with below-median scores. The relationship between alpha and carbon scores is distinctly non-linear and only achieves statistical significance at specific points within the distribution (see Exhibit 10). The most notable findings pertain to governance: funds with above-median governance scores generate higher alpha compared to those with below-median scores (see Exhibit 11). The level of significance initially intensifies at higher quantiles of alpha but then moderates, though it remains highly significant. This dichotomous and non-linear relationship, rather than an incremental one, is confirmed in Exhibit 12. The exhibit illustrates that funds with higher-than-median governance scores are associated with increased alpha starting at the 25^{th} percentile. This relationship continues to grow in significance, peaking between the 40^{th} and 75^{th} percentiles; beyond this threshold, although the relationship weakens somewhat, it remains material. Essentially, as the alpha of the funds improves, the positive impact of higher governance scores becomes more pronounced. However, beyond the 75^{th} percentile, despite the continuing increase in the relationship's strength, the statistical certainty begins to wane—though it remains statistically significant.

Overall, the relationship between governance and alpha appears to be the most compelling. The governance binary variable displays strong statistical and economic significance, not only on an average basis, as corroborated by the results of the static fixed effects regression but also across much of the distribution of alpha.

Exhibit 10 Regressions Examining the Relationship Between Alpha and Carbon Across Various Specifications for Linear and Quantile Regressions

Dependent Variables	ALPHA Scores Only		ALPHA Scores and Median		ALPHA 25%, 50%, 75% Quantile		
Independent Variables	**OLS Regression (1)**	**FE Regression (2)**	**OLS Regression (3)**	**FE Regression (4)**	**25% Quantile FE Regression (5)**	**50% Quantile FE Regression (6)**	**75% Quantile FE Regression (7)**
Carbon Score	**-0.947 ***** *(-8.345)*	-0.049 *(-0.153)*	**-0.531 ***** *(-3.678)*	0.330 *(0.922)*	**-0.303.** *(-1.67)*	0.198 *(0.99)*	**0.848 **** *(3.04)*
Median Carbon Score			**1.506 ***** *(4.660)*	**1.393 **** *(2.823)*	0.152 *(0.52)*	**0.470*** *(2.35)*	0.884 *(1.61)*
Expense Ratio	**0.332.** *(1.731)*	0.379 *(1.575)*	**0.322.** *(1.681)*	**0.398.** *(1.664)*	-0.190 *(-0.98)*	0.272 *(1.34)*	**0.867 ***** *(3.21)*
Fund Age	-0.031 *(-0.417)*	**-0.454 ***** *(-3.692)*	-0.125 *(-1.642)*	**-0.429 **** *(-3.606)*	**-0.535 **** *(-3.15)*	-0.314 *(-1.61)*	-0.023 *(-0.10)*
Flows	0.029 *(0.319)*	**0.247 ***** *(4.222)*	0.025 *(0.277)*	**0.244 ***** *(4.123)*	0.055 *(0.82)*	0.078 *(1.21)*	0.101 *(1.40)*
Fund Size	0.083 *(0.960)*	0.134 *(0.923)*	0.080 *(0.932)*	0.113 *(0.808)*	0.071 *(0.62)*	0.093 *(0.69)*	0.120 *(0.69)*
Fund Volatility	**-0.066 *** *(-2.377)*	0.252 *(0.817)*	**-0.073 **** *(-2.645)*	0.228 *(0.753)*	-0.104 *(-1.27)*	-0.070 *(-0.72)*	-0.026 *(-0.22)*
R^2	1.336%	5.591%	1.570%	5.774%	-	-	-
Adj. R^2	1.271%	5.093%	1.494%	5.267%	-	-	-
Fixed Effects (Year)	No	Yes	No	Yes	Yes	Yes	Yes
Other fixed effects	No	Yes	No	Yes	Yes	Yes	Yes

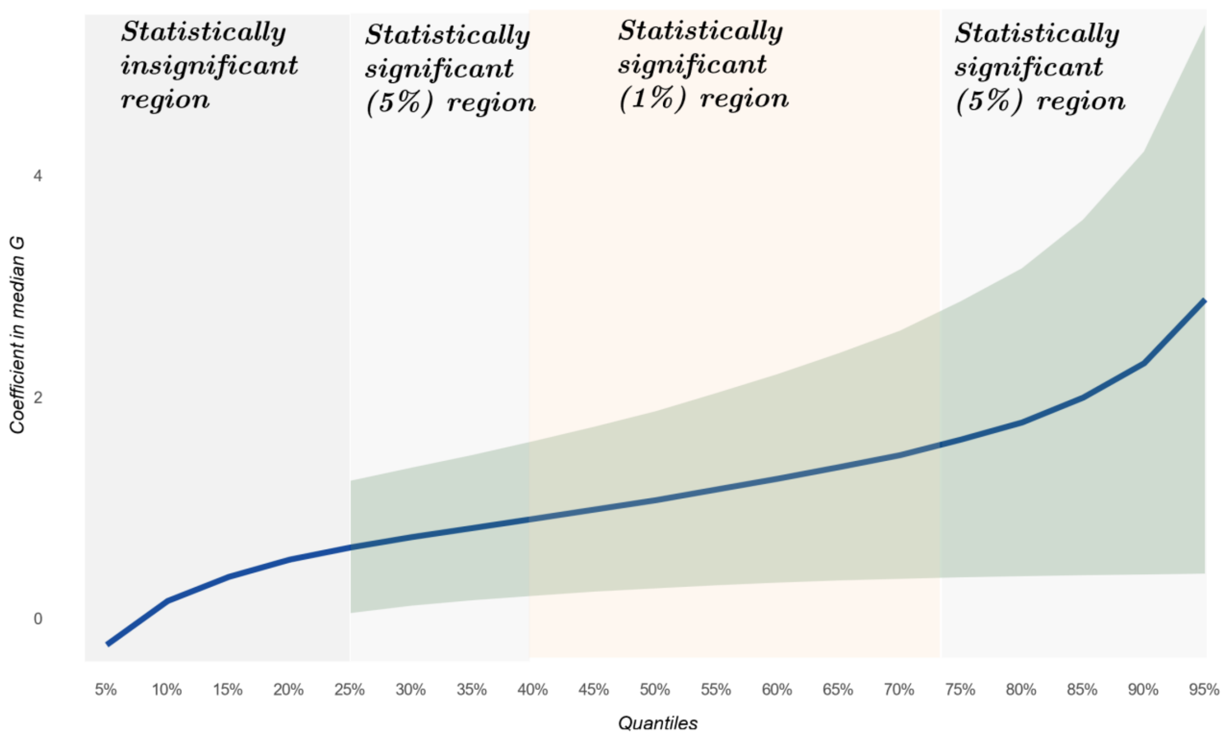
Source: Authors' estimates.

Exhibit 11 Regressions Examining the Relationship Between Alpha and Governance Across Various Specifications for Linear and Quantile Regressions

Dependent Variables	ALPHA Scores Only		ALPHA Scores and Median		ALPHA 25%, 50%, 75% Quantile		
Independent Variables	**OLS Regression (1)**	**FE Regression (2)**	**OLS Regression (3)**	**FE Regression (4)**	**25% Quantile FE Regression (5)**	**50% Quantile FE Regression (6)**	**75% Quantile FE Regression (7)**
Governance Score	0.060 *(0.211)*	0.451 *(0.914)*	**-1.338***** *(-3.293)*	-0.562 *(-0.731)*	0.187 *(0.43)*	-0.449 *(-0.67)*	-1.266 *(-1.14)*
Median Governance Score			**1.741 ***** *(4.828)*	**1.284 **** *(2.777)*	**0.650*** *(2.13)*	**1.076**** *(2.64)*	**1.623*** *(2.55)*
Expense Ratio	**0.611**** *(3.186)*	**0.438.** *(1.926)*	**0.556**** *(2.893)*	**0.447.** *(1.943)*	-0.190 *(-0.98)*	0.272 *(1.34)*	**0.867***** *(3.21)*
Fund Age	**-0.310***** *(-4.670)*	**-0.447***** *(-3.707)*	**-0.281***** *(-4.231)*	**-0.413**** *(-3.406)*	**-0.548***** *(-3.28)*	-0.318 *(-1.63)*	-0.023 *(-0.10)*
Flows	0.032 *(0.351)*	**0.248***** *(4.155)*	0.033 *(0.370)*	**0.249***** *(4.160)*	0.053 *(0.78)*	0.074 *(1.14)*	0.101 *(1.40)*
Fund Size	0.062 *(0.704)*	0.126 *(0.870)*	0.081 *(0.922)*	0.142 *(1.002)*	0.072 *(0.62)*	0.093 *(0.69)*	0.120 *(0.69)*
Fund Volatility	-0.041 *(-1.489)*	0.260 *(0.840)*	-0.039 *(-1.395)*	0.268 *(0.868)*	-0.099 *(-1.20)*	-0.063 *(-0.64)*	-0.016 *(-0.13)*
R^2	0.586%	5.613%	0.838%	5.744%	-	-	-
Adj. R^2	0.52%	5.116%	0.762%	5.237%	-	-	-
Fixed Effects (Year)	No	Yes	No	Yes	Yes	Yes	Yes
Other fixed effects	No	Yes	No	Yes	Yes	Yes	Yes

Source: Authors' estimates.

Exhibit 12 Graph Depicting Variations in the Coefficient of the Median Governance Binary Variable Across Different Alpha Quantiles



Source: Authors' estimates.

5.11 Conclusion and investment implications

5.11.1 The Relationship Between Sustainability and Equity Risk Factors

Sustainability investing is often linked to factor investing, particularly its positive correlation with the quality factor ((Dekhayser and Lawrence 2020); (Clubb, Takahashi, and Tiburzio 2016)). Some studies suggest that sustainable stocks mitigate risk, particularly during market distress, while others argue that they align more closely with momentum. However, this study finds no definitive link beyond market beta being the dominant factor loading.

The holdings-based attribution approach further challenges assumptions that sustainable funds exhibit defensive properties, such as a strong association with low-volatility. Instead, portfolios with high environmental or social scores are primarily influenced by momentum, while governance scores correlate with reduced momentum exposure. Additionally, higher social, governance, and composite ESG scores tend to favour growth stocks over value stocks, contradicting prior studies linking sustainability with defensive characteristics.

This study challenges the prevailing assumption that ESG systematically aligns with defensive factors. Unlike prior research linking sustainability to quality or low volatility, our findings indicate a more complex and conditional relationship with factor exposures. The holdings-based attribution analysis particularly highlights that while high environmental and social scores correlate with momentum, governance scores reduce momentum exposure. These results contradict the widely held belief that sustainability enhances risk mitigation. By employing both time-series regression and holdings-based attribution, this study offers a more granular perspective than many previous aggregate-level analyses.

5.11.2 The Influence of Sustainability on Investment Fund Returns

5.11.2.1 Excess Return

The analysis suggests that excess returns are predominantly driven by systematic factor tilts, as evidenced by the highly significant static factor return variable. Once these factor exposures are accounted for, ESG scores exhibit negligible influence. Other fund-specific characteristics, such as fund flows and fund age, play only a marginal role. Although newer funds and those experiencing larger inflows tend to generate higher excess returns, these effects are unrelated to ESG attributes, suggesting that sustainability does not inherently drive excess returns.

5.11.2.2 Dynamic Return

The findings indicate that sustainability characteristics do not significantly influence dynamic return, which reflects a fund manager's ability to adjust factor exposures and engage in security selection. Across all regression specifications, ESG scores show no material impact on timing strategies, suggesting that fund managers do not systematically incorporate sustainability considerations when reallocating portfolios. Once static factor returns are accounted for, ESG attributes generally exhibit no discernible influence on dynamic portfolio adjustments or excess return generation. Although fund flows are statistically significant across models, their effect on dynamic timing return remains modest, reinforcing the conclusion that ESG integration does not contribute to tactical asset allocation. These findings contradict studies suggesting that ESG factors influence market timing (Krüger 2015).

5.11.2.3 Security Selection Alpha

To further isolate managerial skill, factor timing return is excluded from dynamic return to derive security selection alpha. While broad sustainability scores do not significantly explain security selection alpha, carbon and governance scores exhibit non-linear effects.

Funds with above-median carbon scores generate superior alpha, though this effect is primarily concentrated around the median and mean levels, lacking consistency across the full return distribution. In contrast, governance scores display a more robust and persistent relationship with alpha, particularly in the mid-to-upper performance percentiles. Quantile fixed-effects regression further confirms that governance quality enhances fund performance across most of the alpha distribution, with the strongest effect observed between the 40th and 75th percentiles.

These findings refine prior research (e.g., (Gompers, Ishii, and Metrick 2003); (Klapper and Love 2004)), which generally assumes a much more direct positive relationship between governance and performance. This study instead demonstrates that governance's influence depends on the return distribution, making it particularly relevant for mid-to-high-performing funds.

5.11.2.4 The Role of Governance in Enhancing Alpha

From an investment perspective, governance refers to the practices of companies held within a fund—not the fund's own structure (Trahan 2008). Key factors such as board independence, executive remuneration, and shareholder rights shape managerial decisions, risk oversight, and strategy, thereby influencing financial performance.

Sustainability generally does not drive alpha, except for carbon and governance scores. Among these, governance is the strongest predictor of fund-level security selection alpha. Funds with a higher proportion of stocks scoring above the median on governance consistently generate greater alpha, especially at higher percentiles.

Robust governance is linked to superior operating performance, earnings quality, and risk management ((Gompers, Ishii, and Metrick 2003); (Klapper and Love 2004)). It reduces agency conflicts and aligns managerial decisions with shareholder interests, leading to better financial outcomes. Moreover, well-governed firms achieve higher market valuations (Gompers, Ishii, and Metrick 2003; Klapper and Love 2004) and incur lower agency costs (Jensen and Meckling 1976; Shleifer and Vishny 1997). Effective board composition and oversight enhance decision-making (Hermalin and Weisbach 2003), while robust board oversight and shareholder protections further improve firm performance (Bhagat and Bolton 2008).

5.11.2.5 Implications for Fund Selection and ESG Integration

From an investor's perspective, screening for governance quality can help identify companies with stronger operating profitability, enhanced transparency, and a reduced risk of managerial entrenchment. Our analysis suggests that selecting investments based on governance quality may amplify alpha generation, particularly among higher-performing assets. This finding supports the existence of a threshold effect, whereby governance must exceed a certain standard before material benefits are realised. Investors seeking to maximise security selection alpha should therefore integrate governance assessments into their selection process alongside other fundamental factors.

Although aggregate ESG scores are widely reported by asset managers, these findings indicate that they can serve as an indirect proxy for identifying alpha-generating opportunities.

5.11.3 Limitations and Considerations for Future Research

This study acknowledges several limitations. First, the analysis covers a relatively short time frame, coinciding with the early stages of ESG investing, which may limit its ability to assess long-term performance trends.

Second, the reliance on ESG scores from a single provider presents a caveat, given significant rating divergences across agencies (Berg, Kolbel, and Rigobon 2022). Rating discrepancies stem from differences in scope, materiality, data collection, and weighting methodologies, leading to substantial variations in assessments. Additionally, ESG rating agencies apply distinct penalties for corporate controversies, further affecting scores.

Despite these limitations, empirical evidence suggests that MSCI's ESG ratings are the most widely adopted among institutional investors (Berg, Heeb, and Koelbel 2022). As a result, reliance on MSCI data aligns with market practice, though future research should consider robustness tests using alternative rating providers.

By disaggregating ESG attributes and identifying non-linear governance effects on alpha, this study enhances understanding of ESG investing. However, the absence of standardisation in ESG scoring underscores the need for caution in extrapolating conclusions across frameworks.

5.11.4 Conclusion

In summary, our study makes a significant contribution by advancing our understanding of ESG's role in investment performance. Whereas earlier research has predominantly relied on returns-based analyses and composite ESG scores—with only one study employing a holdings-based granular approach—our dual-method approach for European funds places special emphasis on the holdings-based analysis, where most of our discoveries were made. This approach reveals that while overall ESG scores may not consistently drive excess returns, the non-linear impact of governance quality contributes substantially to enhanced security selection alpha. These contributions underscore the importance of methodological granularity and a regional focus in ESG research, offering valuable insights for both academic inquiry and practical investment strategies

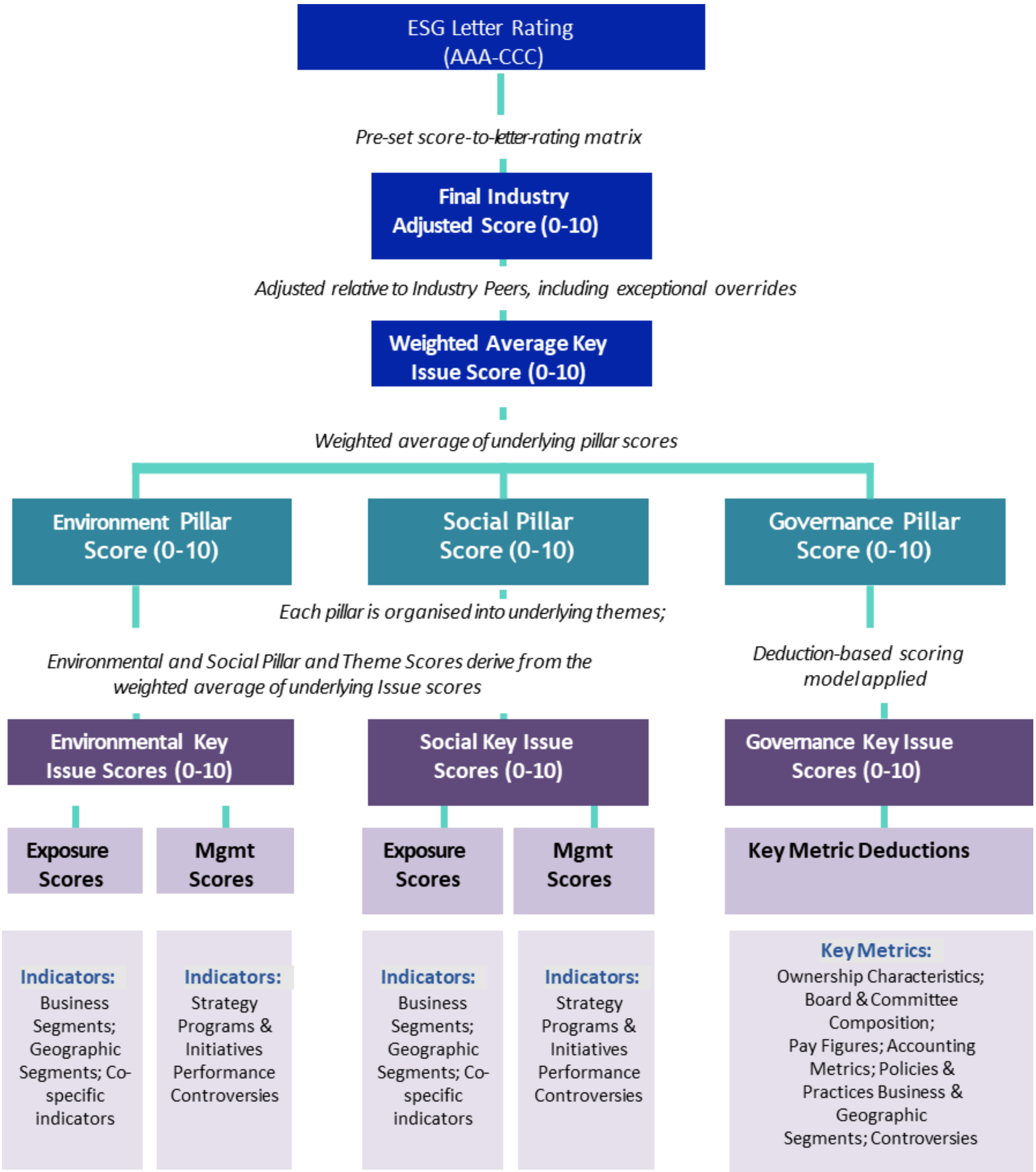
As ESG disclosure improves, future research should examine how greater transparency affects the ESG–performance link. Expanding this analysis to global equity markets would enhance its applicability and provide deeper insights into sustainability's role in investment decisions.

The results provide mixed support for the proposed hypotheses. While ESG was expected to enhance excess and dynamic returns, findings suggest that systematic factor tilts dominate performance, and sustainability attributes play little role. However, the evidence partially supports the hypothesis that governance quality enhances security selection alpha, particularly in the mid-to-upper performance range.

Unlike prior studies assuming a uniform ESG–performance link, this research finds sustainability's impact to be non-linear and factor-specific. Holdings-based analysis highlights ESG's stronger link to momentum factors rather than low-volatility or quality, and governance emerges as the most influential factor for alpha generation.

Appendix 5-A: MSCI ESG Score Methodology

The construction of MSCI ESG scores



Source: *MSCI ESG Ratings Methodology*, MSCI

Appendix 5-B: Time-series regressions of sustainability and return

Return of decile portfolios sorted by Environmental scores

Decile	Model	α	MKT	MKT²	SMB	HML	MOM	RMW	CMA	UMD	BAB	QMJ	R^2
1 (Lowest Score)	FF3M	0.002	**0.958*** **	-0.499*	0.370	-0.336	**-0.442***						*64%*
	FF6F	-0.001	**0.901*** **	-0.085	0.348	0.203	-0.338	0.735	-0.398				*65%*
	AQ6F	0.003	**1.045*** **	-0.606	**0.909*** **	0.341				-0.089	**-0.594** **	**0.728.**	*68%*
2	FF3M	0.002	**1.057*** **	-0.162	-0.155	-0.016	-0.163						*71%*
	FF6F	0.001	**1.045*** **	-0.081	-0.153	0.093	-0.149	0.144	-0.062				*71%*
	AQ6F	0.004	**1.028*** **	-0.327	-0.288	-0.144				-0.035	-0.099	0.725	*73%*
3	FF3M	-0.003	**1.269*** **	-0.139	0.090	0.289	0.296						*69%*
	FF6F	-0.002	**1.312*** **	-0.220	0.220	-0.089	0.229	-0.277	0.504				*69%*
	AQ6F	-0.002	**1.189*** **	-0.220	-0.435	-0.279				0.109	0.320	**-0.704.**	*71%*
4	FF3M	-0.004	**1.242*** **	-0.923	-0.357	-0.299	0.206						*71%*
	FF6F	-0.006	**1.201*** **	-0.528	-0.378	0.168	0.280	**0.689.**	-0.205				*72%*
	AQ6F	-0.007	**1.326*** **	-0.482	-0.122	0.306				**0.661***	**-0.360***	0.340	*73%*
5	FF3M	-0.001	**0.951*** **	-0.278	-0.194	0.184	0.203						*50%*
	FF6F	-0.002	**0.858*** **	-0.637	**-0.528.**	0.736	0.293	-0.182	**-1.395***				*53%*
	AQ6F	0.001	**0.854*** **	-0.371	-0.474	-0.267				0.257	0.099	**-0.874.**	*52%*
6	FF3M	0.002	**0.986*** **	-1.109	**-0.579***	0.006	0.122						*52%*
	FF6F	0.002	**0.962*** **	-1.390	**-0.706***	0.090	0.119	-0.301	-0.458				*53%*
	AQ6F	0.001	**0.921*** **	-1.128	**-0.837***	-0.402				-0.190	0.352	-0.303	*54%*
7	FF3M	**-0.009.**	**1.117*** **	-0.112	-0.214	-0.123	-0.094						*64%*
	FF6F	-0.007	**1.163*** **	-0.340	-0.158	-0.533	-0.171	-0.456	0.409				*64%*
	AQ6F	-0.005	**1.032*** **	-0.607	-0.152	-0.430				-0.216	-0.105	-0.327	*64%*
8	FF3M	**-0.009.**	**1.042*** **	0.964	-0.253	0.272	0.130						*69%*
	FF6F	**-0.009.**	**1.047*** **	1.186	-0.140	0.290	0.124	0.266	0.285				*69%*
	AQ6F	**-0.009.**	**0.951*** **	0.766	-0.360	-0.093				-0.182	**0.345.**	-0.249	*70%*
9	FF3M	-0.003	**1.105*** **	-0.835	-0.012	-0.317	-0.335						*66%*
	FF6F	-0.001	**1.188*** **	-1.103	0.112	**-1.000***	**-0.453***	-0.625	0.796				*68%*
	AQ6F	0.000	**1.056*** **	-1.073	0.034	-0.464				-0.410	-0.087	-0.168	*67%*
10 (Highest Score)	FF3M	-0.005	**1.045*** **	-0.481	-0.094	-0.112	-0.277						*65%*
	FF6F	-0.007	**0.992*** **	-0.222	-0.152	0.363	-0.198	0.520	-0.444				*66%*
	AQ6F	-0.002	**1.053*** **	-0.793	0.133	0.012				-0.129	-0.347	0.106	*67%*

Return of decile portfolios sorted by Social scores

Decile	Model	α	MKT	MKT^2	SMB	HML	MOM	RMW	CMA	UMD	BAB	QMJ	R^2
1 (Lowest Score)	FF3M	0.006	**1.064*** **	-1.561	**0.672***	-0.064	-0.154						*67%*
	FF6F	0.005	**1.102*** **	-1.276	0.865	-0.273	-0.173	0.242	0.654				*68%*
	AQ6F	0.008	**1.075*** **	-1.521	**0.692***	0.183				0.257	**-0.372.**	-0.167	*67%*
2	FF3M	-0.004	**1.141*** **	1.259	-0.158	-0.059	-0.075						*68%*
	FF6F	-0.006	**1.107*** **	1.618	-0.127	0.304	-0.017	0.589	-0.116				*69%*
	AQ6F	-0.004	**1.121*** **	1.124	0.178	0.177				0.084	-0.227	0.153	*68%*
3	FF3M	-0.004	**0.954*** **	-0.443	0.388	-0.296	-0.199						*62%*
	FF6F	-0.005	**0.905*** **	-0.454	0.254	0.05	-0.128	0.143	-0.641				*63%*
	AQ6F	-0.001	**0.970*** **	-0.369	**0.562.**	0.236				0.439	**-0.611** **	-0.133	*65%*
4	FF3M	-0.001	**1.035*** **	-1.371	-0.353	-0.032	-0.063						*63%*
	FF6F	0.001	**1.072*** **	-1.596	-0.302	-0.383	-0.135	-0.432	0.322				*64%*
	AQ6F	0.000	**1.014*** **	-1.692	-0.258	-0.329				-0.388	0.08	0.106	*64%*
5	FF3M	-0.001	**1.050*** **	-0.599	-0.314	**0.459***	0.009						*75%*
	FF6F	0.001	**1.053*** **	-0.927	-0.376	0.309	-0.027	-0.464	-0.161				*75%*
	AQ6F	0.001	**0.963*** **	-0.934	**-0.627***	0.001				-0.037	0.181	**-0.689.**	*75%*
6	FF3M	**-0.010***	**1.219*** **	0.888	0.089	0.03	-0.149						*76%*
	FF6F	-0.012	**1.158*** **	1.104	0.009	0.532	-0.06	0.48	-0.57				*77%*
	AQ6F	**-0.010.**	**1.217*** **	0.851	0.159	0.032				-0.13	-0.044	0.056	*77%*
7	FF3M	-0.007	**1.128*** **	0.22	-0.13	-0.054	0.064						*68%*
	FF6F	-0.006	**1.078*** **	-0.306	-0.371	0.101	0.084	-0.567	**-0.969.**				*70%*
	AQ6F	-0.003	**1.040*** **	-0.337	-0.067	-0.523				-0.187	-0.044	-0.357	*69%*
8	FF3M	-0.001	**1.218*** **	-0.725	**-0.793** **	0.162	0.156						*70%*
	FF6F	-0.001	**1.219*** **	-0.722	**-0.783** **	0.17	0.136	0.007	0.081				*70%*
	AQ6F	0.000	**1.135*** **	-1.119	**-0.626***	-0.029				0.101	-0.047	-0.266	*68%*
9	FF3M	0.005	**1.097*** **	-0.253	-0.065	-0.322	0.079						*65%*
	FF6F	0.007	**1.149*** **	-0.602	-0.045	**-0.806***	-0.006	-0.63	0.359				*66%*
	AQ6F	0.006	**1.097*** **	-0.25	0.283	-0.187				0.18	-0.28	0.117	*65%*
10 (Highest Score)	FF3M	0.000	**0.942*** **	-0.686	0.192	0.161	**-0.342.**						*70%*
	FF6F	0.000	**0.916*** **	-0.744	0.103	0.329	-0.307	0.007	-0.381				*70%*
	AQ6F	0.006	**0.879*** **	-1.475	0.249	-0.158				-0.421	-0.225	-0.264	*71%*

Return of decile portfolios sorted by Governance scores

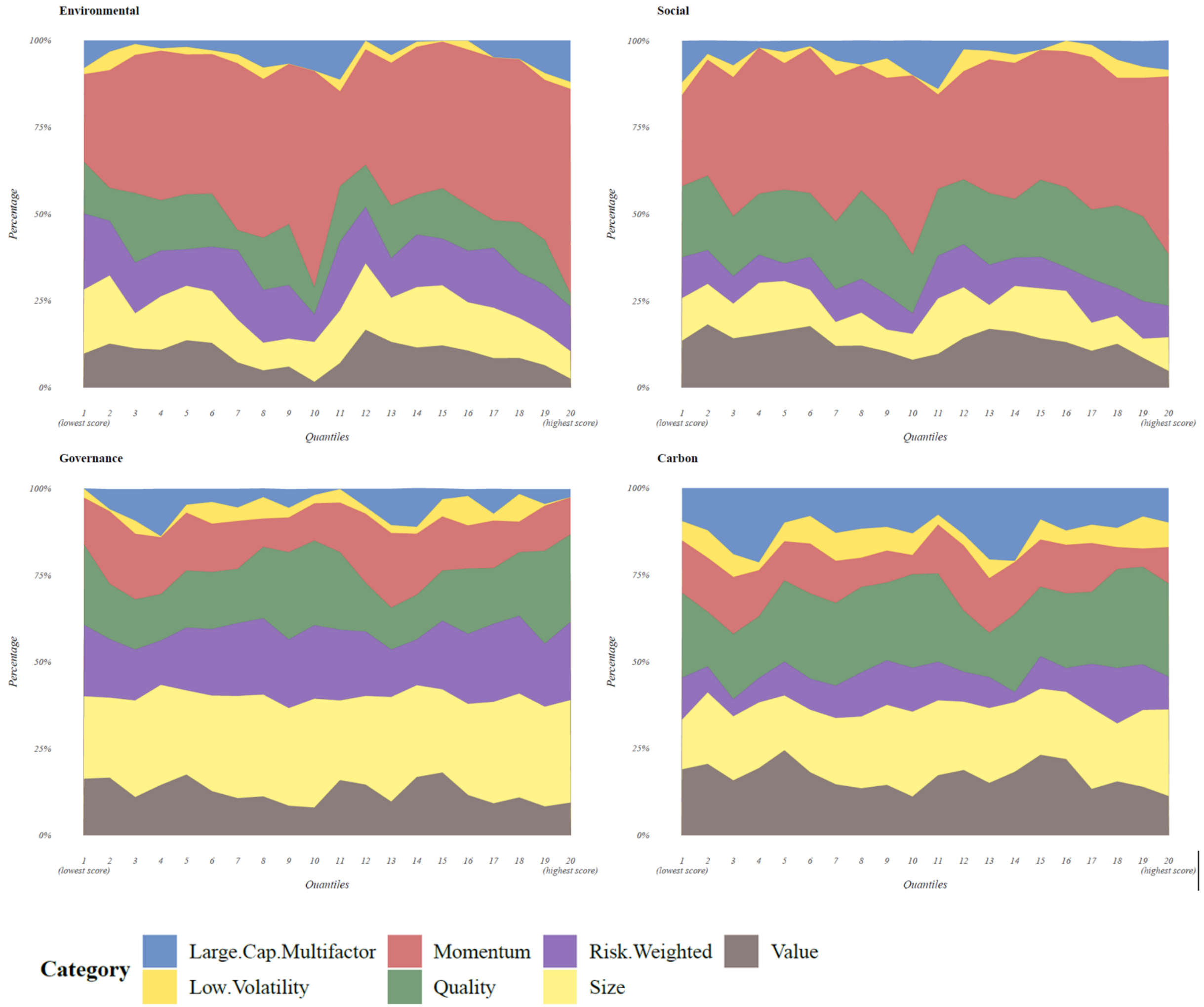
Decile	Model	α	MKT	MKT²	SMB	HML	MOM	RMW	CMA	UMD	BAB	QMJ	R^2
1 (Lowest Score)	FF3M	-0.003	**1.134*** **	**2.919***	0.293	-0.041	0.107						*66%*
	FF6F	-0.005	**1.100*** **	**3.071***	0.239	0.258	0.167	0.317	-0.331				*67%*
	AQ6F	-0.003	**1.168*** **	**2.682***	**0.584.**	0.366				0.265	-0.317	0.477	*67%*
2	FF3M	**-0.013***	**1.258*** **	-1.359	-0.136	-0.149	-0.034						*70%*
	FF6F	**-0.013***	**1.262*** **	-1.245	-0.099	-0.131	-0.034	0.146	0.141				*70%*
	AQ6F	**-0.013***	**1.282*** **	-1.506	-0.009	-0.142				-0.113	-0.103	0.262	*71%*
3	FF3M	0.005	**1.013*** **	-0.355	-0.028	-0.115	-0.284						*69%*
	FF6F	0.006	**0.983*** **	-0.756	-0.218	-0.035	-0.272	-0.445	-0.674				*70%*
	AQ6F	**0.009.**	**0.892*** **	-0.584	-0.256	-0.367				-0.272	0.061	**-0.671.**	*70%*
4	FF3M	0.004	**1.042*** **	-0.549	0.028	0.218	-0.010						*63%*
	FF6F	0.001	**0.987*** **	0.333	0.129	**0.924***	0.115	**1.374***	-0.002				*67%*
	AQ6F	0.001	**1.113*** **	-0.320	0.079	0.604				0.197	-0.093	0.432	*64%*
5	FF3M	-0.008	**1.127*** **	0.728	0.118	-0.223	0.076						*63%*
	FF6F	-0.008	**1.113*** **	0.639	0.068	-0.168	0.088	-0.085	-0.230				*63%*
	AQ6F	-0.008	**1.154*** **	0.699	-0.048	-0.443				-0.192	0.189	0.159	*64%*
6	FF3M	0.000	**1.049*** **	-0.292	-0.377	-0.017	0.002						*65%*
	FF6F	-0.001	**0.972*** **	-0.425	**-0.608***	0.502	0.081	0.073	**-1.013.**				*66%*
	AQ6F	-0.001	**1.097*** **	-0.441	-0.221	0.079				-0.016	-0.106	0.361	*66%*
7	FF3M	**-0.008.**	**0.975*** **	-0.478	**-0.401.**	**-0.690** **	-0.316						*61%*
	FF6F	-0.008	**0.970*** **	-0.662	**-0.467.**	**-0.709.**	-0.330	-0.228	-0.170				*61%*
	AQ6F	**-0.010.**	**1.037*** **	-0.375	-0.341	**-0.890** **				**-0.734***	0.176	0.475	*64%*
8	FF3M	-0.004	**1.135*** **	0.963	-0.013	-0.180	-0.063						*69%*
	FF6F	-0.005	**1.134*** **	1.349	0.094	-0.036	-0.038	0.526	0.280				*70%*
	AQ6F	-0.006	**1.150*** **	1.304	0.079	-0.073				0.019	0.033	0.091	*69%*
9	FF3M	-0.006	**1.065*** **	**1.896.**	-0.058	0.157	0.315						*61%*
	FF6F	-0.007	**1.027*** **	**2.155.**	-0.078	0.518	**0.376.**	0.472	-0.253				*62%*
	AQ6F	-0.007	**1.054*** **	1.801	-0.078	0.294				0.447	-0.068	-0.010	*61%*
10 (Highest Score)	FF3M	0.006	**1.032*** **	**-2.176.**	0.134	-0.069	-0.033						*61%*
	FF6F	0.003	**0.925*** **	-1.893	-0.054	**0.798.**	0.121	0.726	**-1.099.**				*64%*
	AQ6F	0.006	**1.077*** **	**-2.051.**	0.213	0.246				0.183	-0.171	0.234	*61%*

Return of decile portfolios sorted by Carbon scores

Decile	Model	α	MKT	MKT^2	SMB	HML	MOM	RMW	CMA	UMD	BAB	QMJ	R^2
1 (Lowest Score)	FF3M	-0.003*	1.197***	0.607	0.108	0.371.	0.332.						*71%*
	FF6F	-0.006	1.099***	0.936	-0.062	1.201**	0.480*	0.768.	-0.966.				*73%*
	AQ6F	-0.003	1.229***	0.295	0.317	0.405				0.631*	-0.402*	-0.034	*71%*
2	FF3M	-0.009	1.130***	1.347	-0.052	-0.550	-0.213						*73%*
	FF6F	-0.008.	1.140***	1.072	-0.072	-0.739	-0.250	-0.421	-0.058				*73%*
	AQ6F	-0.006	1.090***	0.940	0.246	-0.745*				-0.431	-0.189	0.085.	*74%*
3	FF3M	-0.001	1.087***	-1.839	0.171	0.130	0.119						*67%*
	FF6F	-0.002	1.032***	-1.811.	0.014	0.555	0.199	0.229	-0.692				*68%*
	AQ6F	0.000	1.070***	-1.740	-0.104	0.038				0.273	-0.019	-0.361	*67%*
4	FF3M	-0.003	1.109***	1.308	-0.188	-0.013	0.057.						*73%*
	FF6F	-0.003	1.127***	1.295	-0.141	-0.146	0.029	-0.075	0.228				*74%*
	AQ6F	-0.003	1.050***	0.930	-0.162	-0.432				-0.384	0.267	0.003	*74%*
5	FF3M	0.006	0.915***	-1.202	-0.226	-0.280	-0.368*						*68%*
	FF6F	0.008.	0.921***	-1.785.	-0.354	-0.535	-0.421*	-0.815*	-0.337				*70%*
	AQ6F	0.012	0.808***	-1.862.	-0.287	-0.726*				-0.696*	0.025	-0.344	*70%*
6	FF3M	-0.008	1.060***	0.039	-0.166	-0.040	-0.063						*62%*
	FF6F	-0.007	1.113***	-0.180	-0.052	-0.530	-0.156	-0.490	0.538				*63%*
	AQ6F	-0.005	0.947***	-0.434	-0.378	-0.729*				-0.469	0.207	-0.541	*64%*
7	FF3M	0.000	0.735***	-1.539	0.187	0.066.	-0.256						*57%*
	FF6F	-0.001	0.772***	-1.202	0.372*	-0.088*	-0.276	0.336	0.695				*58%*
	AQ6F	0.000	0.762***	-1.353	0.593	0.762				0.341	-0.481	0.218	*61%*
8	FF3M	-0.006	1.159***	3.011**	-0.390.	0.166	0.464*						*65%*
	FF6F	-0.006	1.199***	3.261	-0.202	-0.039	0.418*	0.205	0.724				*66%*
	AQ6F	-0.010.	1.086***	3.155**	-0.725**	-0.193				0.065.	0.636	-0.205	*69%*
9	FF3M	-0.006	1.305***	-0.831	-0.337	-0.400*	0.026						*72%*
	FF6F	-0.006	1.343***	-0.670	-0.203	-0.604	-0.017	0.103	0.603				*73%*
	AQ6F	-0.010.	1.405***	-0.532	-0.024	0.106				0.184	-0.023	0.683.	*74%*
10 (Highest Score)	FF3M	0.000	0.944***	0.210	-0.676*	0.287	0.277						*53%*
	FF6F	0.003	1.075***	0.143	-0.345	-0.684	0.090.	-0.516	1.623**				*58%*
	AQ6F	-0.003	0.927***	0.277	-0.709*	0.319				0.302	0.155	-0.046	*54%*

Source: Authors' estimates. FF3M refers to the Fama-French 3-factor model with Cahart momentum, FF6F refers to the Fama-French 6 factor model and AQ6F refers to the AQR factor model. *** represents statistical significance at 0.1%, ** represents statistical significance at 1% and * represents statistical significance at 5% levels. MKT represents the market beta exposure, MKT2 represents the square of the market beta exposure which seeks to proxy the non-linear market timing ability, SMB represents the size factor, HML represents the value factor, MOM represents the Carhart momentum factor, RMW represents the operating profitability factor, CMA represents the investment conservatism, UMD represents the AQR momentum factor, BAB represents the betting against beta factor and QMJ represents the quality factor.

Appendix 5-C: Holdings-based analysis between sustainability and investible factors (Static factor return)



Appendix 5-D: Relationship between excess return, dynamic timing return and sustainability

Return and Environmental Scores

Dependent Variables / Independent Variables	EXCESS RETURN: Scores only OLS Regression (1)	EXCESS RETURN: Scores only FE regression (2)	EXCESS RETURN: Scores and median OLS Regression (3)	EXCESS RETURN: Scores and median FE Regression (4)	DYNAMIC RETURN: Scores only OLS Regression (5)	DYNAMIC RETURN: Scores only FE Regression (6)	DYNAMIC RETURN: Scores and median OLS Regression (7)	DYNAMIC RETURN: Scores and median FE Regression (8)
Environmental Score	**-1.242***** *(-7.139)*	0.293 *(-1.269)*	**-1.152***** *(-4.761)*	-0.163 *(-0.568)*	-0.038 *(-0.422)*	**-0.185*** *(-2.122)*	0.027 *(0.217)*	-0.190 *(-1.333)*
Median Environmental Score			-0.151 *(-0.2)*	-0.198 *(-0.871)*			0.109 *(-0.743)*	0.007 *(0.064)*
Expense Ratio	0.181 *(1.176)*	0.203 *(1.196)*	0.179 *(1.165)*	0.209 *(1.227)*	-0.082 *(-1.036)*	-0.069 *(-0.602)*	-0.083 *(-1.051)*	-0.069 *(-0.594)*
Fund Age	**-0.121*** *(-2.255)*	**-0.248*** *(-2.274)*	**-0.125*** *(-2.305)*	**-0.248*** *(-2.278)*	**0.142***** *(5.111)*	**0.123*** *(1.987)*	**0.139***** *(4.971)*	**0.123*** *(1.987)*
Flows	0.059 *(0.808)*	**0.174*** *(2.317)*	0.058 *(0.800)*	**0.173*** *(2.309)*	**0.109**** *(2.926)*	**0.090*** *(2.317)*	**0.109**** *(2.914)*	**0.090*** *(2.323)*
Fund Size	0.034 *(0.496)*	0.064 *(0.605)*	0.033 *(0.475)*	0.063 *(0.593)*	-0.017 *(-0.475)*	-0.049 *(-1.079)*	-0.018 *(-0.503)*	-0.049 *(-1.082)*
Fund Volatility	**-0.040.** *(-1.819)*	0.125 *(0.712)*	**-0.041.** *(-1.835)*	0.124 *(0.708)*	**0.066***** *(5.807)*	-0.007 *(-0.213)*	**0.066***** *(5.780)*	-0.007 *(-0.213)*
Static Return	**1.477***** *(132.1)*	**1.461***** *(22.55)*	**1.477***** *(132.1)*	**1.460***** *(22.57)*				
R^2	66.379%	67.105%	66.380%	67.107%	1.611%	4.590%	1.574%	4.595%
Adj. R^2	66.353%	66.928%	66.351%	66.926%	1.547%	4.087%	1.499%	4.082%
Fixed Effects (Year)	No	Yes	No	Yes	No	Yes	No	Yes
Other fixed effects (Morningstar rating, Morningstar Category, Sustainability Rating, Index Fund)	No	Yes	No	Yes	No	Yes	No	Yes

Return and Social Scores

Dependent Variables	EXCESS RETURN: Scores only		EXCESS RETURN: Scores and median		DYNAMIC RETURN: Scores only		DYNAMIC RETURN: Scores and median	
Independent Variables	**OLS Regression (1)**	**FE regression (2)**	**OLS Regression (3)**	**FE Regression (4)**	**OLS Regression (5)**	**FE Regression (6)**	**OLS Regression (7)**	**FE Regression (8)**
Social Score	**-1.455***** *(-5.793)*	**-0.957*** *(-2.169)*	**-1.573***** *(-4.542)*	**-1.266*** *(-2.311)*	-0.192 *(-1.486)*	0.006 *(0.042)*	-0.235 *(-1.318)*	0.162 *(0.835)*
Median Social Score			0.140 *(0.495)*	0.349 *(0.987)*			0.051 *(0.351)*	-0.716 *(-1.465)*
Expense Ratio	0.164 *(1.057)*	0.165 *(0.966)*	0.165 *(1.061)*	0.165 *(0.970)*	-0.101 *(-1.260)*	-0.057 *(-0.490)*	-0.100 *(-1.257)*	-0.057 *(-0.491)*
Fund Age	-0.034 *(-0.568)*	**-0.253*** *(-2.335)*	-0.023 *(-0.357)*	**-0.256*** *(-2.351)*	**0.160***** *(5.231)*	**0.126*** *(2.025)*	**0.164***** *(5.018)*	**0.128*** *(2.052)*
Flows	0.049 *(0.670)*	**0.173*** *(2.316)*	0.049 *(0.680)*	**0.175*** *(2.352)*	**0.109**** *(2.913)*	**0.089*** *(2.281)*	**0.109**** *(2.920)*	**0.088*** *(2.250)*
Fund Size	-0.002 *(-0.028)*	0.051 *(0.482)*	-0.001 *(-0.016)*	0.056 *(0.530)*	-0.019 *(-0.526)*	-0.048 *(-1.062)*	-0.019 *(-0.518)*	-0.050 *(-1.114)*
Fund Volatility	**-0.040.** *(-1.782)*	0.113 *(0.652)*	**-0.039.** *(-1.749)*	0.115 *(0.663)*	**0.065***** *(5.732)*	-0.004 *(-0.106)*	**0.066***** *(5.743)*	-0.004 *(-0.130)*
Static Return	**1.481***** *(132.8)*	**1.460***** *(22.45)*	**1.481***** *(132.8)*	**1.460***** *(22.45)*	0.051 *(0.351)*	-0.176 *(-1.465)*		
R^2	66.30%	67.10%	66.30%	67.10%	1.60%	4.60%	1.60%	4.60%
Adj. R^2	66.30%	67.00%	66.30%	67.00%	1.50%	4.10%	1.50%	4.10%
Fixed Effects (Year)	No	Yes	No	Yes	No	Yes	No	Yes
Other Fixed Effects (Morningstar rating, Morningstar Category, Sustainability Rating, Index Fund)	No	Yes	No	Yes	No	Yes	No	Yes

Return and Governance Scores

Dependent Variables / Independent Variables	EXCESS RETURN: Scores only OLS Regression (1)	FE regression (2)	EXCESS RETURN: Scores and median OLS Regression (3)	FE Regression (4)	DYNAMIC RETURN: Scores only OLS Regression (5)	FE Regression (6)	DYNAMIC RETURN: Scores and median OLS Regression (7)	FE Regression (8)
Governance Score	-0.223 *(-0.975)*	0.027 *(0.077)*	**-1.317****** *(-4.039)*	-0.861 *(-1.595)*	-0.059 *(-0.500)*	-0.093 *(-0.789)*	-0.239 *(-1.424)*	-0.188 *(-1.024)*
Median Governance Score			**1.363****** *(4.706)*	**1.126***** *(3.215)*			0.224 *(1.505)*	0.121 *(0.802)*
Expense Ratio	**0.318**** *(2.062)*	0.225 *(1.473)*	**0.275.** *(1.784)*	0.233 *(1.513)*	-0.083 *(-1.049)*	-0.069 *(-0.581)*	-0.09 *(-1.138)*	-0.068 *(-0.575)*
Fund Age	**-0.188****** *(-3.531)*	**-0.242**** *(-2.232)*	**-0.166***** *(-3.103)*	**-0.213.** *(-1.933)*	**0.141****** *(5.146)*	**0.124**** *(1.995)*	**0.145****** *(5.259)*	**0.128**** *(2.068)*
Flows	0.050 *(0.691)*	**0.173**** *(2.310)*	0.052 *(0.716)*	**0.175**** *(2.334)*	**0.109***** *(2.924)*	**0.089**** *(2.284)*	**0.109***** *(2.930)*	**0.089**** *(2.288)*
Fund Size	0.013 *(0.188)*	0.065 *(0.625)*	0.028 *(0.403)*	0.079 *(0.789)*	-0.016 *(-0.435)*	-0.046 *(-1.037)*	-0.013 *(-0.367)*	-0.045 *(-0.998)*
Fund Volatility	-0.033 *(-1.462)*	0.131 *(0.731)*	-0.030 *(-1.357)*	0.138 *(0.773)*	**0.066****** *(5.815)*	-0.005 *(-0.156)*	**0.067****** *(5.844)*	-0.004 *(-0.134)*
Static Return	**1.486****** *(133.4)*	**1.461****** *(22.51)*	**1.484****** *(133.2)*	**1.460****** *(22.52)*				
R^2	66.195%	67.099%	66.277%	67.152%	1.569%	4.575%	1.593%	4.582%
Adj. R^2	66.169%	66.922%	66.247%	66.972%	1.504%	4.072%	1.518%	4.068%
Year Fixed Effect	No	Yes	No	Yes	No	Yes	No	Yes
Other Fixed Effects (Morningstar rating, Morningstar Category, Sustainability Rating, Index Fund)	No	Yes	No	Yes	No	Yes	No	Yes

Return and Carbon Scores

Dependent Variables / Independent Variables	EXCESS RETURN: Scores only OLS Regression (1)	EXCESS RETURN: Scores only FE regression (2)	EXCESS RETURN: Scores and median OLS Regression (3)	EXCESS RETURN: Scores and median FE Regression (4)	DYNAMIC RETURN: Scores only OLS Regression (5)	DYNAMIC RETURN: Scores only FE Regression (6)	DYNAMIC RETURN: Scores and median OLS Regression (7)	DYNAMIC RETURN: Scores and median FE Regression (8)
Carbon Score	**-0.565***** *(-6.147)*	-0.060 *(-0.272)*	**-0.342**** *(-2.939)*	0.131 *(0.511)*	**-0.079.** *(-1.679)*	-0.097 *(-1.260)*	**-0.155**** *(-2.585)*	-0.152 *(-1.579)*
Median Carbon Score			**0.810**** *(3.115)*	**0.704*** *(2.149)*			**-0.274*** *(-2.045)*	-0.202 *(-1.456)*
Expense Ratio	0.181 *(1.171)*	0.218 *(1.303)*	0.175 *(1.138)*	0.229 *(1.367)*	-0.100 *(-1.257)*	-0.062 *(-0.540)*	-0.098 *(-1.234)*	-0.065 *(-0.565)*
Fund Age	-0.028 *(-0.465)*	**-0.24*** *(-2.195)*	-0.078 *(-1.270)*	**-0.228*** *(-2.105)*	**0.163***** *(5.329)*	**0.130*** *(2.077)*	**0.180***** *(5.682)*	**0.126*** *(1.995)*
Flows	0.049 *(0.681)*	**0.173*** *(2.325)*	0.048 *(0.656)*	**0.171*** *(2.316)*	**0.109**** *(2.914)*	**0.088*** *(2.251)*	**0.109**** *(2.933)*	**0.089*** *(2.259)*
Fund Size	0.017 *(0.244)*	0.064 *(0.609)*	0.016 *(0.227)*	0.054 *(0.516)*	-0.016 *(-0.455)*	-0.050 *(-1.101)*	-0.016 *(-0.442)*	-0.047 *(-1.040)*
Fund Volatility	**-0.045*** *(-2.021)*	0.129 *(0.733)*	**-0.049*** *(-2.193)*	0.117 *(0.672)*	**0.065***** *(5.637)*	-0.006 *(-0.174)*	**0.066***** *(5.747)*	-0.002 *(-0.070)*
Static Return	**1.478***** *(132.1)*	**1.461***** *(22.52)*	**1.477***** *(131.9)*	**1.459***** *(22.56)*				
R^2	66.3%	67.1%	66.4%	67.1%	1.60%	4.60%	1.60%	4.60%
Adj. R^2	66.3%	66.9%	66.4%	66.9%	1.50%	4.10%	1.60%	4.10%
Fixed Effects (Year)	No	Yes	No	Yes	No	Yes	No	Yes
Other fixed effects (Morningstar rating, Morningstar Category, Sustainability Rating, Index Fund)	No	Yes	No	Yes	No	Yes	No	Yes

Source: Authors' estimates. Regressions explain various return components: excess return and dynamic return. The key explanatory variable is industry-adjusted sustainability information from MSCI as of the prior month; other variables include expense ratio, fund age, flows, fund size, fund volatility. Fixed effect, where indicated, add additional controls for the calendar month, Morningstar fund category, Morningstar analyst rating, Morningstar Sustainability Label, and whether it is an index fund for a given fund. t-Statistics are based on robust standard errors, double clustered at the individual fund and the date level. ***, **, and * indicate statistical significance at the 0.01%, 1%, and 5% level, respectively. The sample covers investment funds invested in European stocks between 2014 to 2021. "FE regression" represents specifications of fixed effects panel regression and "OLS regression" represents specifications of OLS regression.

Appendix 4-E: Relationship between alpha and sustainability

Alpha and Environmental Scores

Dependent Variables	ALPHA		ALPHA		ALPHA		
	Scores Only		Scores and Median		25%, 50%, 75% Quantile		
Independent Variables	**OLS Regression (1)**	**FE Regression (2)**	**OLS Regression (3)**	**FE Regression (4)**	**25% Quantile FE Regression (5)**	**50% Quantile FE Regression (6)**	**75% Quantile FE Regression (7)**
Environmental Score	**-2.046***** *(-9.522)*	-0.290 *(-0.765)*	**-1.895***** *(-6.312)*	-0.028 *(-0.061)*	-0.063 *(-0.12)*	-0.089 *(-0.16)*	-0.122 *(-0.19)*
Median Environmental Score			-0.255 *(-0.723)*	-0.399 *(-1.162)*	-0.205 *(-0.67)*	-0.424 *(-1.20)*	-0.698 *(-1.40)*
Expense Ratio	**0.336.** *(1.760)*	0.363 *(1.473)*	**0.333.** *(1.745)*	0.376 *(1.520)*	-0.303 *(-1.58)*	0.191 *(0.90)*	**0.811**** *(2.79)*
Fund Age	**-0.190**** *(-2.842)*	**-0.461***** *(-3.746)*	**-0.196**** *(-2.912)*	**-0.462***** *(-3.751)*	**-0.542***** *(-3.53)*	**-0.320.** *(-1.78)*	-0.041 *(-0.19)*
Flows	0.044 *(0.485)*	**0.249***** *(4.159)*	0.043 *(0.473)*	**0.247***** *(4.133)*	0.054 *(0.79)*	0.073 *(1.15)*	0.098 *(1.39)*
Fund Size	0.111 *(1.288)*	0.134 *(0.916)*	0.109 *(1.260)*	0.131 *(0.902)*	0.070 *(0.62)*	0.080 *(0.60)*	0.094 *(0.53)*
Fund Volatility	**-0.0578*** *(-2.102)*	0.247 *(0.809)*	**-0.0585*** *(-2.124)*	0.246 *(0.805)*	-0.102 *(-1.22)*	-0.067 *(-0.67)*	-0.022 *(-0.19)*
R^2	1.561%	5.600%	1.566%	5.613%	-	-	-
Adj. R^2	1.496%	5.103%	1.500%	5.106%	-	-	-
Fixed Effects (Year)	No	Yes	No	Yes	Yes	Yes	Yes
Other fixed effects	No	Yes	No	Yes	Yes	Yes	Yes

Alpha and Social Scores

Dependent Variables	ALPHA Scores Only		ALPHA Scores and Median		ALPHA 25%, 50%, 75% Quantile		
Independent Variables	OLS Regression (1)	FE Regression (2)	OLS Regression (3)	FE Regression (4)	25% Quantile FE Regression (5)	50% Quantile FE Regression (6)	75% Quantile FE Regression (7)
Social Score	**-2.107***** *(-6.757)*	**-1.225.** *(-1.733)*	**-2.240***** *(-5.203)*	**-1.555.** *(-1.887)*	-0.445 *(-0.75)*	-0.586 *(-0.82)*	-0.764 *(-0.77)*
Median Social Score			0.158 *(0.449)*	0.371 *(0.813)*	-0.292 *(-1.03)*	-0.258 *(-0.70)*	-0.214 *(-0.38)*
Expense Ratio	**0.347.** *(1.796)*	0.309 *(1.243)*	**0.348.** *(1.799)*	0.309 *(1.248)*	**-0.360.** *(-1.94)*	0.127 *(0.60)*	**0.738*** *(2.51)*
Fund Age	-0.077 *(-1.044)*	**-0.470***** *(-3.840)*	-0.065 *(-0.819)*	**-0.473***** *(-3.883)*	**-0.496***** *(-3.85)*	**-0.264.** *(-1.68)*	0.028 *(0.14)*
Flows	0.029 *(0.320)*	**0.247***** *(4.165)*	0.030 *(0.329)*	**0.250***** *(4.248)*	0.052 *(0.75)*	0.071 *(1.08)*	0.095 *(1.31)*
Fund Size	0.053 *(0.617)*	0.117 *(0.817)*	0.054 *(0.627)*	0.122 *(0.861)*	0.055 *(0.54)*	0.066 *(0.52)*	0.079 *(0.45)*
Fund Volatility	**-0.054.** *(-1.958)*	0.231 *(0.767)*	**-0.053.** *(-1.928)*	0.233 *(0.774)*	-0.102 *(-1.25)*	-0.067 *(-0.69)*	-0.023 *(-0.19)*
R^2	1.079%	5.708%	1.081%	5.719%	-	-	-
Adj. R^2	1.014%	5.211%	1.005%	5.212%	-	-	-
Fixed Effects (Year)	No	Yes	No	Yes	Yes	Yes	Yes
Other fixed effects	No	Yes	No	Yes	Yes	Yes	Yes

Source: Authors' estimates. Regressions explain security selection alpha. The key explanatory variable is industry-adjusted sustainability information from MSCI as of the prior month; other variables include expense ratio, fund age, flows, fund size, fund volatility. Other fixed effects, where indicated, add additional controls for the calendar month, Morningstar fund category, Morningstar analyst rating, Morningstar Sustainability Label, and whether it is an index fund for a given fund. t-Statistics are based on robust standard errors, double clustered at the individual fund and the date level. ***, **, * and . indicate statistical significance at the 0.01%, 1%, 5% and 10% level, respectively. The sample covers investment funds invested in European stocks between 2014 to 2021. "FE regression" represents specifications of fixed effects panel regression, "OLS regression" represents specifications of OLS regression and "Quantile Regression" represents specifications of fixed-effects quantile regressions at a particular quantile of alpha.

6 *Chapter 2*: Do high sustainability ratings really mitigate financial risks?

6.1 Introduction

A plethora of empirical studies on the return potential of sustainable investments has been published, yet there remains a conspicuous lack of agreement. Broadly speaking, the findings can be categorised into three groups. Some studies, such as (Filbeck, Filbeck, and Zhao 2019) and (Consolandi et al. 2009), suggest that ESG investments outperform. Conversely, research by (El Ghoul and Karoui 2017), indicates that sustainable funds exhibit consistently poorer performance compared to their non-sustainable counterparts. Lastly, there are studies like (e.g. (Hartzmark and Sussman 2019), which show that ESG factors do not significantly influence performance, whether positively or negatively. For example, Hartzmark and Sussman found no evidence that high-sustainability funds outperformed low-sustainability funds in terms of returns.

In contrast, the relationship between financial risk and ESG appears to enjoy much more consensus (Le Sourd 2024). Indeed, the intuition behind the connection between sustainability and financial risk seems manifest. If risk is deemed to be any form of uncertainty and ESG concerns addressing the impact of corporate activities and behaviour on stakeholders, then it would be logical to hypothesise a direct association between how companies handle relevant sustainability topics and their impact on risk. Equally, it follows that companies neglecting to manage their ESG exposures adequately may expose themselves to higher financial risks than their more ESG-conscious peers. This hypothesis can be illustrated with simple examples. If a firm does not have stringent governance controls and procedures, it may be more prone to corporate scandals, leading to a loss of confidence in the company and even its demise. Similarly, if a firm emits high levels of carbon emissions from its manufacturing activities and does not pay due regard to it, it may be more susceptible to future legislation that might impose a carbon tax or a consumer boycott that interrupts its activities. All the events described so far only represent some of the issues that can afflict the performance of a company if material ESG issues are not appropriately handled, leading to a potential loss of profit and firm value. Though the timing of these events and the magnitude of the impact may be uncertain.

The sporadic occurrence of these events, coupled with the difficulty in modelling potential outcomes, suggests that the risks associated with ESG exposures may not be fully captured by traditional risk measures. Insofar as ESG does reflect some dimension of risk, there should be some correlation between ESG scores and traditional risk measures. While some research has examined the link between ESG and financial risk, most of it focuses on active funds or indices rather than individual stocks (e.g. (Hoepner

2010)). The limited studies that analyse the effect of ESG on stocks may produce misleading results due to inadequate control for endogeneity issues. Indeed, empirical research in finance is often fraught with significant challenges related to endogeneity, as it is typically difficult to identify exogenous factors or natural experiments that can accurately establish the relationships being studied. If endogeneity is not properly addressed, the implications for the usefulness of empirical work can be substantial, resulting in biased and inconsistent parameter estimates that render reliable inferences virtually impossible(Roberts and Whited 2013). In this paper, the principal objective is to ascertain whether equities with superior ESG scores exhibit a reduced financial risk profile, while simultaneously addressing the endogeneity concerns that previous analyses have left unresolved. The investigation focuses on total risk, stock-specific risk, and historical market beta. These metrics are estimated using the Axioma Fundamental Equity Risk Model, a tool widely employed in the financial industry for evaluating and managing equity portfolio risks, as well as for portfolio construction and risk attribution.

This study seeks to make several contributions to the existing literature. Specifically, our study makes two key contributions: First, many previous analyses (e.g. (Dunn, Fitzgibbons, and Pomorski 2018)) that link sustainability to risk often overlook temporal dynamics and endogeneity, which can introduce significant bias. We address this by employing an instrumental variable approach alongside panel fixed-effects regression, applying these methods to more recent data. This enables a clearer distinction between genuine ESG-driven risk mitigation and spurious correlations caused by omitted variables. This methodological advancement is a central contribution of our work. Second, we explore how the relationship between sustainability and risk varies across the extreme ends of the risk distribution, as well as during tail risk events like the COVID-19 pandemic, and we also examine the relationship between sustainability and future risk over a one-year horizon. By integrating these dynamic and forward-looking analyses, we provide novel insights into how ESG factors impact company-level financial risk.

The motivation for this chapter is to address a critical gap in the literature by exploring how and whether ESG factors influence company-level financial risk—particularly by tackling endogeneity concerns—thereby shedding light on risk management practices that have been largely overlooked. This focus is driven by the need to improve upon prior studies that did not adequately account for the dynamic nature of risk. In this chapter, we focus specifically on ESG and *equity-level* risk for two main reasons. First, while Chapter 1 employed Andrew Lo's Active–Passive Decomposition to examine how ESG factors influence European mutual fund returns—and relied on passive factor building blocks to replicate fund exposures—risk was not its central focus. By shifting from fund-level returns to *individual companies*, we directly assess company-level risk, free from confounding factors such as manager skill, fees, or style tilts. Second, broadening the geographic scope to include the United States, Developed Markets excluding the United States, and other Developed Markets allows us to test whether the ESG–

risk relationships suggested in the European context extend across diverse regulatory, cultural, and economic environments. While some of the fundamental factors used as control variables resemble those embedded in the prior chapter's passive replication approach, this study more explicitly concentrates on company-level risk measures—namely market beta, stock-specific risk, and total risk—to provide a more granular perspective of how ESG quality may influence volatility, idiosyncratic threats, and systematic exposures in a global setting.

The structure of this paper is as follows: Section 2 provides an overview of the literature. Section 3 presents the theoretical framework and hypotheses. Section 4 describes the data used in the analysis, while Section 5 presents the descriptive statistics. Section 6 details the methodology, followed by Section 7, which discusses the empirical results. Finally, Section 8 concludes with investment implications.

6.2 Literature Review

The nexus between sustainability and risk is widely acknowledged. (Hoepner 2010) contends that ESG investments offer diversification benefits due to the lower firm-specific risks in high ESG-rated companies, based on global equity data comparing ESG-screened portfolios with unscreened ones—which exhibit reduced idiosyncratic risk. However, his study omits dynamic volatility factors (e.g. lagged risk), potentially introducing endogeneity biases. Similarly, (De and Clayman 2015) find a robust inverse correlation between ESG ratings and stock return volatility across multiple industries using cross-sectional regressions; yet their analysis is contemporaneous and excludes lagged volatility, possibly overstating ESG's impact on current risk.

While many studies examine ESG–risk linkages at the fund or index level, such an approach may obscure individual stock dynamics. (Dunn, Fitzgibbons, and Pomorski 2018) and (Lööf and Stephan 2019) investigate the ESG–risk relationship at the single-stock level. Dunn et al. (2018) construct firm-level portfolios for U.S. equities, demonstrating that higher ESG ratings correlate with lower total volatility, downside deviation and value-at-risk—even after controlling for size and style—using a factor model and panel regressions. Lööf and Stephan (2019) utilising European panel data, reveal a negative relationship between ESG and tail risk, particularly during volatile phases; however, they too do not fully incorporate lagged volatility, which may fail to capture risk persistence.

Most studies do not address the endogeneity arising from omitting lagged volatility—a dynamic characterised by autocorrelation and risk clustering—potentially leading to misleading coefficients, as the ESG variable might merely capture prior low-volatility regimes rather than a true causal effect.

(Pedersen, Fitzgibbons, and Pomorski 2021) argue that ESG scores reflect firm fundamentals (e.g. operational efficiency, risk management practices and governance quality) that influence long-term stability. (Giese et al. 2019) further distinguish between idiosyncratic and systematic risk channels, suggesting that robust ESG can reduce exposure to market shocks and firm-specific adverse events (see Exhibit 13).

Exhibit 13 Company-specific risk channel according to (Giese et al. 2019)

Endogeneity remains a key concern in ESG–risk research, with studies often facing omitted variable bias, reverse causality and spurious correlations—particularly when lagged risk (with its autocorrelation and clustering) is omitted. Seminal works by (Arellano and Bond 1991) and (Blundell and Bond 1998) demonstrate that omitting lagged dependent variables in the presence of persistent volatility yields biased results. Our approach mitigates this by incorporating a single lagged risk variable via an instrumental variable method.

A closer look at these prominent studies underscores a common methodological gap. (Hoepner 2010) relied on a static cross-sectional setup, so lower volatility in ESG-screened portfolios might partly reflect pre-existing risk profiles. (De and Clayman 2015) similarly adopted cross-sectional regressions without controlling for lagged volatility, making it difficult to separate a genuine ESG effect from prior low-volatility trends. Dunn, Fitzgibbons, and Pomorski (2018) employed factor models and panel regressions but did not introduce a lagged dependent variable, raising endogeneity concerns if volatility clustering drives both ESG adoption and subsequent low risk. (Lööf and Stephan 2019) addressed tail risk in European firms yet also omitted lagged volatility, which may capture persistent regimes of stability or turmoil. Consequently, many findings linking ESG to lower volatility might partly be attributing historical market calm to ESG credentials, rather than establishing a clear causal link. By using a dynamic panel approach and instrumental variables, we seek to sidestep these pitfalls and more reliably isolate ESG's role in mitigating risk.

Although some studies suggest that ESG factors may attenuate tail risks, few explicitly test extreme outcomes (e.g. value-at-risk, expected shortfall or implied skewness) while accounting for the dynamic nature of risk. (Zhang, De Spiegeleer and Schoutens 2021) show that high-ESG firms exhibit lower implied volatility and less negative skewness, while (Bax et al. 2023) utilise vine copula modelling to document reduced tail dependencies during the 2008 financial crisis. Nonetheless, the role of lagged risk in tail events remains underexplored. Our research examines tail risk via quantile regression across different risk segments and during COVID-19, capturing risk clustering and conditioning on past volatility within a dynamic framework.

In all, although evidence suggests that ESG can mitigate financial risk, many studies neglect lagged volatility, potentially overstating ESG's direct effect. Our study addresses this gap by incorporating lagged volatility into a dynamic framework, thereby isolating the true impact of ESG on current risk profiles and providing clearer insights for investors, policymakers and researchers—particularly in the context of extreme events such as the COVID-19 pandemic.

6.3 Theoretical framework and hypotheses

ESG performance is posited to affect financial risk via multiple transmission channels. Firms with robust ESG integration exhibit superior corporate governance, regulatory compliance, and strategic risk management, thereby reducing exposure to financial volatility and exogenous shocks. A comprehensive ESG framework enhances transparency, stakeholder relations and resource efficiency, mitigating both firm-specific and market-wide risks. A principal challenge in establishing a causal ESG–risk relationship is addressing endogeneity stemming from volatility clustering and regime persistence. This study employs instrumental variables for lagged risk to control for these effects, ensuring that our estimates capture the genuine impact of ESG on risk. Better governance reduces agency costs, curbs managerial opportunism, and strengthens financial oversight, thus lowering risk exposure across multiple dimensions. (Giese et al. 2019) find that firms with robust ESG performance exhibit lower return volatility and greater resilience to adverse market conditions, while (Dunn, Fitzgibbons and Pomorski 2018) emphasise that governance, in particular, is critical in mitigating financial instability.

Bridging gaps in the literature, this study examines both composite ESG scores and individual ESG dimensions, including carbon scores, to analyse the relationship between ESG and financial risk while addressing endogeneity concerns that may have confounded earlier studies. Specifically, the analysis considers total risk (overall volatility), idiosyncratic (stock-specific) risk, and market risk (beta), exploring the mechanisms by which sustainability practices shape a firm's risk profile. Unlike prior studies that may neglect risk persistence, our research controls for volatility clustering and regime dependence using instrumental variables for lagged risk, ensuring a more robust evaluation of ESG's risk-mitigating effects.

The analysis begins with an assessment of the impact of composite ESG scores and their individual dimensions—including carbon scores—on total risk. Firms that integrate sustainability into their corporate strategy typically experience lower operational uncertainty, reduced litigation risk, and improved capital efficiency, which collectively contribute to diminished overall volatility. This supports the premise that sustainability practices enhance financial stability by mitigating exposure to regulatory, reputational and operational risks. In particular, firms with high governance scores exhibit lower total risk as enhanced board oversight diminishes the likelihood of financial mismanagement, curbs excessive risk-taking, and ensures regulatory compliance. Governance-driven risk controls help firms avert crises arising from weak internal controls or opaque reporting structures. For instance, (Beasley, Clune and Hermanson 2005) found that effective risk governance structures maximise shareholder value by reducing organisational risk, thereby lowering the cost of capital.

Subsequently, the analysis turns to idiosyncratic risk, examining the role of both composite ESG scores and individual ESG dimensions. Strong environmental performance can mitigate firm-specific risks by lowering exposure to regulatory penalties, climate liabilities, and resource scarcity shocks. Similarly, robust social performance—evidenced by fair labour practices, effective stakeholder engagement and sustainable supply chain management—reduces exposure to reputational damage and operational disruptions. Governance mitigates idiosyncratic risk by reducing information asymmetry, enforcing financial discipline, and ensuring management accountability. Firms with independent boards, transparent reporting and well-structured shareholder rights are expected to experience fewer governance-related shocks, thereby reducing firm-specific volatility. Moreover, enhanced governance bolsters investor confidence, dampening speculative trading and stabilising stock price fluctuations. For example, (Alzayed et al. 2024) found that effective corporate governance mechanisms are associated with reduced risk-taking in financial institutions, thus lowering idiosyncratic risk.

Finally, the study examines the relationship between ESG performance and market risk (beta). Firms with higher ESG scores—particularly those excelling in governance and carbon transition strategies—are better positioned to navigate macroeconomic and sector-wide shifts. Superior sustainability credentials act as a hedge against systemic risks, reducing a firm's sensitivity to market-wide fluctuations. By incorporating instrumental variables for lagged risk, the study accounts for persistent risk dynamics that might otherwise bias estimates of the ESG–market risk relationship. (Gompers, Ishii and Metrick 2003) find that firms with robust governance structures display lower exposure to macroeconomic shocks, while (La Porta et al. 1998) demonstrate that well-managed firms typically have lower capital costs and reduced earnings volatility. Moreover, firms with low carbon intensity may encounter diminished risks from regulatory tightening, carbon taxation and climate-related market repricing, further supporting the expectation that effective ESG integration reduces market risk.

The transmission mechanisms described above suggest that firms with superior ESG performance should experience lower total, idiosyncratic and market risks. Accordingly, we propose the following hypotheses:

1. Total Risk Hypothesis: *Firms with stronger sustainability credentials maintain lower total risk (volatility) due to improved operational stability, regulatory compliance, and risk management integration. This relationship is tested both on average and during extreme risk events, including COVID-19 and periods of heightened volatility.*

2. Idiosyncratic Risk Hypothesis: *Firms with stronger sustainability performance face lower stock-specific risk due to reduced exposure to firm-specific disruptions and governance failures.*

The analysis tests whether this effect holds on average and in extreme firm-specific risk scenarios, such as financial crises and high quantiles of the risk distribution.

3. Market Risk Hypothesis: *Firms with higher sustainability scores demonstrate lower market beta due to superior strategic oversight, enhanced resilience to macroeconomic shocks, and reduced exposure to carbon transition risks. This hypothesis assesses whether the risk-reducing effect of ESG persists across normal market conditions and extreme systemic risk events, including COVID-19 and high-volatility periods.*

6.4 Data used in the analysis

The primary objective of this analysis is to evaluate the relationship between sustainability and contemporaneous risk dimensions across various geographical regions.

6.4.1 Stock data

The stock universe for this analysis is derived from the MSCI World, MSCI World ex-US, and S&P 900 indices. As of July 2024, the MSCI World index includes 1,430 constituents, capturing large- and mid-cap companies across 23 developed markets and covering 85% of the free float market capitalisation. The MSCI World ex-US index represents 22 developed markets, excluding the US, and comprises 829 constituents, covering approximately 85% of the free float market capitalisation in each country. The S&P 900 index encompasses both the large-cap and mid-cap segments of the US equity market, including the S&P 500 and S&P 400 indices.

1. ESG data

The ESG data utilised in this analysis is sourced from MSCI and assessed at the stock level. MSCI's ESG data coverage includes 8,500 companies and more than 680,000 equity and fixed-income securities globally, rated across environmental, social, and governance pillars. These pillars encompass ten sustainability themes and 35 ESG key issues, aimed at evaluating a company's resilience to long-term, financially relevant ESG risks and opportunities. In the environmental pillar, the focus is on themes such as climate change, carbon emissions, natural capital, pollution and waste, and environmental opportunities. The social pillar covers themes like human capital, product liability, stakeholder opposition, and social opportunities. The governance pillar focuses on corporate governance and behaviour.

To determine a final ESG rating for a company, the weighted average of individual environmental and social key issue scores, along with the governance pillar score, is computed and normalised relative to industry peers. Known as the Industry-Adjusted Score (IAS), this final rating ranges from 0 to 10, where scores vary from the lowest sustainability (0) to the highest (10). The assessments of a company's ESG performance are intended for comparative purposes against industry peers rather than absolute measures.

This research additionally evaluates carbon scores, which are normalised relative to industry peer footprints. This methodology rewards companies that implement low-carbon technologies and penalises those that exploit regulatory variances to their advantage. The carbon scores are graded on a scale from 0 (the weakest) to 10 (the strongest).

The carbon scores used in this analysis are derived from the climate change theme score of the environmental pillar of the MSCI ESG Industry-Adjusted Scores. This theme score, varying from 0 to 10, evaluates various dimensions of a company's response to climate change, including carbon emissions management, energy management, renewable energy usage, climate change policies and commitments, climate risk management, and climate opportunities, among others.

2. Estimation of risk measures

This study estimates equity risk using the Axioma Fundamental Equity Risk Model, which is widely[14] employed in the finance industry for managing equity portfolio risk by integrating both systematic and idiosyncratic components. Systematic risks stem from broad market influences such as country and industry exposures, as well as style factors including momentum, value, and volatility, while idiosyncratic risks are stock-specific and unexplained by these broader factors.

While total volatility can be decomposed using simpler frameworks, such as the Fama-French three-factor model—which attributes risk to market, size, and value factors, with residual standard deviation as a proxy for idiosyncratic risk—Axioma extends this approach. It incorporates a more granular set of factors, including additional style, industry, and country classifications, offering a more comprehensive risk decomposition. This richer factor structure enhances the attribution of both systematic and residual risks, providing more precise visibility into what drives a stock's volatility. As noted by Grinold and Kahn (2000), factor-based models provide a sophisticated framework that not only decomposes risk into its systematic and idiosyncratic components but also enhances the understanding of the risk-return trade-off essential for superior portfolio construction.

[14]https://www.prnewswire.com/news-releases/axioma-risk-recognized-as-best-buy-side-risk-management-solution-by-risknet-for-second-consecutive-year-301485103.html

A key reason for selecting Axioma over a simple volatility measure is its ability to distinguish between systematic and idiosyncratic risk. Unlike standard deviation, which aggregates all sources of volatility, Axioma's factor-based framework enables more precise identification of risk exposures, facilitating more targeted portfolio adjustments. Additionally, Axioma is widely adopted by institutional investors, aligning with the methodologies used in professional risk management. Its factor-based approach reflects how portfolio managers construct and monitor risk, ensuring consistency with industry practices. The model's detailed factor breakdown and broad market coverage enhance its applicability in multi-asset and global equity portfolios.

Axioma also adapts to changing market conditions through its exponential weighting scheme, which assigns greater weight to recent observations. This approach allows volatility estimates and correlations to adjust dynamically, in contrast to fixed-window volatility measures that may lag shifts in market regimes. The model further refines risk estimation through its half-life parameter, which determines the point at which past observations retain half their initial weighting, ensuring that historical data informs risk assessments without overwhelming recent dynamics.

Nevertheless, factor models like Axioma have limitations. They require substantial data inputs and are inherently more complex than simple volatility measures. Their proprietary nature may also reduce transparency for some users. Conversely, a standard deviation-based approach is computationally straightforward and easily interpretable, though it lacks the granularity needed for advanced portfolio risk management. The Axioma model employs regression techniques to estimate each stock's sensitivity to systematic factors, providing a more nuanced risk decomposition than traditional volatility measures. The covariance matrix, a critical component, captures factor interactions and portfolio-wide risk structure. By incorporating a dynamic weighting approach, Axioma ensures that risk estimates remain statistically robust while adapting to market shifts.

The Axioma model is extensively used for portfolio construction, risk attribution, and performance analysis, enabling investment managers to align portfolios with specific risk-return objectives while maintaining control over factor exposures. Additionally, it plays a pivotal role in designing effective hedging strategies to mitigate identified risks. In the context of this study, Axioma's factor-based decomposition allows us to separately measure total, systematic, and idiosyncratic risk components, which is crucial for analysing how ESG characteristics may differentially influence each dimension.

6.5 Descriptive Statistics

6.5.1 Description of data and summary statistics

To begin, we present an overview of the main statistics of our dataset in Exhibit 14, which encompasses many of the variables utilised in the subsequent analyses. This overview aims to provide preliminary insights into the potential relationship between sustainability information and various forms of financial risk. We achieve this by sorting our universe of stocks into ESG quintiles on a monthly basis from 2014 to 2024 and calculating averages of fundamental and other statistical information for stocks within these quintiles. This approach offers a broad overview of the typical characteristics of the stocks in each quintile. Furthermore, we present information on the differences between the best and worst ESG quintiles and their corresponding t-statistics.

From Exhibit 14, we observe that stocks with poorer ESG scores (i.e., those in the higher quintiles) tend to achieve higher returns, although the t-statistics suggest that this difference may not be statistically significant. Conversely, the risk profile reveals an inverse pattern: the better ESG quintiles incur lower total risk, idiosyncratic risk, and market beta, with these risk measures progressively and monotonically increasing across the quintiles. Exhibit 15 illustrates how different risk metrics evolve over time.

In terms of fundamental characteristics, the patterns observed across the quintiles do not display a universally clear trend across all variables. Notably, better ESG quintiles exhibit higher dividend yields, return on equity, and cash profitability compared to their lower ESG counterparts. Additionally, these better ESG quintiles have lower debt-to-enterprise value and asset growth than the worse ESG quintiles, with the t-statistics generally supporting these relationships. However, there appears to be no strong relationship between average market capitalisation and ESG scores.

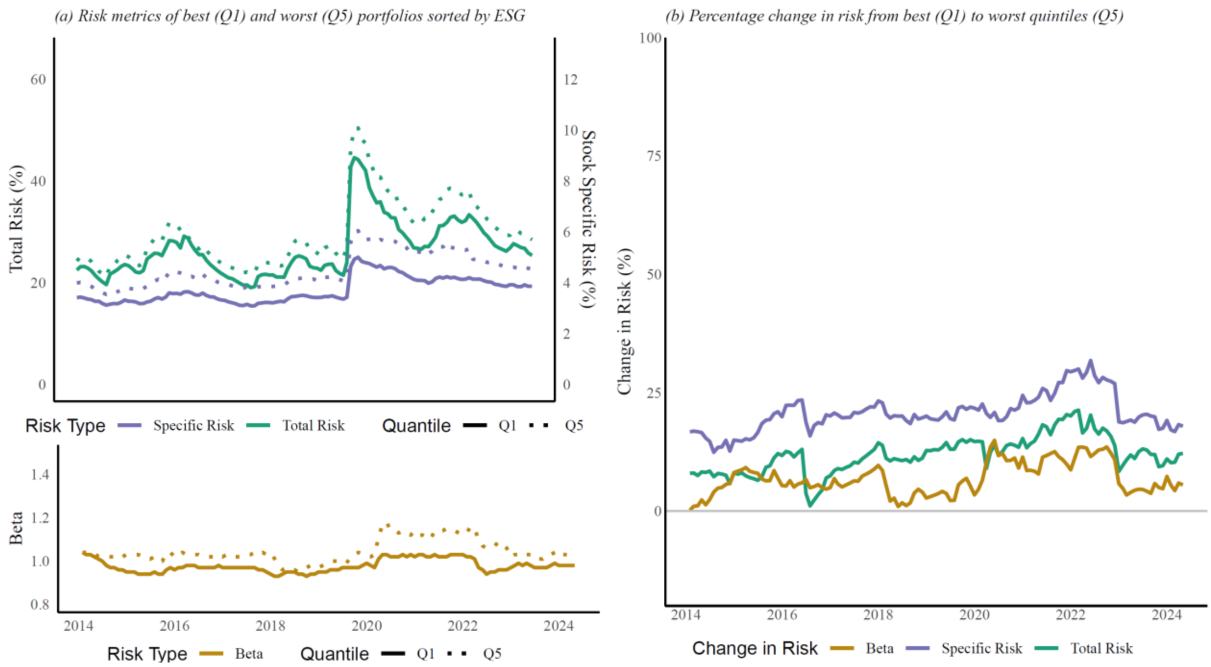
Turning to the regional universes, we observe a comparable pattern where the worse ESG quintiles earn a higher return but also incur higher risk than the better ESG quintiles, consistent for both US and World ex-US universes. Correspondingly, better ESG quintiles also have stronger fundamental characteristics, including higher dividend yield, higher return on equity, higher cash profitability, and lower debt-to-enterprise value ratios. For details of the analysis for other regions, refer to Appendix 5-A.

Exhibit 14 Characteristics of MSCI World Stocks by ESG Quintiles and Differences Between the First and Fifth Quintiles

	Q1 (best ESG)	Q2	Q3	Q4	Q5 (worst ESG)	Q5-Q1
Risk-return metrics						
Annual Return	6.39	6.78	7.01	8.20	7.98	1.59 (-0.824)
Total Risk	26.55	27.59	27.98	28.39	29.77	3.22 (-5.419)
Stock-speci/c risk	18.58	19.89	20.41	20.99	22.47	3.89 (-10.258)
Market beta	0.98	1.01	1.02	1.02	1.04	0.067 (-12.253)
Fundamental characteristics						
Market cap (USD billion)	34.92	32.68	32.42	35.49	35.45	0.54 (-0.301)
ROE	25.92	22.68	17.27	25.29	14.68	-11.27 (2.027)
Dividend Yield	2.72	2.48	2.41	2.04	1.88	-0.84 (25.481)
Cash pro%t	29.66	28.89	28.63	28.95	28.77	-0.89 (3.816)
Asset growth	7.23	8.45	9.83	10.49	11.28	4.05 (-11.812)
Debt-to-enterprise value	23.30	25.01	24.55	24.72	24.70	1.40 (-5.202)

Source: Authors' estimates, FactSet. Monthly data from January 2014 to June 2024. Numbers in parentheses represent the t-statistics comparing the best and worst quintiles.

Exhibit 15 Differences in Risk Metrics Over Time Between the First and Fifth ESG Quintiles

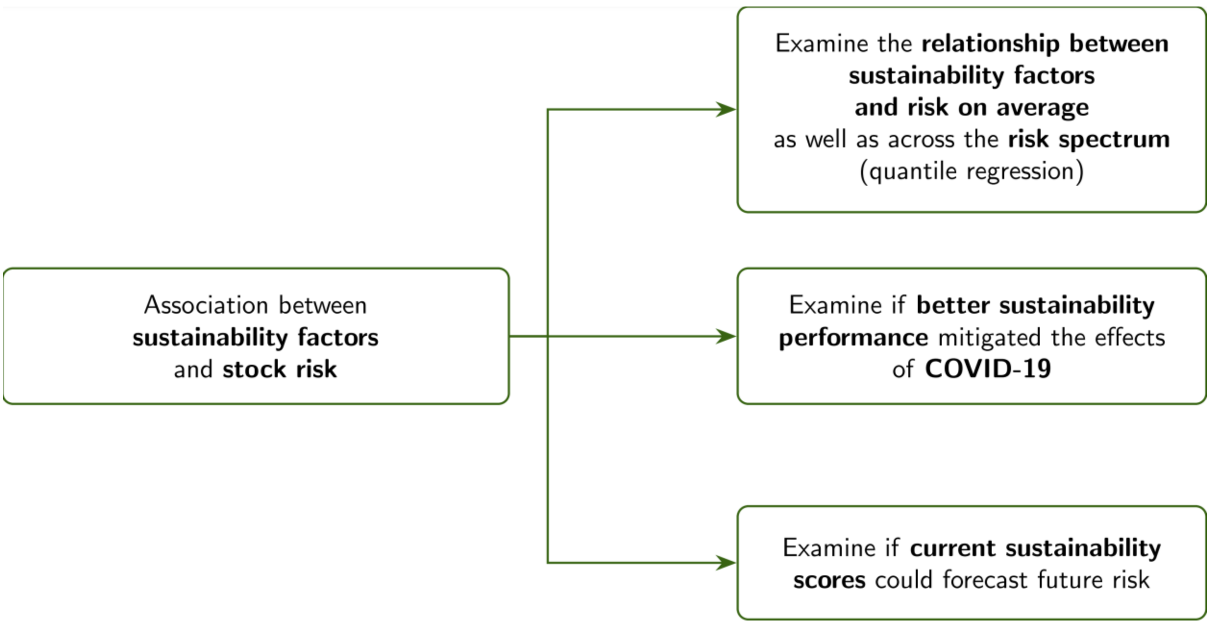


Source: Authors' estimates, FactSet, Axioma. Monthly data from January 2014 to June 2024.

6.6 Analysis Methodology

To analyse and quantify the associations between sustainability factors and risk dimensions across stocks in multiple geographical regions, the following methodology, as summarised in the diagram below, has been adopted (see Exhibit 16)

Exhibit 16 Analysis methodology to study the relationship between ESG ans risks



Specifically, we re-evaluate the relationship between risk dimensions and sustainability factors, considering both composite and individual ESG scores across different regions. This assessment employs a range of regression methods, some of which are more commonly utilised than others, to determine the general (average) relationship between risk and sustainability. This analysis is further enriched by the application of quantile regression, focusing on various segments of the risk distribution spectrum. The subsequent investigation examines whether companies with stronger sustainability credentials were better able to mitigate the adverse impacts of COVID-19. Finally, the analysis explores the predictive power of current sustainability scores in forecasting future risks.

6.6.1 Specifications of regression analyses

Commencing with a simple linear regression model (Specification A) offers a foundational analysis of the direct association between the variables. The subsequent introduction of fundamental variables within a multiple regression framework (Specification B) aims to better isolate the distinct impact of sustainability information by controlling for additional covariates, thereby mitigating the risk of omitted variable bias. In Specification C, the inclusion of fixed effects addresses unobserved, time-invariant characteristics, further refining the robustness of the analysis. However, many prior studies fail to account for endogeneity concerns, particularly the persistence of risk through lagged effects and volatility clustering. The omission of past risk measures in ESG-risk regressions may lead to biased coefficients and spurious relationships, misrepresenting the actual influence of sustainability factors on financial risk. Specification D enhances this approach even further by incorporating a lagged risk variable, which accounts for temporal dependencies and mitigates endogeneity concerns, thereby clarifying how historical risk influences current outcomes. Finally, Specification E applies dynamic fixed effects in a quantile regression context, enabling an exploration of how the relationship between sustainability and risk fluctuates across different points of the risk distribution. This comprehensive, multi-specification methodology ensures a detailed examination, effectively addressing potential biases and revealing the intricate dynamics underlying the relationship.

Speci/cation A: Simple Linear Regression Between Risk Variables and Sustainability Variables

In this specification, we examine the association between risk variables—specifically, current total risk (Total Risk), current stock-specific risk (Stock Specific Risk), and current beta (Market Beta)—and sustainability information, including ESG scores, and the individual environmental (E), social (S), governance (G), and carbon.

$$Y_{it} = \beta_0 + \beta_1 X_{\mathrm{SUST}\_it} + \epsilon_{it}$$

where: Y_i can be Total Risk_i, $\text{Stock Specific Risk}_i$ and Market Beta_i (i.e. risk-related metrics, namely the current total risk, stock-specific risk and market beta), $X_{\text{SUST\_i}}$ are sustainability variables (e.g., ESG scores and their individual components as well as the carbon scores), β_1 is the slope coefficient, β_0 is the intercept and ϵ_i is the error term.

Speci/cation B: Multiple Linear Regression Between Risk Variables, Sustainability Variables, and Fundamental Variables

This specification is similar to the simple linear regression in Specification A, but includes additional fundamental variables such as market capitalisation, dividend yield, price momentum, liquidity, return on equity, asset growth, earnings volatility, and debt-to-enterprise value.

$$Y_{it} = \beta_0 + \beta_1 X_{\text{SUST\_}it} + \beta_2 X_{1it} + \cdots + \beta_k X_{kit} + \epsilon_{it}$$

where: $X_{1i}, \ldots, X_{ki}$ are fundamental variables (SIZE, DIVY, PRICE_MOM, DVOL, ROE, ASSET_GROWTH, EARN_VOL, DEBTEV). Fundamental variables are defined as follows: SIZE represents the logarithm of the market capitalisation of the company; DIVY represents the dividend yield; PRICE_MOM represents the logarithm of price momentum; DVOL represents the logarithm of liquidity, proxied using the dollar volume; ROE represents the logarithm of return on equity; ASSET_GROWTH represents the logarithm of percentage growth of assets; EARN_VOL represents the logarithm of earnings volatility; and DEBTEV represents the logarithm of the debt-to-enterprise value ratio.

Speci/cation C: Static /xed eˆects linear regression between risk variables, sustainability variables and fundamental variables

This specification makes use of the static fixed effects regression that controls for unobserved heterogeneity across entities (such as firms, or countries) that is expected to be constant over time. This model is particularly useful for addressing the issue of omitted variable bias that arises from these unobserved, time-invariant factors, which traditional multiple ordinary least square regression does not account for. By incorporating fixed effects, the model effectively removes the influence of these unobserved variables, further isolating the effect of the independent variables on the dependent variable. The key assumptions of the fixed effects model include: (1) the unobserved heterogeneity (fixed effects) is correlated with the independent variables, (2) the error term is uncorrelated with the independent variables, and (3) there is no perfect multicollinearity among the regressors.

Two-way error clustering is employed to account for correlation in the error terms that may occur across two dimensions, such as firms and time periods. This is specifically important when errors are correlated within clusters (e.g., firms) over time and within time periods across clusters (e.g., firms on the same date). By clustering standard errors in two dimensions, it is possible to obtain robust standard errors that correct for these intra-cluster and inter-cluster correlations, leading to more reliable inference. This method ensures that the standard errors are not underestimated, which could otherwise result in misleading and erroneous statistical significance of the estimated coefficients.

$$Y_{it} = \beta_0 + \beta_1 X_{\mathrm{SUST\_}it} + \beta_2 X_{1it} + \cdots + \beta_k X_{kit} + \alpha_i + \lambda_t + \delta_c + \gamma_s + \epsilon_{it}$$

Where: α_i is the firm fixed effect, λ_t is the month fixed effect, δ_c is the country fixed effect. γ_s is the sector fixed effect. Errors are clustered by firm and date.

Speci/cation D: Dynamic Fixed E˜ects Linear Regression Using Instrumental Variables To Address Endogeneity

Endogeneity issues pervade the finance literature, and failure to address them can lead to erroneous inferences, as highlighted by (Wintoki, Linck, and Netter 2012). Typically, instrumental variables are employed to mitigate these issues, often via dynamic panel generalised method of moments estimators (e.g., (Arellano and Bond 1991), (Blundell and Bond 2023)) or through a two-stage least squares approach using instruments for the endogenous variable. The choice of method depends on computational feasibility and concerns regarding overfitting.

In this specification, we adopt the latter approach by incorporating a lagged dependent variable in a panel regression. This strategy captures the dynamic nature of the dependent variable by accounting for its past values—a valuable feature when current states are influenced by previous periods, as is the case with financial risk metrics. Including a lagged dependent variable explicitly models the persistence of risk over time, thereby yielding more precise insights into its drivers.

Moreover, risk clustering is widely documented, with seminal works such as (Cont 2001), (Engle 1982) and (Ferson and Harvey 1991) demonstrating that total risk, market beta, and stock-specific risk exhibit time-varying volatility where elevated (or subdued) risk levels persist over successive periods. By incorporating a lagged risk variable, the model directly captures this persistence, thereby reducing the likelihood of biased estimates when examining the influence of ESG on financial risk.

Nevertheless, this dynamic specification can itself introduce endogeneity. One potential source arises from omitted variables: unobserved shocks that affect both past and current risk may render the lagged dependent variable correlated with the error term. If these shocks are serially correlated, standard panel regressions that assume strict exogeneity become inappropriate, thus necessitating instrumental variables or GMM-based estimators to avoid biased estimates. The theoretical rationale for including lagged risk stems from volatility clustering and serial correlation in financial markets. By recognising that present risk depends on its recent history, the model captures a realistic feature of risk dynamics that is well supported by empirical evidence. Nonetheless, the use of a lagged dependent variable is not without drawbacks. In line with (Achen 2000), including the lag may substantially improve model fit but could diminish the estimated significance of other regressors, thereby obscuring valid relationships. More recent research, however, suggests that such trade-offs are acceptable when a strong theoretical or empirical case supports the dynamic specification. For instance, (Keele and Kelly 2006) contend that lagged dependent variables are integral to modelling state dependence in political and economic contexts, and (Roodman 2009) notes that dynamic panel estimations remain valid provided that instruments and other specification choices are carefully managed. Given the evidence of persistence in risk measures (e.g., (Cont 2001); (Engle 1982); (Ferson and Harvey 1991)), we contend that this approach is both theoretically and empirically justified to capture the temporal structure of financial risk.

To address potential endogeneity, we implement the Wu-Hausman test. Should the test indicate endogeneity, we consider the use of instrumental variables. We then conduct a first-stage F-test to confirm that our chosen instruments are strongly correlated with the lagged dependent variable. Fixed effects are incorporated to account for unobserved time-invariant heterogeneity, while standard errors are clustered by firm and date to accommodate any residual dependence.

Step 1: Add a lagged dependent variable in the panel regression

$$Y_{it} = \beta_0 + \beta_1 Y_{it-1} + \beta_2 X_{\mathrm{SUST\_}it} + \beta_k X_{1it} + \cdots + \beta_k X_{kit} + \alpha_i + \lambda_t + \delta_c + \gamma_s + \epsilon_{it}$$

where: Y_{it-1} is the first lagged dependent variable.

Step 2: Conduct Wu-Hausman test to verify model endogeneity

The Wu-Hausman test compares the estimates from ordinary least squares and instrumental variables regressions to determine if there is endogeneity in the model. The null hypothesis posits that the regressors are exogenous. Rejection of the null hypothesis indicates endogeneity, requiring the use of the two-stage least squares regression method. To handle endogeneity, it is essential to identify appropriate instrumental variables. In the initial estimation, two lags are used, and sensitivity analysis is conducted using instrumental variables with additional lags, consistent with the methodology of (Judson and Owen 1999)[15]. Only the risk variables have been utilised as instrumental variables.

Step 3: Conduct /rst-stage F-test to ensure instrument strength

[15] (Judson and Owen 1999) uses a moderate number of lags, typically ranging from one to two lags, depending on the sample size and the context of the study. They stress the importance of conducting robustness checks and sensitivity analyses to determine the optimal number of lags for a given dataset and research question

This represents the first stage of the two-stage least squares regression. After the first stage, we verify that the instrumental variable is correlated enough with the initial variable to ensure it is a credible instrument.

First Stage Regression:

$$Y_{it-1} = \pi_0 + \pi_1 Y_{\mathrm{it-n}} + \pi_2 X_{\mathrm{SUST}\_it} + \pi_3 X_{1it} + \cdots + \pi_k X_{kit} + \alpha_i + \lambda_t + \delta_c + \gamma_s + \nu_{it}$$

where: Y_{it-1} is the first lag of the dependent variable and represents the endogenous variable, $Y_{\mathrm{it-n}}$ is the n-th lag of the dependent variable, used as the instrumental variable. $\alpha_i, \lambda_t, \delta_c$ and γ_s are fixed effects as defined earlier, ν_{it} is the error term of the first stage.

Step 4: Conduct second stage of two-staged least squared regression

We then use the predicted values from the first stage regression in place of the endogenous lagged dependent variable and cluster the errors by firm and date to estimate the regression coefficients.

Second Stage Regression:

$$Y_{it} = \beta_0 + \beta_1 \widehat{Y_{it-1}} + \beta_2 X_{\mathrm{SUST}\_it} + \beta_3 X_{1it} + \cdots + \beta_k X_{kit} + \alpha_i + \lambda_t + \delta_c + \gamma_s + \epsilon_{it}$$

Where: $\widehat{Y_{it-n}}$ are the predicted values of the n-th lagged dependent variable from the first stage.

Speci/cation E: Dynamic Fixed E˜ects Quantile Regression Using Two-Stage Least Squares for Instrumental Variables

The dynamic quantile fixed effects regression is a statistical method that estimates conditional quantile functions in panel data models, accounting for individual heterogeneity. Unlike standard mean regression techniques, quantile regression provides a more comprehensive analysis by estimating the effects of covariates at different points in the conditional distribution of the dependent variable. This approach is particularly instrumental for understanding the impact of variables across various percentiles, especially in the presence of heteroskedasticity or outliers.

Akin to dynamic fixed effects regression, a lagged dependent variable is included to account for persistence and temporal dynamics. However, while dynamic fixed effects regression captures the average effect of the covariates, quantile fixed effects regression focuses on distributional impacts, providing a more comprehensive understanding of relationships at different quantiles. This method is based on the work of (Machado and Santos Silva 2019).

In this specification, the model setup is comparable to that of dynamic fixed effects regression, except that we examine different percentiles (25%, 50%, and 75%). The second stage regression is detailed as follows and as before, errors are clustered by firm and date:

Second Stage Regression:

$$Q_{\tau}(Y_{it} \mid X_{\text{SUST\_}it}, X_{it}, \alpha_i, \lambda_t, \delta_c, \gamma_s) \\ = \beta_{0,\tau} + \beta_{1,\tau}\widehat{Y_{it-1}} + \beta_2 X_{\text{SUST\_}it} + \beta_{3,\tau}X_{2it} + \cdots + \beta_{k,\tau}X_{kit} + \alpha_{it} + \lambda_{it} + \delta_{ct} + \gamma_{st} + \epsilon_{it,\tau}$$

where $\epsilon_{it,\tau}$ is the error term of the second stage for the quantile. Errors are clustered by firm and date.

This formulation ensures that the quantile fixed effects regression captures the distributional characteristics of the data, offering a nuanced understanding of the effects of covariates at different quantiles of the dependent variable's distribution.

6.7 Empirical Analysis

6.7.1 Average relationship with ESG

Upon reviewing Exhibits 14 and 15 (shown earlier), the average relationship between sustainability information and financial risks appears robust, corroborated by similar findings in other studies. Companies in the top ESG quintile (Q1) exhibit significantly lower risk—whether measured as total risk, idiosyncratic risk, or market beta—compared to those in the bottom quintile (Q5) within the MSCI World universe. However, the results presented in Exhibit 17 reveal a more nuanced and complex relationship between sustainability and risk.

In the context of total risk, the introduction of additional control variables causes the relationship between ESG and risk to fluctuate, initially shifting from negative to positive, and then reverting to negative across the first three regression specifications. In the third specification, which employs a linear fixed-effects model, the relationship turns negative when fundamental variables are accounted for. These variables include size, dividend yield, liquidity, cash profitability, ROE, asset growth, earnings volatility, and debt-to-enterprise value, following frameworks similar to those established by (Dunn, Fitzgibbons, and Pomorski 2018) and (Brennan, Chordia, and Subrahmanyam 1998). The results from the initial three specifications in Exhibit 17 demonstrate that the inclusion of additional control variables substantially reduces the statistical significance of the ESG variable. This suggests that the observed relationship between ESG and risk in earlier specifications may have been confounded by omitted variables. Notably, when the lagged risk variable is incorporated into the fourth specification for total risk, the relationship between ESG and total risk becomes statistically and economically insignificant, as indicated by a low t-statistic (-1.113) and a tenfold reduction in the ESG coefficient to -0.022.

The decline in the absolute significance of the ESG variable not only suggests its insignificance but is also evident when comparing the magnitude of the coefficients of the other control variables, which are often orders of magnitude higher than the ESG coefficient. Moreover, the statistical significance and magnitude of the t-statistic for the lagged risk variable (27.668) suggest that its omission—whether explicit or implicit, as is common practice—likely contributes to the distortion of regression results. Additionally, the use of instrumental variables for the endogenous variable (i.e., lagged risk) in this specification, based on a two-stage least squares approach, provides stronger evidence of causality—or lack thereof—than the previous three regression specifications. Put differently, it appears that some of the economic and statistical significance of ESG in relation to risk has been supplanted by the lagged (past) risk variables from Specification 3 to Specification 4, and that the current risk profile is explained to a much greater extent by past risk variables.

As for stock-specific risks in the MSCI World universe, the initial three regression models consistently reveal a negative relationship between ESG factors and risk. That said, incorporating additional control variables precipitates a significant reduction in the t-statistic of the ESG coefficient, decreasing from -50.03 to -1.822. This change suggests a shift from a highly statistically significant negative relationship to a marginally significant one. The economic significance, as indicated by the magnitude of the ESG coefficient, also diminishes considerably. A parallel pattern emerges in the regression analysis of market beta and ESG in Specifications 9-12. Despite the inclusion of the lagged risk variable in Specification 12, the statistical significance remains robust. Nevertheless, the economic significance appears dubious, as the coefficient is minimal at -0.001.

Turning now to the regional universes, consistent with the MSCI World universe previously analysed, the inclusion of the lagged risk variable as a control has diminished both the statistical and economic significance of the ESG variable across all regression specifications, irrespective of the risk variables considered. For the World ex-US universe, ESG shows some statistical significance for total risk and stock-specific risk, with coefficients of -0.043 and -0.019, respectively, while it is highly significant for market beta, reporting a coefficient of -0.001 (see Exhibit 18). In all instances, the economic significance remains minor. Contrastingly, within the US stock universe, ESG is not statistically significant for either total risk or stock-specific risk, with market beta displaying only some statistical significance. As with previous cases where statistical significance was observed, the economic significance remains marginal, at -0.001(see Exhibit 19).

These overall relationships are supported by a robustness analysis, wherein additional lags—specifically lags 3, 4, and 5—are incorporated into the regression analysis as instrumental variables for the lagged risk variables. By rigorously addressing volatility persistence and potential endogeneity, our approach differs from much of the prior literature, which commonly relies on static models without fully capturing the dynamic nature of risk. Notably, within the World ex-US universe, ESG demonstrates a significant negative relationship with total risk and stock-specific risk across all lags, with significance increasing as longer lags are introduced, both in statistical and economic terms. The strengthening of coefficients with extended lags reinforces the validity of the initial findings and indicates that risk variables lagged further back in time are indeed relevant and appropriately linked to ESG. However, it should be noted that while the economic significance is more pronounced, it remains modest. In contrast, within the US universe, the relationship between ESG and risk appears unconvincing, both statistically and economically.

6.7.2 Average Relationship with ESG Dimensions and Carbon Scores

In accordance with the findings on the composite ESG scores above, the incorporation of the lagged risk variable in the dynamic fixed effects panel regression significantly reduces the economic and statistical significance of individual ESG dimensions and carbon scores. Generally, their significance is minimal or non-existent, contingent upon the specific sustainability dimension examined.

An analysis of MSCI World universe stocks indicates that environmental scores have marginal statistical significance at the 10% level, suggesting a slight potential reduction in total risk. Conversely, Social, Governance, and Carbon scores do not exhibit statistical significance. Notably, environmental scores also show stronger statistical significance in relation to idiosyncratic risk, as do governance scores, both demonstrating a negative relationship with stock-specific risk, significant at the 5% level, with coefficients of -0.016 and -0.019, respectively. Governance scores also reveal a negative association with market beta, although with marginal statistical significance at the 10% level. The relationship between ESG dimensions and risk generally lacks consistency, with the most prominent finding being the subtle negative association between environmental and governance scores and stock-specific risks.

Similar observations are discernible within the MSCI ex-US universes, where a statistically significant relationship between total risk and environmental scores is evident. The negative association between environmental scores and stock-specific risk is particularly pronounced statistically, achieving significance at the 1% level, albeit with a small coefficient of -0.021. Likewise, governance scores exhibit a statistically significant relationship with stock-specific risks but not with market beta, on the basis of the 12^{th} regression specification.

In the US universe, environmental, carbon, and social scores exhibit a statistically significant relationship with total risk, with environmental scores being negatively correlated (-0.025) and social scores positively correlated (0.045). The latter is particularly striking, as it suggests that companies excelling in their management of social dimensions are associated with higher levels of risk—an outcome that appears counterintuitive. Nevertheless, the economic significance remains negligible due to the relatively small coefficients attributed to these scores. Furthermore, none of the ESG dimensions, including governance scores, display any substantive relationship with either total or stock-specific risk for these stocks. In all instances, the relationship between these sustainability variables and market beta remains centred around zero, albeit with varying degrees of statistical significance.

As previously, robustness tests incorporating additional lags as instrumental variables have largely confirmed the results obtained thus far. When considering all observations, a clear distinction emerges between the MSCI World, MSCI World ex-US, and US universes. Across these three universes, a degree of consistency is observed in the statistical significance of the negative relationship between total risk and environmental scores, even when further lags are incorporated into the analysis. However, the economic significance remains immaterial.

In the former two universes, stronger environmental and governance scores are associated with lower risk, particularly in terms of total and stock-specific risk, although the extent of this reduction remains limited. In contrast, the relationship within the US universe is less clear-cut.

6.7.3 Relationship between sustainability and risk across the risk spectrum

Next, we scrutinise the interplay between sustainability and risk across the risk distribution spectrum utilising a quantile fixed effects regression, employing a lagged risk variable as the instrumental variable. This regression framework aligns with the previous analyses but aims to investigate how this relationship varies across different segments of the risk distribution, specifically at the 25^{th}, 50^{th}, and 75^{th} percentiles. Exhibit 20 presents the primary results of these regressions across all universes, with control variables omitted for clarity. As noted in previous analyses, the lagged risk terms are profoundly significant, as evidenced by their substantial coefficients and pronounced t-statistics across all stock universes.

With respect to the impact of ESG factors, their relevance appears minimal within the lower risk spectrum but progressively gains both statistical and economic significance as risk levels increase. This finding, which is more compelling for measures of total and stock-specific risk, suggests that ESG factors may exert a more pronounced influence on companies encountering higher levels of risk. However, the economic significance remains secondary, as the magnitude of the coefficients is relatively modest.

The relationship between the individual dimensions of sustainability and risk is more complex (see Appendix 6-D). In the context of total and idiosyncratic risk, the economic and statistical significance of environmental and carbon scores frequently increases as one moves up the risk spectrum across various geographical regions, with the relationship to total risk being somewhat more convincing. However, as previously noted, the coefficients remain of marginal significance. In contrast, for governance and social scores, no consistent pattern emerges for either total or stock-specific risk, and across all model specifications, no discernible trend is observed between market beta and any sustainability dimensions.

Exhibit 17 Regression Specifications Analysing the Relationship Between Risk and ESG for Stocks in the MSCI World Universe

	TOTAL RISK				STOCK SPECIFIC RISK				MARKET BETA			
	Spec 1: Simple OLS	*Spec 2: Multi OLS*	*Spec 3: Static FE*	*Spec 4: Dyn FE*	*Spec 5: Simple OLS*	*Spec 6: Multi OLS*	*Spec 7: Static FE*	*Spec 8: Dyn FE*	*Spec 9: Simple OLS*	*Spec 10: Multi OLS*	*Spec 11: Static FE*	*Spec 12: Dyn FE*
Lagged past risk	-	-	-	0.873*** (27.668)	-	-	-	0.939*** (106.230)	-	-	-	0.954*** (89.402)
ESG	-0.189*** (-18.17)	0.095*** (10.42)	-0.218*** (-3.467)	-0.022 (-1.113)	-0.411*** (-50.03)	-0.145*** (-20.25)	-0.330*** (-6.974)	-0.014. (-1.822)	-0.011*** (-26.62)	-0.001*** (-3.612)	-0.009*** (-3.602)	-0.001** (-3.318)
Size	-	-4.599*** (-135.49)	-6.434*** (-15.643)	-0.857** (-3.283)	-	-4.178*** (-156.970)	-5.639*** (-21.985)	-0.351*** (-3.922)	-	-0.090*** (-60.242)	-0.101*** (-8.816)	-0.008*** (-3.843)
Dividend Yield	-	-0.451*** (-48.81)	-0.527*** (-4.856)	-0.085*** (-4.220)	-	-0.620*** (-85.600)	-0.584*** (-5.648)	-0.039*** (-5.076)	-	-0.016*** (-40.028)	-0.020*** (-5.719)	-0.001* (-2.434)
Price Momentum	-	-3.658*** (-83.24)	-3.224*** (-7.509)	-1.169*** (-5.208)	-	-2.199*** (-63.810)	-1.848*** (-5.586)	-0.693*** (-8.169)	-	-0.075*** (-38.537)	-0.077*** (-4.717)	-0.020*** (-5.022)
Liquidity (Dollar Vol)	-	2.965*** (120.54)	5.482*** (15.317)	0.737*** (3.732)	-	2.252*** (116.730)	4.284*** (17.178)	0.245*** (3.998)	-	0.087*** (79.460)	0.119*** (11.714)	0.008*** (4.461)
Cash profit	-	-1.188*** (-47.89)	-1.376** (-2.741)	-0.608. (-1.928)	-	-0.217*** (-11.140)	-0.431* (-2.014)	-0.262** (-2.604)	-	-0.011*** (-10.253)	-0.007 (-1.550)	-0.002 (-1.202)
ROE	-	-2.130*** (-103.99)	-2.226*** (-4.268)	-0.754. (-1.673)	-	-0.985*** (-61.320)	-1.032*** (-5.452)	-0.283. (-1.921)	-	-0.017*** (-19.127)	-0.017*** (-5.123)	-0.003 (-1.591)
Asset Growth	-	4.201*** (89.35)	3.960*** (6.627)	0.670 (1.644)	-	2.599*** (70.480)	2.362*** (6.708)	0.299* (2.307)	-	-0.015*** (-7.335)	-0.014 (-1.576)	0.007*** (3.865)
Earnings volatility	-	1.507*** (102.02)	1.074*** (12.661)	0.071* (2.153)	-	1.234*** (106.560)	0.990*** (14.786)	0.008 (1.032)	-	0.044*** (67.455)	0.033*** (8.800)	-0.000 (-0.751)
Debt/EV	-	1.551*** (99.36)	1.645*** (5.842)	0.133 (0.543)	-	1.203*** (98.220)	1.219*** (9.076)	0.057 (0.730)	-	0.011*** (15.551)	0.018*** (5.703)	0.002* (2.159)
Fixed Effects	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES
Other statistics												
Adj R^2	*0.18%*	*29.32%*	*40.37%*	*87.31%*	*1.35%*	*30.81%*	*42.36%*	*94.51%*	*0.39%*	*9.27%*	*23.94%*	*93.22%*
Durban-Wu-Hausman test				855.55 *(p=0.00) ****				1847.38 *(p=0.00) ****				342.32 *(p=0.00) ****
First stage F-test				4.43×10^{31}				1.46×10^{31}				1.479×10^{29}

Source: Authors' estimates. Regressions and t-statistics are based on robust standard errors, double clustered at the individual company and date levels. ***, **, *, and . indicate statistical significance at the 0.01%, 1%, 5%, and 10% levels, respectively. The sample covers stocks from 2014 to 2024. "Simple OLS" represents a basic linear regression, "Multiple OLS" represents a multiple OLS regression, "FE regression" represents a static fixed effects linear regression, and "Dyn regression" represents a dynamic fixed effects regression using 2SLS based on instrumental variables (IVs).

Exhibit 18 Regression Specifications Analysing the Relationship Between Risk and ESG for Stocks in the MSCI World ex-US Universe

	TOTAL RISK				STOCK SPECIFIC RISK				MARKET BETA			
	Spec 1: Simple OLS	*Spec 2: Multi OLS*	*Spec 3: Static FE*	*Spec 4: Dyn FE*	*Spec 5: Simple OLS*	*Spec 6: Multi OLS*	*Spec 7: Static FE*	*Spec 8: Dyn FE*	*Spec 9: Simple OLS*	*Spec 10: Multi OLS*	*Spec 11: Static FE*	*Spec 12: Dyn FE*
Lagged past risk	-	-	-	0.879*** (30.931)	-	-	-	0.940*** (116.761)	-	-	-	0.961*** (114.236)
ESG	-0.317*** (-26.020)	-0.169*** (-15.780)	-0.334*** (-5.190)	-0.043. (1.876)	-0.579*** (-59.390)	-0.390*** (-46.160)	-0.403*** (-7.323)	-0.019* (1.973)	-0.006*** (-11.940)	-0.005*** (-10.473)	-0.009*** (-2.887)	-0.001*** (-3.298)
Size	-	-4.592*** (-112.280)	-5.292*** (-11.306)	-0.668** (-2.631)	-	-4.286*** (-132.690)	-4.676*** (-16.260)	-0.301** (-3.310)	-	-0.073*** (-37.464)	-0.056*** (-3.895)	-0.005** (-2.636)
Dividend Yield	-	-0.518*** (-53.550)	-0.515*** (-4.034)	-0.088*** (-3.360)	-	-0.650*** (-85.200)	-0.549*** (-4.540)	-0.041*** (-3.947)	-	-0.009*** (-19.379)	-0.013*** (-4.085)	-0.001. (-1.936)
Price Momentum	-	-3.116*** (-68.380)	-3.001*** (-8.443)	-0.967*** (-5.936)	-	-1.985*** (-55.160)	-1.916*** (-6.724)	-0.585*** (-8.754)	-	-0.072*** (-33.237)	-0.076*** (-5.808)	-0.019*** (-5.877)
Liquidity (Dollar Vol)	-	3.345*** (100.730)	3.809*** (10.581)	0.489** (2.706)	-	2.510*** (95.710)	2.818*** (11.965)	0.160** (2.706)	-	0.109*** (68.409)	0.097*** (8.755)	0.006*** (3.543)
Cash profit	-	-1.058*** (-44.010)	-1.227*** (-5.674)	-0.438*** (-3.297)	-	-0.225*** (-11.860)	-0.454*** (-3.515)	-0.197*** (-5.354)	-	-0.018*** (-15.641)	-0.012** (-2.656)	-0.001 (-1.071)
ROE	-	-1.627*** (-68.980)	-1.617*** (-4.443)	-0.232 (-0.910)	-	-1.008*** (-54.140)	-1.031*** (-5.989)	-0.097 (-1.235)	-	-0.022*** (-19.615)	-0.024*** (-5.164)	-0.001 (-1.636)
Asset Growth	-	3.132*** (64.060)	3.016*** (4.985)	0.483 (1.567)	-	1.751*** (45.340)	1.609*** (4.672)	0.217* (2.199)	-	-0.014*** (-5.841)	-0.009 (-1.002)	0.004* (2.346)
Earnings volatility	-	1.319*** (77.240)	0.979*** (9.979)	0.049. (1.907)	-	1.050*** (77.910)	0.925*** (10.955)	0.002 (0.206)	-	0.044*** (54.143)	0.036*** (7.497)	-0.001. (-1.774)
Debt/EV	-	0.688*** (43.050)	0.685** (3.181)	-0.072 (-0.504)	-	0.700*** (55.430)	0.662*** (6.089)	-0.017 (-0.366)	-	0.001* (1.779)	0.008** (3.125)	0.000 (0.544)
Fixed Effects	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES
Other statistics												
Adj R^2	0.58%	28.28%	35.81%	86.06%	2.96%	31.88%	38.94%	93.96%	0.12%	9.04%	23.13%	93.97%
Durban-Wu-Hausman test				1014.059 *(p=0.00)****				2381.826 *(p=0.00) ****				280.589 *(p=0.00) ****
First stage F-test				8.40×10^{32}				8.41×10^{29}				5.45×10^{30}

Exhibit 19 Regression Specifications Analysing the Relationship Between Risk and ESG for Stocks in the US Universe

	TOTAL RISK				STOCK SPECIFIC RISK				MARKET BETA			
	Spec 1: Simple OLS	*Spec 2: Multi OLS*	*Spec 3: Static FE*	*Spec 4: Dyn FE*	*Spec 5: Simple OLS*	*Spec 6: Multi OLS*	*Spec 7: Static FE*	*Spec 8: Dyn FE*	*Spec 9: Simple OLS*	*Spec 10: Multi OLS*	*Spec 11: Static FE*	*Spec 12: Dyn FE*
Lagged past risk	-	-	-	0.879*** (31.887)	-	-	-	0.917*** (72.249)	-	-	-	0.946*** (62.468)
ESG	-0.079*** (-4.415)	0.107*** (7.409)	0.172* (1.972)	-0.009 (-0.320)	-0.224*** (-17.08)	-0.002 (-0.242)	0.034 (0.604)	-0.013 (-1.048)	-0.017*** (-27.780)	-0.007*** (-12.521)	-0.008* (-2.519)	-0.001* (-2.119)
Size	-	-9.894*** (-172.577)	-9.202*** (-11.219)	-1.312*** (-3.907)	-	-7.716*** (-193.942)	-7.296*** (-17.121)	-0.669*** (-4.308)	-	-0.202*** (-87.939)	-0.171*** (-11.340)	-0.015*** (-3.668)
Dividend Yield	-	-0.573*** (-33.125)	-0.348** (-3.082)	-0.038 (-1.183)	-	-0.805*** (-67.081)	-0.397*** (-4.332)	-0.022 (-1.494)	-	-0.041*** (-59.514)	-0.026*** (-5.638)	0.000 (0.235)
Price Momentum	-	-5.372*** (-91.235)	-5.216*** (-8.910)	-1.671*** (-4.066)	-	-3.087*** (-75.558)	-2.839*** (-9.633)	-1.032*** (-5.356)	-	-0.027*** (-11.328)	-0.037* (-2.116)	-0.012** (-2.26)
Liquidity (Dollar Vol)	-	8.236*** (151.756)	7.334*** (10.363)	1.080*** (3.921)	-	5.782*** (153.524)	5.052*** (14.232)	0.459*** (3.889)	-	0.159*** (73.124)	0.134*** (9.207)	0.012*** (3.581)
Cash profit	-	0.716*** (20.646)	0.616. (1.721)	-0.507* (-2.450)	-	1.164*** (48.339)	0.672*** (3.917)	-0.093 (-1.118)	-	-0.027*** (-19.734)	-0.027*** (-3.426)	0.006** (2.316)
ROE	-	1.449*** (62.076)	1.479*** (3.631)	0.195 (0.870)	-	0.776*** (47.931)	0.796*** (4.083)	0.131 (1.381)	-	-0.008*** (-9.029)	-0.007* (-1.996)	0.006*** (3.905)
Asset Growth	-	1.034*** (15.305)	1.128* (2.380)	0.464* (2.083)	-	0.563*** (11.995)	0.565. (1.915)	0.192* (2.018)	-	-0.016*** (-5.749)	-0.008 (0.703)	0.008** (2.511)
Earnings volatility	-	1.361*** (61.948)	1.091*** (8.116)	0.009 (0.170)	-	1.210*** (79.383)	0.987*** (11.725)	0.009 (0.531)	-	0.040*** (45.551)	0.037*** (7.587)	-0.000 (-0.479)
Debt/EV	-	1.509*** (75.943)	1.518*** (6.581)	-0.215. (-1.935)	-	1.207*** (87.552)	1.174*** (8.135)	-0.126 (-1.689)	-	0.039*** (49.581)	0.041*** (10.640)	0.003** (2.675)
Fixed Effects	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES
Other statistics												
Adj R^2	0.017%	40.660%	43.950%	86.900%	0.274%	46.390%	51.880%	92.260%	0.865%	16.940%	29.270%	92.240%
Durban-Wu-Hausman test				855.2837 *(p=0.00)****				1654.003 *(p=0.00) ****				342.075 *(p=0.00) ****
First stage F-test				1.92 x 10^{31}				7.50 x 10^{31}				9.16 x 10^{29}

Exhibit 20 Quantile Regression Specifications Analysing the Relationship Between Risk and ESG Scores Across The Risk Spectrum

	TOTAL RISK			STOCK SPECIFIC RISK			MARKET BETA		
	Spec 1: 25% Percentile	*Spec 2: 50% Percentile*	*Spec 3: 75% Percentile*	*Spec 4: 25% Percentile*	*Spec 5: 50% Percentile*	*Spec 6: 75% Percentile*	*Spec 7: 25% Percentile*	*Spec 8: 50% Percentile*	*Spec 9: 75% Percentile*
World Universe									
Lagged past risk	0.747*** (478.283)	0.749*** (394.849)	0.752*** (261.106)	0.860*** (499.486)	0.874*** (510.130)	0.897*** (398.818)	0.922*** (652.252)	0.931*** (813.634)	0.939*** (548.909)
ESG	0.001 (0.212)	-0.015** (3.089)	-0.043*** (5.453)	0.004. (1.747)	-0.006** (2.425)	-0.023*** (5.672)	-0.000 (0.954)	-0.001*** (5.452)	-0.002*** (7.952)
Fixed E}ects	YES	YES	YES	YES	YES	YES	YES	YES	YES
World ex-US Universe									
Lagged past risk	0.734*** (437.341)	0.732*** (366.017)	0.729*** (232.872)	0.839 (338.441)	0.852*** (360.532)	0.873*** (310.212)	0.967*** (518.724)	0.977*** (665.304)	0.987*** (417.756)
ESG	-0.002 (0.508)	-0.028*** (4.801)	-0.068*** (7.172)	0.006. (1.808)	-0.008* (2.477)	-0.031*** (5.714)	0.000 (0.347)	-0.001 *** (3.981)	-0.002*** (6.763)
Fixed E}ects	YES	YES	YES	YES	YES	YES	YES	YES	YES
US Universe									
Lagged past risk	0.760*** (378.237)	0.771*** (353.263)	0.789*** (254.577)	0.810*** (190.229)	0.831*** (216.164)	0.862*** (212.216)	0.786*** (439.592)	0.800*** (580.589)	0.814*** (470.928)
ESG	0.036*** (5.127)	0.004 (0.551)	-0.049*** (3.852)	0.003 (0.646)	-0.009* (1.969)	-0.027*** (3.782)	-0.001* (2.025)	-0.001*** (4.703)	-0.002*** (5.978)
Fixed E}ects	YES	YES	YES	YES	YES	YES	YES	YES	YES

Source: Authors' estimates. Regressions and t-statistics are based on robust standard errors, double clustered at the individual company and date levels. ***, **, *, and . indicate statistical significance at the 0.01%, 1%, 5%, and 10% levels, respectively. The regressions above are dynamic fixed effects regressions using 2SLS based on instrumental variables (IVs) for different percentile range of risks.

6.7.4 Average Relationship with sustainability during COVID-19

Numerous studies posit a correlation between companies with robust ESG credentials and their risk profiles during periods of market turmoil, with particular emphasis on the COVID-19 pandemic (e.g. (Broadstock et al. 2021), (Huang 2024)), (Albuquerque et al. 2020)). These investigations consistently assert that firms with stronger ESG credentials or specific ESG dimensions tend to demonstrate a lower financial risk profile. This section aims to empirically examine this hypothesis utilising a dynamic fixed effects linear regression model, designated as Specification D in Section 5.1. The model retains the previously established control variables while introducing COVID-19 as an indicator variable to delineate the period from March 2020 to December 2022. Additionally, it incorporates an interaction term between COVID-19 and sustainability to analyse whether the effect of sustainability on financial risk varies during the pandemic period compared to other times. Mathematically, the regression can be specified as follows:

$$Y_{it} = \beta_0 + \beta_1 \widehat{Y_{it-1}} + \beta_2 X_{\mathrm{SUST\_}it} + \beta_3 I(\mathrm{COVID}) + \beta_4 (I(\mathrm{COVID}) \times X_{\mathrm{SUST\_}it}) + \beta_5 X_{1it} \cdots + \beta_k X_{kit} + \lambda_t + \delta_c + \gamma_s + \epsilon_{it}$$

where: $\widehat{Y_{it-1}}$ is the first lagged dependent variable, $I(\mathrm{COVID})$ is the indicator variable denoting the COVID-19 period and $(I(\mathrm{COVID}) \times X_{\mathrm{SUST\_}it})$ is the interaction term.

The results depicted in Exhibit 21 across all stock universes underscore the COVID-19 period as a significant determinant of risk across nearly all regression specifications, with pronounced positive coefficients highlighting its critical role in elevating both total and idiosyncratic risk. ESG factors, while frequently achieving statistical significance, exhibit only a modest economic impact in mitigating some of the pandemic-related risk, with the magnitude of this attenuation varying across specifications. Additionally, the relationship between ESG and risk—encompassing both total and idiosyncratic dimensions—tends to intensify once the pandemic period is controlled for within the regressions, suggesting an enhanced, although still modest, association. In contrast, the relationship between ESG and market beta remains weak and largely unaffected.

The regression outcomes for the individual sustainability dimensions and risk fail to display the same consistency observed with the overall ESG score (see Appendix 6-E). Social, governance, and environmental scores did not effectively temper the COVID-19-related risk, irrespective of the risk metric applied, nor did the significance of the coefficients for these sustainability variables consistently increase when the pandemic period was incorporated into the analysis. By contrast, carbon scores demonstrated a modest ability to mitigate the effects of the pandemic, particularly in relation to total and idiosyncratic risk measures.

Overall, the ability of ESG to moderate the impacts of COVID-19 is limited, with individual sustainability factors showing inconsistent effects across various dimensions and regions.

6.7.5 The association of current sustainability ratings with future risks

In the concluding section of our analysis, we delve into the potential nexus between current sustainability ratings and prospective risks. The study by (Dunn, Fitzgibbons, and Pomorski 2018), which extends the analysis horizon up to five years, posits that current sustainability ratings can indeed serve as prognostic indicators of future risks, although their predictive power diminishes over time. Given the marked drop in the correlation between sustainability ratings and risk variables upon the inclusion of the lagged risk variable in our regressions, we have opted to scrutinise the relationship solely up to a one-year forward-looking period. Exhibit 8 and Appendix 6-F elucidate the association between sustainability measures and 6-month and 1-year forward risk.

Across all model specifications, we observe a material diminution in the coefficient of lagged risk, despite its standing as the most substantial variable from both economic and statistical perspectives. This reduction coincides with a decline in model fit, as indicated by the adjusted R-squared values. The regressions concerning environmental and carbon scores are particularly noteworthy, showing an enhancement in both economic and statistical significance—a consistency not reflected in the composite ESG scores or other sustainability metrics. A plausible explanation for the increasing significance of environmental scores from 6 to 12 months across all forward risk measures may lie in the intrinsic nature of environmental impacts, which often require an extended period to manifest within a company's risk profile. For example, the coefficient associated with the environmental score in the World stock universe increased from -0.043 to -0.092, with its statistical significance intensifying from 10% to 0.1%. Environmental initiatives or exposures typically have long-term consequences, and their effects on corporate risk may not be immediately apparent within a shorter timeframe, such as 6 months. However, as time progresses, these factors may exert a more pronounced influence, thereby becoming more discernible in the 1-year forward risk assessment. This trend of increasing significance is not observed across other dimensions of sustainability.

Exhibit 21 Dynamic Fixed Effects Regression Specifications Analysing the Relationship Between Risk and ESG Scores during COVID

	TOTAL RISK		STOCK SPECIFIC RISK		MARKET BETA	
	Spec 1: All Period	*Spec 2: With COVID Binary Variable*	*Spec 3: All Period*	*Spec 4: With COVID Binary Variable*	*Spec 5: All Period*	*Spec 6: With COVID Binary Variable*
World Universe						
Lagged past risk	0.873*** (27.668)	0.826*** (17.442)	0.939*** (106.230)	0.931*** (74.339)	0.954*** (89.402)	0.955*** (92.955)
COVID		3.513* (2.188)		0.984* (2.057)		0.012 (1.212)
COVID × ESG		-0.162. (-1.658)		-0.060. (-1.802)		-0.002* (-2.102)
ESG	-0.022 (1.113)	-0.032. (-1.701)	-0.014. (-1.822)	-0.012. (1.657)	-0.001** (-3.318)	-0.000 (-1.487)
Adj R^2	*87.31%*	*88.15%*	*94.51%*	*94.70%*	*93.22%*	*93.38%*
World ex US Universe						
Lagged past risk	0.879*** (30.931)	0.821*** (17.731)	0.940*** (116.761)	0.930*** (83.228)	0.961*** (114.236)	0.961*** (114.308)
COVID		3.440* (2.322)		1.101* (2.414)		-0.005 (1.035)
COVID × ESG		-0.061 (1.176)		-0.046* (-2.081)		0.000 (0.287)
ESG	-0.043. (-1.876)	-0.100** (-2.847)	-0.019. (-1.973)	-0.026* (-2.295)	-0.001*** (3.298)	-0.001** (-2.847)
Adj R^2	*86.06%*	*87.19%*	*93.96%*	*94.09%*	*93.97%*	*93.97%*
US Universe						
Lagged past risk	0.879*** (31.887)	0.768*** (12.888)	0.917*** (72.249)	0.883*** (38.679)	0.946*** (62.468)	0.945*** (61.492)
COVID		6.649* (2.331)		1.985. (1.975)		0.026 (1.079)
COVID × ESG		-0.320. (-1.774)		-0.086 (1.314)		-0.005* (2.068)
ESG	-0.009 (-0.320)	-0.022 (0.926)	-0.013 (-1.048)	-0.025* (2.186)	-0.001* (-2.119)	-0.000 (0.295)
Adj R^2	*86.90%*	*88.58%*	*92.26%*	*92.63%*	*92.24%*	*92.24%*

Source: Authors' estimates. Regressions and t-statistics are based on robust standard errors, double clustered at the individual company and date levels. ***, **, *, and . indicate statistical significance at the 0.01%, 1%, 5%, and 10% levels, respectively. The regressions above are dynamic fixed effects regressions using 2SLS based on instrumental variables (IVs) with COVID as a binary variable.

Exhibit 22 Dynamic Fixed Effects Regression Specifications Analysing the Relationship Between Future Risk and ESG Scores

	TOTAL RISK		STOCK SPECIFIC RISK		MARKET BETA	
	Spec 1: 6 month forward risk	*Spec 2: 1 year forward risk*	*Spec 3: 6 month forward risk*	*Spec 4: 12 month forward risk*	*Spec 5: 6 month forward risk*	*Spec 6: 12 month forward risk*
World Universe						
Lagged past risk	0.896*** (21.751)	0.666*** (21.536)	0.943*** (72.648)	0.821*** (61.910)	0.408*** (33.089)	0.379*** (30.998)
ESG	0.018 (0.651)	-0.051 (-1.602)	0.004 (0.359)	-0.042** (-3.122)	-0.006*** (7.386)	-0.006*** (6.602)
Adj R^2	*76.10%*	*70.00%*	*89.40%*	*80.70%*	*69.10%*	*62.30%*
World ex US Universe						
Lagged past risk	0.883*** (21.05)	0.674*** (21.71)	0.929*** (74.83)	0.674*** (21.71)	0.376*** (34.34)	0.349*** (28.43)
ESG	-0.019 (-0.65)	-0.101** (-2.76)	-0.014 (-1.14)	-0.064*** (-3.53)	-0.006*** (-6.59)	-0.008*** (-6.75)
Adj R^2	*73.10%*	*65.80%*	*88.40%*	*65.80%*	*68.90%*	*59.90%*
US Universe						
Lagged past risk	0.941*** (22.823)	0.635*** (23.355)	0.920*** (38.083)	0.755*** (32.987)	0.431*** (21.767)	0.375*** (22.190)
ESG	0.014 (0.266)	0.083. (1.701)	0.008 (0.343)	0.006 (0.229)	-0.007*** (-4.915)	-0.005*** (-3.446)
Adj R^2	*74.20%*	*71.90%*	*83.90%*	*77.30%*	*67.10%*	*64.00%*

Source: Authors' estimates. Regressions and t-statistics are based on robust standard errors, double clustered at the individual company and date levels. ***, **, *, and . indicate statistical significance at the 0.01%, 1%, 5%, and 10% levels, respectively. The regressions above are dynamic fixed effects regressions using 2SLS based on instrumental variables (IVs) with COVID for different forward risk levels.

6.8 Conclusion and Investment Implications

In summary, our study makes a significant contribution to the ESG–risk literature. Specifically, we advance the field by employing a dynamic panel framework with instrumental variables to rigorously address endogeneity and capture dynamic risk effects. This methodological improvement allows us to isolate the genuine impact of ESG factors on company-level financial risk, challenging previous findings that may have overstated ESG's risk-mitigating role. Sustainability investments are frequently lauded for their potential to mitigate risks. Firms with robust sustainability practices exhibit lower financial risks and superior risk management capabilities (e.g., (Devalle, Fiandrino, and Cantino 2017); (Kotsantonis, Pinney, and Serafeim 2016)). Moreover, these firms often garner enhanced stakeholder trust and bolster brand value (Zou et al. 2024). However, research on the impact of sustainability scores on risk is affected by significant endogeneity issues, potentially leading to overstated and misleading inferences. Furthermore, by examining the ESG–risk relationship across different risk measures and over forward-looking periods, our study provides novel insights into how sustainability impacts risk across various market conditions and geographies

To address endogeneity concerns, we include a lagged risk variable in our regression specifications and employ a two-stage least squares (2SLS) regression with instrumental variables. This framework isolates the true impact of sustainability on risk by effectively controlling for potential confounders. Our analysis reveals that much of the previously reported statistical significance between sustainability and risk diminishes when the 2SLS approach is employed. Where significance persists, the economic magnitude—as reflected in the regression coefficients for sustainability—is reduced by multiple orders of magnitude relative to models not utilising 2SLS. Unlike control variables, which retain sizeable coefficients and statistical significance even in dynamic panel regressions, ESG variables experience a disproportionately large decline in explanatory power. In some cases, the reduction in ESG coefficients exceeds a factor of hundreds, underscoring the relative insignificance of sustainability credentials at the stock level.

A key limitation of our study is the potential weakness of our instrumental variables. Although we use robustness checks to validate instrument strength, residual endogeneity may persist, potentially affecting our estimates. Another key constraint is that our analysis primarily captures short- to medium-term effects. Longer-term sustainability initiatives, particularly in environmental and carbon transitions, may take years or decades to materially influence financial risk. This temporal limitation should be considered when interpreting our findings. Additionally, our results indicate that sustainability's impact on financial risk varies across geographies. The effect is generally weaker for US equities and more pronounced for non-US equities, suggesting that institutional and regulatory differences may influence ESG-risk relationships.

The precise impact of sustainability varies by dimension and region, with a lesser influence on US equities than non-US equities. Analysis across the risk spectrum suggests higher sensitivity to ESG factors in higher-risk stocks globally, although this relationship is inconsistent across all sustainability facets. During the COVID-19 pandemic, sustainability considerations provided only minor mitigation of both total and idiosyncratic risks, and this effect was not consistent across all sustainability variables. Macroeconomic forces and firm-specific circumstances during extreme events can overshadow sustainability factors, limiting their consistent risk-mitigating role. Furthermore, sustainability metrics have limited prognosticative capability for future risk, particularly for environmental and carbon factors, as such initiatives often require extended timeframes to materialise. This suggests that while ESG factors may contribute to risk mitigation over the long run, their short-term impact is limited and inconsistent. Consequently, the relationship between sustainability and risk may modestly strengthen over time.

Regarding the hypotheses set out in the theoretical framework, the evidence indicates that the relationship between sustainability and financial risk is substantially weaker than previously documented in the literature, with coefficient magnitudes reduced by a factor of hundreds in some cases. This contrasts with the control variables included in our dynamic panel regressions, many of which, despite experiencing some reduction in their coefficients, retain considerable economic and statistical significance—far exceeding what is observed for sustainability credentials at the stock level.

The results provide negligible empirical support for the Total Risk Hypothesis, which posits that firms with strong sustainability credentials have lower total risk. While an initial negative association between ESG scores and total risk is observed, this relationship becomes statistically and economically insignificant once past volatility is accounted for. The coefficient on ESG declines by orders of magnitude, reinforcing the view that much of the perceived reduction in total risk attributed to ESG factors in previous studies may, in fact, be explained by firms' pre-existing risk profiles rather than an independent ESG effect.

Similarly, the evidence for the Idiosyncratic Risk Hypothesis, which posits that ESG mitigates firm-specific risk, is substantially weaker than previously reported. Governance scores exhibit a small negative association with idiosyncratic risk, but the effect is marginal. Once lagged risk is accounted for, the relationship loses statistical significance and its economic impact becomes trivial. In contrast, control variables such as firm size and earnings volatility continue to exhibit larger, statistically significant coefficients, underscoring that ESG's influence on firm-specific risk is both small and disproportionately weak compared to other risk determinants.

The Market Risk Hypothesis, which asserts that firms with superior ESG scores have lower market beta due to enhanced resilience to macroeconomic shocks and reduced exposure to systemic risk factors, is also not supported. Across all model specifications, the inclusion of instrumental variables and controls for past volatility renders the ESG-market beta relationship negligible. As in the case for the Total Risk and Idiosyncratic Hypotheses, the coefficient on ESG is an order of magnitude smaller than those associated with fundamental financial characteristics, further reinforcing the conclusion that sustainability considerations, while potentially beneficial from a corporate governance or reputational perspective, do not provide a material hedge against market-wide fluctuations.

Taken together, these findings suggest that the relationship between sustainability and financial risk is both weaker and far less economically meaningful than that of other risk determinants. Unlike control variables that retain sizeable coefficients and statistical significance in dynamic panel regressions even when past volatility is introduced as a control variable, ESG's explanatory power nearly vanishes once methodological rigour is applied.

The primary investment implication is that, although sustainability may contribute to long-term corporate resilience, its impact on financial risk appears secondary—if not negligible—relative to traditional risk drivers. Investors may wish to align sustainability considerations with broader fiduciary, governance, or stewardship goals rather than relying solely on ESG as a hedge against financial volatility. This finding contrasts with previous literature, which often ascribes a strong risk-mitigation role to ESG factors. Our results suggest that much of this prior evidence may be overstated due to methodological shortcomings, particularly endogeneity bias. Future research should examine whether the impact of sustainability on risk becomes more pronounced over extended time horizons, particularly regarding environmental initiatives that may take decades to materially influence financial stability. Overall, our contributions underscore the importance of methodological rigour in ESG research, demonstrating that once dynamic risk and endogeneity are properly accounted for, the impact of sustainability on financial risk is considerably weaker than previously reported.

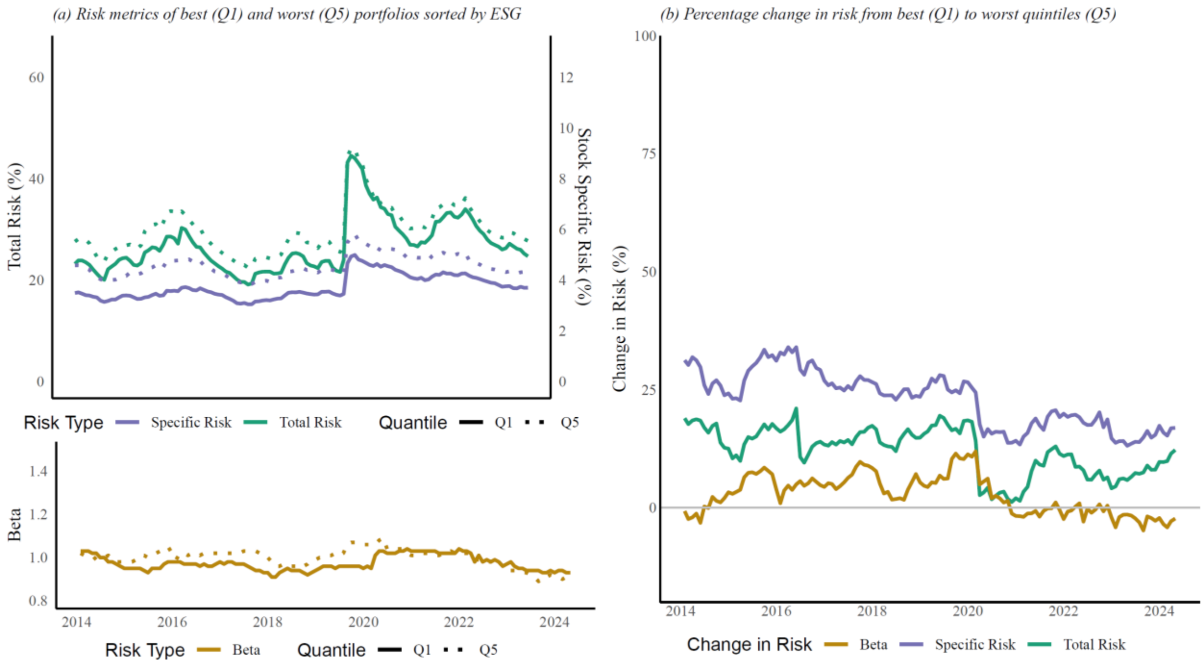
Appendix 6-A: Stock characteristics in ESG quintiles across regions

Exhibit A-1: Characteristics of MSCI World ex US Stocks by ESG Quintiles and Differences Between the First and Fifth Quintiles

	Q1 (best ESG)	Q2	Q3	Q4	Q5 (worst ESG)	Q5-Q1
Risk-return metrics						
Annual Return	4.20	5.19	5.10	4.42	3.79	-0.41 (0.225)
Total Risk	26.84	27.44	28.17	28.82	29.86	3.02 (-4.618)
Stock-speci/c risk	18.63	19.50	20.50	21.22	22.80	4.18 (-14.353)
Market beta	0.97	1.00	1.00	1.00	1.00	0.03 (-5.385)
Fundamental characteristics						
Market cap (USD billion)	22.10	20.11	22.62	19.04	15.03	-7.07 (15.806)
ROE	15.13	13.00	10.29	7.03	11.34	-3.8 (7.217)
Dividend Yield	3.00	2.78	2.76	2.41	2.25	-0.75 (14.320)
Cash pro%t	26.57	26.24	24.99	26.28	26.42	-0.16 (0.590)
Asset growth	8.11	8.92	9.39	11.11	11.85	3.74 (-8.332)
Debt-to-enterprise value	25.13	27.24	27.88	26.35	28.12	2.99 (-11.374)

Source: Authors' estimates, FactSet. Monthly data from January 2014 to June 2024. Numbers in parentheses represent the t-statistics comparing the best and worst quintiles.

Exhibit A-2: Differences in Risk Metrics Over Time Between the First and Fifth ESG Quintiles



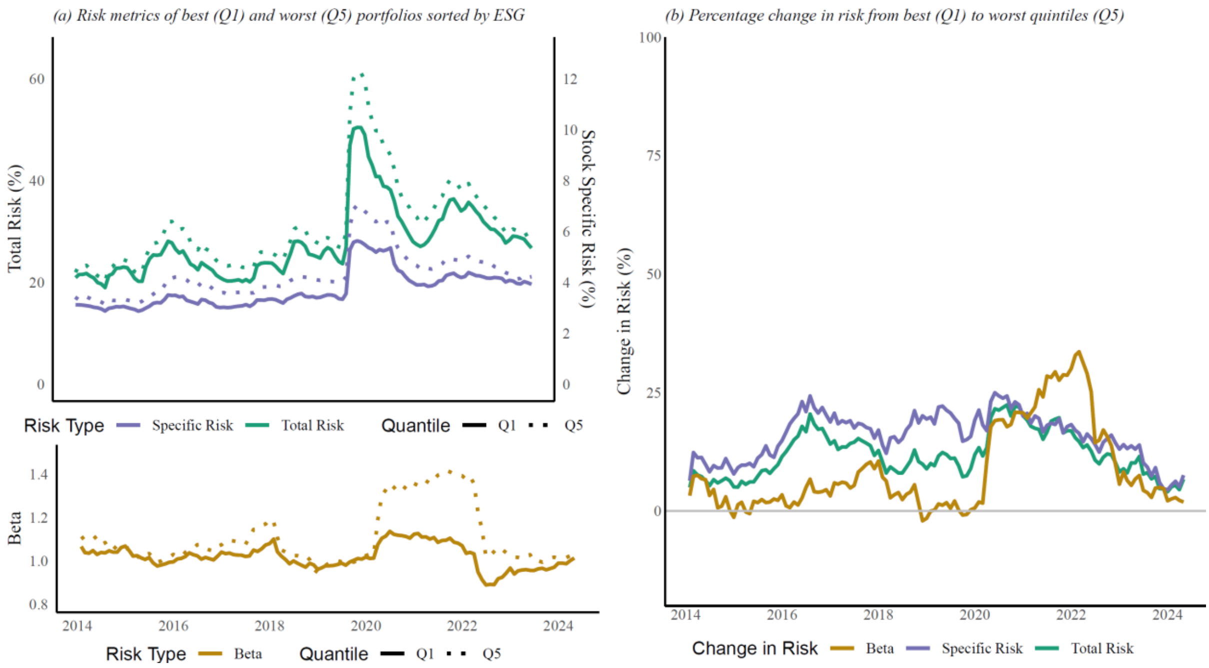
Source: Authors' estimates, FactSet, Axioma. Monthly data from January 2014 to June 2024.

Exhibit A-3: Characteristics of US Stocks by ESG Quintiles and Differences Between the First and Fifth Quintiles

	Q1 (best ESG)	Q2	Q3	Q4	Q5 (worst ESG)	Q5-Q1
Risk-return metrics						
Annual Return	11.7	10.0	10.5	10.4	10.1	-1.6 (0.732)
Total Risk	16.2	17.0	19.0	18.5	19.7	3.5 (-3.777)
Stock-speci/c risk	27.8	28.8	29.5	30.3	31.3	3.5 (-3.369)
Market beta	18.6	19.3	20.0	20.6	21.6	3.0 (-5.703)
Fundamental characteristics						
Market cap (USD billion)	49.1	34.6	35.2	37.2	30.1	-18.92 (10.717)
ROE	39.1	23.6	15.3	12.5	17.1	-22.04 (2.565)
Dividend Yield	1.7	1.6	1.5	1.5	1.2	-0.41 (12.595)
Cash pro/t	37.5	33.3	32.0	31.8	31.1	-6.47 (22.263)
Asset growth	8.7	10.4	10.8	18.0	12.7	4.08 (-8.828)
Debt-to-enterprise value	19.2	21.2	22.9	21.5	29.1	9.88 (-6.672)

Source: Authors' estimates, FactSet. Monthly data from January 2014 to June 2024. Numbers in parentheses represent the t-statistics comparing the best and worst quintiles.

Exhibit A-4: Differences in Risk Metrics Over Time Between the First and Fifth ESG Quintiles



Source: Authors' estimates, FactSet, Axioma. Monthly data from January 2014 to June 2024.

Appendix 6-B: Relationship between sustainability and risks

World Universe

Exhibit B-W-1: Regression Specifications Analysing the Relationship Between Risk and Environmental for Stocks in the MSCI World Universe

	TOTAL RISK				STOCK SPECIFIC RISK				MARKET BETA			
	Spec 1: Simple OLS	*Spec 2: Multi OLS*	*Spec 3: Static FE*	*Spec 4: Dyn FE*	*Spec 5: Simple OLS*	*Spec 6: Multi OLS*	*Spec 7: Static FE*	*Spec 8: Dyn FE*	*Spec 9: Simple OLS*	*Spec 10: Multi OLS*	*Spec 11: Static FE*	*Spec 12: Dyn FE*
Lagged past risk	-	-	-	0.873*** (27.697)	-	-	-	0.939*** (106.716)	-	-	-	0.954*** (89.772)
Environmental	-0.350*** (-33.88)	-0.105*** (-11.67)	-0.204*** (-4.221)	-0.030. (-1.959)	-0.425*** (-52.05)	-0.166*** (-23.64)	-0.266*** (-6.106)	-0.016* (-2.289)	-0.011*** (-28.11)	-0.006*** (-16.056)	-0.003 (-1.218)	-0.000 (-0.309)
Size	-	-4.474*** (-131.13)	-6.367*** (-15.377)	-0.846** (-3.291)	-	-4.144*** (-154.950)	-5.557*** (-21.340)	-0.345*** (-3.926)	-	-0.087*** (-57.604)	-0.100*** (-8.609)	-0.008*** (-3.823)
Dividend Yield	-	-0.434*** (-47.34)	-0.533*** (-4.877)	-0.085*** (-4.201)	-	-0.631*** (-87.640)	-0.594*** (-5.662)	-0.039*** (-5.062)	-	-0.016*** (-40.056)	-0.020*** (-5.777)	-0.001* (-2.525)
Price Momentum	-	-3.661*** (-83.31)	-3.245*** (-7.551)	-1.172*** (-5.203)	-	-2.215*** (-64.290)	-1.877*** (-5.645)	-0.695*** (-8.158)	-	-0.075*** (-38.793)	-0.078*** (-4.739)	-0.021*** (-5.027)
Liquidity (Dollar Vol)	-	2.905*** (118.95)	5.424*** (15.056)	0.731*** (3.767)	-	2.270*** (118.570)	4.197*** (16.588)	0.241*** (4.002)	-	0.086*** (79.280)	0.117*** (11.435)	0.008*** (4.412)
Cash profit	-	-1.185*** (-47.78)	-1.393** (-2.788)	-0.609. (-1.930)	-	-0.227*** (-11.690)	-0.457* (-2.182)	-0.263* (-2.606)	-	-0.011*** (-10.435)	-0.008 (-1.706)	-0.002 (-1.250)
ROE	-	-2.121*** (-103.58)	-2.235*** (-4.304)	-0.754. (-1.674)	-	-0.991*** (-61.700)	-1.047*** (-5.693)	-0.283. (-1.922)	-	-0.017*** (-19.062)	-0.018*** (-5.214)	-0.003 (-1.618)
Asset Growth	-	4.205*** (89.43)	3.945*** (6.611)	0.667 (1.642)	-	2.596*** (70.440)	2.344*** (6.669)	0.298* (2.303)	-	-0.015*** (-7.329)	-0.014 (-1.579)	0.007*** (3.879)
Earnings volatility	-	1.499*** (101.52)	1.094*** (13.037)	0.073* (2.179)	-	1.236*** (106.820)	1.021*** (15.137)	0.009 (1.174)	-	0.044*** (67.340)	0.034*** (9.049)	-0.000 (-0.524)
Debt/EV	-	1.578*** (101.74)	1.610*** (5.824)	0.130 (0.534)	-	1.184*** (97.400)	1.165*** (8.970)	0.055 (0.706)	-	0.011*** (15.872)	0.016*** (5.181)	0.002* (2.041)
Fixed Effects	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES
Other statistics												
Adj R^2	0.62%	29.33%	40.34%	87.32%	1.46%	30.86%	42.10%	94.51%	0.43%	9.39%	23.77%	93.22%

Exhibit B-W-2: Regression Specifications Analysing the Relationship Between Risk and Social for Stocks in the MSCI World Universe

	TOTAL RISK				STOCK SPECIFIC RISK				MARKET BETA			
	Spec 1: Simple OLS	*Spec 2: Multi OLS*	*Spec 3: Static FE*	*Spec 4: Dyn FE*	*Spec 5: Simple OLS*	*Spec 6: Multi OLS*	*Spec 7: Static FE*	*Spec 8: Dyn FE*	*Spec 9: Simple OLS*	*Spec 10: Multi OLS*	*Spec 11: Static FE*	*Spec 12: Dyn FE*
Lagged past risk	-	-	-	0.873*** (27.840)	-	-	-	0.939*** (108.046)	-	-	-	0.954*** (89.835)
Social	0.059*** (4.179)	0.232*** (19.15)	0.009 (0.146)	0.011 (0.692)	-0.138*** (-12.31)	0.027** (2.864)	-0.109* (-2.075)	-0.003 (-0.500)	-0.003*** (-4.753)	0.005*** (9.920)	0.002 (0.794)	-0.000 (-1.093)
Size	-	-4.593*** (-136.59)	-6.455*** (-15.591)	-0.858** (-3.290)	-	-4.264*** (-161.418)	-5.661*** (-21.740)	-0.349*** (-3.930)	-	-0.092*** (-62.051)	-0.102*** (-8.830)	-0.008*** (-3.856)
Dividend Yield	-	-0.449*** (-48.90)	-0.540*** (-4.895)	-0.086*** (-4.205)	-	-0.639*** (-88.647)	-0.601*** (-5.683)	-0.040*** (-5.066)	-	-0.017*** (-41.257)	-0.020*** (-5.782)	-0.001* (-2.515)
Price Momentum	-	-3.658*** (-83.30)	-3.238*** (-7.534)	-1.171*** (-5.212)	-	-2.205*** (-63.904)	-1.864*** (-5.599)	-0.693*** (-8.173)	-	-0.075*** (-38.618)	-0.078*** (-4.738)	-0.021*** (-5.028)
Liquidity (Dollar Vol)	-	2.979*** (121.74)	5.433*** (15.085)	0.731*** (3.771)	-	2.313*** (120.303)	4.207*** (16.672)	0.240*** (3.996)	-	0.088*** (81.414)	0.117*** (11.449)	0.008*** (4.419)
Cash profit	-	-1.185*** (-47.80)	-1.394** (-2.794)	-0.609. (-1.931)	-	-0.225*** (-11.530)	-0.455* (-2.171)	-0.263* (-2.606)	-	-0.011*** (-10.363)	-0.008. (-1.719)	-0.002 (-1.247)
ROE	-	-2.120*** (-103.60)	-2.244*** (-4.325)	-0.755. (-1.673)	-	-0.995*** (-61.871)	-1.061*** (-5.754)	-0.283. (-1.922)	-	-0.017*** (-19.154)	-0.018*** (-5.234)	-0.003 (-1.622)
Asset Growth	-	4.200*** (89.40)	3.965*** (6.642)	0.669 (1.643)	-	2.594*** (70.280)	2.370*** (6.723)	0.298* (2.303)	-	-0.015*** (-7.393)	-0.014 (-1.541)	0.007*** (3.882)
Earnings volatility	-	1.505*** (102.06)	1.101*** (13.019)	0.074* (2.211)	-	1.242*** (107.137)	1.024*** (15.069)	0.009 (1.159)	-	0.044*** (67.736)	0.034*** (9.095)	-0.000 (-0.564)
Debt/EV	-	1.546*** (99.49)	1.600*** (5.758)	0.127 (0.521)	-	1.170*** (95.809)	1.165*** (8.884)	0.055 (0.695)	-	0.010*** (14.358)	0.016*** (4.980)	0.002* (2.040)
Fixed Effects	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES
Other statistics												
Adj R^2	0.01%	29.42%	40.18%	87.31%	0.08%	30.65%	41.72%	94.51%	0.01%	9.31%	23.75%	93.22%

Exhibit B-W-3: Regression Specifications Analysing the Relationship Between Risk and Governance for Stocks in the MSCI World Universe

	TOTAL RISK				STOCK SPECIFIC RISK				MARKET BETA			
	Spec 1: Simple OLS	*Spec 2: Multi OLS*	*Spec 3: Static FE*	*Spec 4: Dyn FE*	*Spec 5: Simple OLS*	*Spec 6: Multi OLS*	*Spec 7: Static FE*	*Spec 8: Dyn FE*	*Spec 9: Simple OLS*	*Spec 10: Multi OLS*	*Spec 11: Static FE*	*Spec 12: Dyn FE*
Lagged past risk	-	-	-	0.873*** (27.846)	-	-	-	0.939*** (109.00)	-	-	-	0.954*** (89.475)
Governance	-0.278*** (-20.84)	-0.209*** (-18.24)	-0.393*** (-4.984)	-0.015 (-0.573)	-0.453*** (-42.91)	-0.406*** (-45.34)	-0.418*** (-7.416)	-0.019* (-1.977)	-0.012*** (-22.83)	-0.009*** (-18.178)	-0.017*** (-6.198)	-0.001. (-1.655)
Size	-	-4.574*** (-136.24)	-6.604*** (-15.927)	-0.864*** (-3.304)	-	-4.313*** (-164.46)	-5.830*** (-22.433)	-0.360*** (-4.042)	-	-0.093*** (-62.300)	-0.108*** (-9.439)	-0.008*** (-3.937)
Dividend Yield	-	-0.416*** (-45.00)	-0.528*** (-4.887)	-0.086*** (-4.193)	-	-0.593*** (-82.12)	-0.590*** (-5.691)	-0.039*** (-5.049)	-	-0.016*** (-37.952)	-0.020*** (-5.784)	-0.001** (-2.516)
Price Momentum	-	-3.632*** (-82.68)	-3.193*** (-7.465)	-1.169*** (-5.197)	-	-2.161*** (-62.97)	-1.821*** (-5.515)	-0.692*** (-8.152)	-	-0.074*** (-38.082)	-0.076*** (-4.677)	-0.020*** (-5.025)
Liquidity (Dollar Vol)	-	2.933*** (120.54)	5.531*** (15.478)	0.736*** (3.783)	-	2.316*** (121.86)	4.314*** (17.264)	0.247*** (4.099)	-	0.087*** (81.055)	0.121*** (12.049)	0.008*** (4.447)
Cash profit	-	-1.127*** (-45.13)	-1.267* (-2.507)	-0.604. (-1.906)	-	-0.116*** (-5.930)	-0.322 (-1.524)	-0.257* (-2.533)	-	-0.009*** (-8.023)	-0.002 (-0.507)	-0.001 (-1.068)
ROE	-	-2.129*** (-104.01)	-2.246*** (-4.293)	-0.756. (-1.676)	-	-1.005*** (-62.84)	-1.062*** (-5.630)	-0.284. (-1.926)	-	-0.018*** (-19.503)	-0.018*** (-5.326)	-0.003 (-1.623)
Asset Growth	-	4.212*** (89.63)	3.967*** (6.614)	0.670 (1.646)	-	2.610*** (71.11)	2.373*** (6.710)	0.300* (2.312)	-	-0.015*** (-7.190)	-0.014 (-1.551)	0.007*** (3.875)
Earnings volatility	-	1.506*** (102.09)	1.081*** (12.976)	0.073* (2.164)	-	1.250*** (108.43)	1.009*** (15.031)	0.009 (1.118)	-	0.044*** (67.942)	0.033*** (8.937)	-0.000 (-0.584)
Debt/EV	-	1.580*** (101.96)	1.622*** (5.851)	0.129 (0.534)	-	1.191*** (98.37)	1.175*** (9.098)	0.055 (0.717)	-	0.011*** (15.838)	0.017*** (5.476)	0.002* (2.060)
Fixed Effects	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES
Other statistics												
Adj R^2	0.24%	29.41%	40.55%	87.31%	0.99%	31.42%	42.35%	94.51%	0.28%	9.42%	24.20%	93.22%

Exhibit B-W-4 : Regression Specifications Analysing the Relationship Between Risk and Carbon for Stocks in the MSCI World Universe

	TOTAL RISK				STOCK SPECIFIC RISK				MARKET BETA			
	Spec 1: Simple OLS	*Spec 2: Multi OLS*	*Spec 3: Static FE*	*Spec 4: Dyn FE*	*Spec 5: Simple OLS*	*Spec 6: Multi OLS*	*Spec 7: Static FE*	*Spec 8: Dyn FE*	*Spec 9: Simple OLS*	*Spec 10: Multi OLS*	*Spec 11: Static FE*	*Spec 12: Dyn FE*
Lagged past risk	-	-	-	0.873*** (27.813)	-	-	-	0.939*** (107.362)	-	-	-	0.954*** (89.757)
Carbon	-0.197*** (-21.5)	0.021** (2.637)	-0.074 (-1.617)	-0.016 (-1.581)	-0.270*** (-37.38)	-0.056*** (-8.985)	-0.178*** (-4.368)	-0.011. (-1.776)	-0.004*** (-10.83)	0.001* (2.135)	0.003 (1.207)	-0.000 (-1.312)
Size	-	-4.562*** (-133.621)	-6.404*** (-15.345)	-0.846** (-3.280)	-	-4.215*** (-157.306)	-5.549*** (-21.363)	-0.344*** (-3.930)	-	-0.092*** (-60.828)	-0.104*** (-8.756)	-0.008*** (-3.754)
Dividend Yield	-	-0.439*** (-47.904)	-0.534*** (-4.848)	-0.085*** (-4.199)	-	-0.637*** (-88.550)	-0.589*** (-5.614)	-0.039*** (-5.081)	-	-0.017*** (-40.786)	-0.020*** (-5.786)	-0.001* (-2.471)
Price Momentum	-	-3.653*** (-83.096)	-3.249*** (-7.574)	-1.173*** (-5.207)	-	-2.209*** (-64.019)	-1.896*** (-5.698)	-0.695*** (-8.146)	-	-0.075*** (-38.532)	-0.077*** (-4.700)	-0.021*** (-5.030)
Liquidity (Dollar Vol)	-	2.934*** (120.024)	5.426*** (15.061)	0.729*** (3.767)	-	2.292*** (119.498)	4.191*** (16.666)	0.240*** (3.995)	-	0.087*** (80.675)	0.117*** (11.447)	0.008*** (4.401)
Cash profit	-	-1.185*** (-47.732)	-1.391** (-2.783)	-0.609. (-1.928)	-	-0.220*** (-11.312)	-0.451* (-2.143)	-0.263* (-2.605)	-	-0.011*** (-10.370)	-0.008 (-1.727)	-0.002 (-1.244)
ROE	-	-2.125*** (-103.716)	-2.241*** (-4.311)	-0.755. (-1.673)	-	-0.993*** (-61.780)	-1.053*** (-5.673)	-0.283. (-1.922)	-	-0.017*** (-19.276)	-0.018*** (-5.260)	-0.003 (-1.614)
Asset Growth	-	4.206*** (89.412)	3.949*** (6.607)	0.666 (1.639)	-	2.589*** (70.147)	2.331*** (6.638)	0.297* (2.300)	-	-0.015*** (-7.319)	-0.013 (-1.476)	0.007*** (3.844)
Earnings volatility	-	1.503*** (101.747)	1.100*** (13.087)	0.074* (2.185)	-	1.238*** (106.777)	1.029*** (15.148)	0.010 (1.199)	-	0.044*** (67.629)	0.034*** (9.074)	-0.000 (-0.526)
Debt/EV	-	1.568*** (100.773)	1.608*** (5.815)	0.129 (0.533)	-	1.182*** (96.806)	1.169*** (8.964)	0.055 (0.706)	-	0.010*** (15.004)	0.016*** (5.024)	0.002* (2.059)
Fixed Effects	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES
Other statistics												
Adj R^2	0.25%	29.28%	40.20%	87.31%	0.76%	30.68%	41.90%	94.51%	0.06%	9.26%	23.77%	93.22%

World ex-US Universe

Exhibit B-X-1: Regression Specifications Analysing the Relationship Between Risk and ESG for Stocks in the MSCI World ex US Universe

	TOTAL RISK				STOCK SPECIFIC RISK				MARKET BETA			
	Spec 1: Simple OLS	*Spec 2: Multi OLS*	*Spec 3: Static FE*	*Spec 4: Dyn FE*	*Spec 5: Simple OLS*	*Spec 6: Multi OLS*	*Spec 7: Static FE*	*Spec 8: Dyn FE*	*Spec 9: Simple OLS*	*Spec 10: Multi OLS*	*Spec 11: Static FE*	*Spec 12: Dyn FE*
Lagged past risk	-	-	-	0.879*** (30.931)	-	-	-	0.940*** (116.761)	-	-	-	0.961*** (114.236)
ESG	-0.317*** (-26.020)	-0.169*** (-15.780)	-0.334*** (-5.190)	-0.043. (1.876)	-0.579*** (-59.390)	-0.390*** (-46.160)	-0.403*** (-7.323)	-0.019* (1.973)	-0.006*** (-11.940)	-0.005*** (-10.473)	-0.009*** (-2.887)	-0.001*** (-3.298)
Size	-	-4.592*** (-112.280)	-5.292*** (-11.306)	-0.668** (-2.631)	-	-4.286*** (-132.690)	-4.676*** (-16.260)	-0.301** (-3.310)	-	-0.073*** (-37.464)	-0.056*** (-3.895)	-0.005** (-2.636)
Dividend Yield	-	-0.518*** (-53.550)	-0.515*** (-4.034)	-0.088*** (-3.360)	-	-0.650*** (-85.200)	-0.549*** (-4.540)	-0.041*** (-3.947)	-	-0.009*** (-19.379)	-0.013*** (-4.085)	-0.001. (-1.936)
Price Momentum	-	-3.116*** (-68.380)	-3.001*** (-8.443)	-0.967*** (-5.936)	-	-1.985*** (-55.160)	-1.916*** (-6.724)	-0.585*** (-8.754)	-	-0.072*** (-33.237)	-0.076*** (-5.808)	-0.019*** (-5.877)
Liquidity (Dollar Vol)	-	3.345*** (100.730)	3.809*** (10.581)	0.489** (2.706)	-	2.510*** (95.710)	2.818*** (11.965)	0.160** (2.706)	-	0.109*** (68.409)	0.097*** (8.755)	0.006*** (3.543)
Cash profit	-	-1.058*** (-44.010)	-1.227*** (-5.674)	-0.438*** (-3.297)	-	-0.225*** (-11.860)	-0.454*** (-3.515)	-0.197*** (-5.354)	-	-0.018*** (-15.641)	-0.012** (-2.656)	-0.001 (-1.071)
ROE	-	-1.627*** (-68.980)	-1.617*** (-4.443)	-0.232 (-0.910)	-	-1.008*** (-54.140)	-1.031*** (-5.989)	-0.097 (-1.235)	-	-0.022*** (-19.615)	-0.024*** (-5.164)	-0.001 (-1.636)
Asset Growth	-	3.132*** (64.060)	3.016*** (4.985)	0.483 (1.567)	-	1.751*** (45.340)	1.609*** (4.672)	0.217* (2.199)	-	-0.014*** (-5.841)	-0.009 (-1.002)	0.004* (2.346)
Earnings volatility	-	1.319*** (77.240)	0.979*** (9.979)	0.049. (1.907)	-	1.050*** (77.910)	0.925*** (10.955)	0.002 (0.206)	-	0.044*** (54.143)	0.036*** (7.497)	-0.001. (-1.774)
Debt/EV	-	0.688*** (43.050)	0.685** (3.181)	-0.072 (-0.504)	-	0.700*** (55.430)	0.662*** (6.089)	-0.017 (-0.366)	-	0.001* (1.779)	0.008** (3.125)	0.000 (0.544)
Fixed Effects	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES
Other statistics												
Adj R^2	0.58%	28.28%	35.81%	86.06%	2.96%	31.88%	38.94%	93.96%	0.12%	9.04%	23.13%	93.97%
Durban-Wu-Hausman test				1014.059 *(p=0.00)****				2381.826 *(p=0.00) ****				280.589 *(p=0.00) ****
First stage F-test				8.40×10^{32}				8.41×10^{29}				5.45×10^{30}

Exhibit B-X-2: Regression Specifications Analysing the Relationship Between Risk and Environmental for Stocks in the MSCI World ex US Universe

	TOTAL RISK				STOCK SPECIFIC RISK				MARKET BETA			
	Spec 1: Simple OLS	*Spec 2: Multi OLS*	*Spec 3: Static FE*	*Spec 4: Dyn FE*	*Spec 5: Simple OLS*	*Spec 6: Multi OLS*	*Spec 7: Static FE*	*Spec 8: Dyn FE*	*Spec 9: Simple OLS*	*Spec 10: Multi OLS*	*Spec 11: Static FE*	*Spec 12: Dyn FE*
Lagged past risk	-	-	-	0.880*** (31.175)	-	-	-	0.941*** (119.129)	-	-	-	0.961*** (114.462)
Environmental	-0.398*** (-32.920)	-0.203*** (-19.240)	-0.256*** (-4.411)	-0.044* (-2.400)	-0.507*** (-52.080)	-0.267*** (-31.940)	-0.296*** (-5.518)	-0.021** (-2.646)	-0.012*** (-24.030)	-0.012*** (-22.913)	-0.006. (-1.843)	-0.000 (-1.547)
Size	-	-4.544*** (-110.640)	-5.244*** (-11.130)	-0.657** (-2.629)	-	-4.269*** (-130.930)	-4.621*** (-15.788)	-0.296*** (-3.305)	-	-0.069*** (-35.349)	-0.054*** (-3.764)	-0.005* (-2.560)
Dividend Yield	-	-0.522*** (-54.230)	-0.524*** (-4.042)	-0.088*** (-3.340)	-	-0.672*** (-87.980)	-0.560*** (-4.538)	-0.041*** (-3.932)	-	-0.009*** (-19.136)	-0.013*** (-4.121)	-0.001* (-2.003)
Price Momentum	-	-3.137*** (-68.900)	-3.034*** (-8.547)	-0.970*** (-5.930)	-	-2.033*** (-56.230)	-1.957*** (-6.828)	-0.586*** (-8.748)	-	-0.073*** (-33.642)	-0.077*** (-5.858)	-0.019*** (-5.902)
Liquidity (Dollar Vol)	-	3.327*** (100.290)	3.736*** (10.308)	0.479** (2.801)	-	2.468*** (93.700)	2.729*** (11.332)	0.156** (2.691)	-	0.108*** (68.209)	0.095*** (8.470)	0.006*** (3.423)
Cash profit	-	-1.068*** (-44.470)	-1.243*** (-5.839)	-0.439** (-3.301)	-	-0.243*** (-12.750)	-0.473*** (-3.763)	-0.198*** (-5.351)	-	-0.018*** (-16.112)	-0.013** (-2.723)	-0.001 (-1.105)
ROE	-	-1.631*** (-69.270)	-1.632*** (-4.501)	-0.232 (-0.911)	-	-1.030*** (-55.120)	-1.050*** (-6.165)	-0.097 (-1.234)	-	-0.022*** (-19.543)	-0.024*** (-5.280)	-0.001. (-1.696)
Asset Growth	-	3.121*** (63.880)	2.978*** (4.930)	0.477 (1.557)	-	1.718*** (44.300)	1.564*** (4.559)	0.214* (2.187)	-	-0.014*** (-5.945)	-0.010 (-1.122)	0.003* (2.284)
Earnings volatility	-	1.314*** (76.960)	1.005*** (10.237)	0.052* (1.984)	-	1.051*** (77.550)	0.958*** (11.169)	0.003 (0.308)	-	0.044*** (53.655)	0.037*** (7.677)	-0.001 (-1.631)
Debt/EV	-	0.672*** (42.350)	0.641** (3.046)	-0.077 (-0.549)	-	0.648*** (51.430)	0.608*** (5.835)	-0.019 (-0.422)	-	0.001 (1.643)	0.007** (2.645)	0.000 (0.299)
Fixed Effects	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES
Other statistics												
Adj R^2	0.93%	28.36%	35.55%	86.06%	2.29%	31.23%	38.32%	93.95%	0.50%	9.38%	22.99%	93.97%

Exhibit B-X-3: Regression Specifications Analysing the Relationship Between Risk and Social for Stocks in the MSCI World ex US Universe

	TOTAL RISK				STOCK SPECIFIC RISK				MARKET BETA			
	Spec 1: Simple OLS	*Spec 2: Multi OLS*	*Spec 3: Static FE*	*Spec 4: Dyn FE*	*Spec 5: Simple OLS*	*Spec 6: Multi OLS*	*Spec 7: Static FE*	*Spec 8: Dyn FE*	*Spec 9: Simple OLS*	*Spec 10: Multi OLS*	*Spec 11: Static FE*	*Spec 12: Dyn FE*
Lagged past risk	-	-	-	0.880*** (31.412)	-	-	-	0.941*** (120.944)	-	-	-	0.961*** (114.315)
Social	-0.100*** (-6.123)	-0.056*** (-4.025)	-0.095 (-1.367)	0.009 (0.618)	-0.266*** (-20.050)	-0.193*** (-17.440)	-0.161* (-2.505)	0.002 (0.261)	0.001 (1.333)	0.002*** (3.657)	0.000 (0.089)	-0.000 (-0.475)
Size	-	-4.637*** (-113.566)	-5.296*** (-11.202)	-0.664** (-2.638)	-	-4.388*** (-135.140)	-4.678*** (-15.929)	-0.298*** (-3.313)	-	-0.075*** (-38.363)	-0.056*** (-3.886)	-0.005** (-2.626)
Dividend Yield	-	-0.532*** (-55.240)	-0.526*** (-4.048)	-0.089** (-3.344)	-	-0.682*** (-89.010)	-0.562*** (-4.548)	-0.041*** (-3.935)	-	-0.010*** (-20.756)	-0.013*** (-4.127)	-0.001* (-2.006)
Price Momentum	-	-3.133*** (-68.697)	-3.037*** (-8.549)	-0.970*** (-5.937)	-	-2.022*** (-55.750)	-1.958*** (-6.798)	-0.586*** (-8.755)	-	-0.073*** (-33.564)	-0.077*** (-5.885)	-0.019*** (-5.908)
Liquidity (Dollar Vol)	-	3.327*** (100.147)	3.721*** (10.255)	0.475** (2.796)	-	2.469*** (93.470)	2.711*** (11.247)	0.153** (2.660)	-	0.108*** (68.042)	0.095*** (8.441)	0.006*** (3.392)
Cash profit	-	-1.062*** (-44.136)	-1.240*** (-5.877)	-0.438** (-3.297)	-	-0.235*** (-12.280)	-0.470*** (-3.763)	-0.197*** (-5.342)	-	-0.018*** (-15.738)	-0.013** (-2.705)	-0.001 (-1.092)
ROE	-	-1.644*** (-69.698)	-1.652*** (-4.562)	-0.234 (-0.916)	-	-1.048*** (-55.910)	-1.073*** (-6.349)	-0.098 (-1.240)	-	-0.023*** (-20.048)	-0.025*** (-5.415)	-0.001. (-1.753)
Asset Growth	-	3.118*** (63.715)	2.988*** (4.955)	0.475 (1.551)	-	1.721*** (44.220)	1.578*** (4.604)	0.214* (2.181)	-	-0.014*** (-6.129)	-0.009 (-1.112)	0.003* (2.298)
Earnings volatility	-	1.325*** (77.524)	1.016*** (10.245)	0.054* (2.052)	-	1.063*** (78.220)	0.967*** (11.131)	0.003 (0.385)	-	0.044*** (54.472)	0.037*** (7.727)	-0.001 (-1.599)
Debt/EV	-	0.661*** (41.549)	0.632** (3.002)	-0.082 (-0.581)	-	0.642*** (50.770)	0.601*** (5.786)	-0.021 (-0.467)	-	0.000 (0.254)	0.007* (2.453)	0.000 (0.259)
Fixed Effects	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES
Other statistics												
Adj R^2	0.03%	28.14%	35.31%	86.05%	0.35%	30.81%	37.89%	93.95%	0.00%	8.97%	22.90%	93.97%

Exhibit B-X-4: Regression Specifications Analysing the Relationship Between Risk and Governance for Stocks in the MSCI World ex US Universe

	TOTAL RISK				STOCK SPECIFIC RISK				MARKET BETA			
	Spec 1: Simple OLS	*Spec 2: Multi OLS*	*Spec 3: Static FE*	*Spec 4: Dyn FE*	*Spec 5: Simple OLS*	*Spec 6: Multi OLS*	*Spec 7: Static FE*	*Spec 8: Dyn FE*	*Spec 9: Simple OLS*	*Spec 10: Multi OLS*	*Spec 11: Static FE*	*Spec 12: Dyn FE*
Lagged past risk	-	-	-	0.880*** (31.464)	-	-	-	0.941*** (121.697)	-	-	-	0.961*** (113.994)
Governance	-0.217*** (-14.88)	-0.055*** (-4.324)	-0.322*** (-4.461)	-0.012 (-0.592)	-0.438*** (-37.24)	-0.327*** (-32.552)	-0.363*** (-5.964)	-0.018* (-2.135)	-0.011*** (-17.08)	-0.009*** (-15.598)	-0.017*** (-5.319)	-0.001 (-1.305)
Size	-	-4.642*** (-113.685)	-5.441*** (-11.540)	-0.670** (-2.651)	-	-4.412*** (-136.332)	-4.846*** (-16.644)	-0.308*** (-3.406)	-	-0.075*** (-38.606)	-0.063*** (-4.481)	-0.005** (-2.710)
Dividend Yield	-	-0.528*** (-54.433)	-0.524*** (-4.061)	-0.089*** (-3.337)	-	-0.655*** (-85.132)	-0.560*** (-4.567)	-0.041*** (-3.944)	-	-0.009*** (-18.379)	-0.013*** (-4.155)	-0.001* (-2.009)
Price Momentum	-	-3.131*** (-68.655)	-3.004*** (-8.455)	-0.969*** (-5.927)	-	-2.006*** (-55.498)	-1.923*** (-6.703)	-0.585*** (-8.743)	-	-0.072*** (-33.228)	-0.075*** (-5.787)	-0.019*** (-5.902)
Liquidity (Dollar Vol)	-	3.329*** (100.187)	3.823*** (10.610)	0.479** (2.810)	-	2.480*** (94.178)	2.826*** (11.886)	0.160** (2.759)	-	0.108*** (68.341)	0.100*** (9.087)	0.006*** (3.419)
Cash profit	-	-1.045*** (-42.931)	-1.125*** (-5.219)	-0.434** (-3.264)	-	-0.137*** (-7.107)	-0.340** (-2.707)	-0.191*** (-5.204)	-	-0.015*** (-13.159)	-0.007 (-1.417)	-0.001 (-0.859)
ROE	-	-1.634*** (-69.058)	-1.596*** (-4.391)	-0.233 (-0.909)	-	-0.994*** (-53.017)	-1.010*** (-6.004)	-0.096 (-1.206)	-	-0.021*** (-18.721)	-0.022*** (-4.825)	-0.001 (-1.641)
Asset Growth	-	3.119*** (63.738)	3.004*** (4.958)	0.477 (1.561)	-	1.736*** (44.760)	1.593*** (4.613)	0.216* (2.204)	-	-0.013*** (-5.764)	-0.008 (-0.992)	0.003* (2.318)
Earnings volatility	-	1.330*** (77.726)	1.006*** (10.215)	0.053* (2.008)	-	1.089*** (80.319)	0.959*** (11.101)	0.003 (0.332)	-	0.045*** (55.180)	0.036*** (7.634)	-0.001 (-1.638)
Debt/EV	-	0.657*** (41.357)	0.626** (2.989)	-0.081 (-0.577)	-	0.626*** (49.764)	0.590*** (5.786)	-0.021 (-0.458)	-	0.000 (0.427)	0.007* (2.552)	0.000 (0.246)
Fixed Effects	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES
Other statistics												
Adj R^2	0.19%	28.14%	35.58%	86.05%	1.19%	31.26%	38.35%	93.95%	0.25%	9.15%	23.37%	93.97%

Exhibit B-X-5: Regression Specifications Analysing the Relationship Between Risk and Carbon for Stocks in the MSCI World ex US Universe

	TOTAL RISK				STOCK SPECIFIC RISK				MARKET BETA			
	Spec 1: Simple OLS	*Spec 2: Multi OLS*	*Spec 3: Static FE*	*Spec 4: Dyn FE*	*Spec 5: Simple OLS*	*Spec 6: Multi OLS*	*Spec 7: Static FE*	*Spec 8: Dyn FE*	*Spec 9: Simple OLS*	*Spec 10: Multi OLS*	*Spec 11: Static FE*	*Spec 12: Dyn FE*
Lagged past risk	-	-	-	0.880*** (31.428)	-	-	-	0.941*** (120.552)	-	-	-	0.961*** (114.247)
Carbon	-0.151*** (-14.21)	-0.028** (-3.027)	-0.062 (-1.146)	-0.016 (-1.417)	-0.232*** (-26.98)	-0.092*** (-12.49)	-0.148** (-2.923)	-0.009 (-1.301)	-0.002*** (-4.128)	-0.001* (-2.183)	0.004 (1.217)	-0.000 (-1.610)
Size	-	-4.627*** (-112.769)	-5.274*** (-11.083)	-0.657** (-2.627)	-	-4.355*** (-133.400)	-4.619*** (-15.687)	-0.294*** (-3.310)	-	-0.074*** (-37.914)	-0.058*** (-3.937)	-0.005* (-2.480)
Dividend Yield	-	-0.534*** (-55.528)	-0.526*** (-4.034)	-0.088*** (-3.342)	-	-0.689*** (-90.050)	-0.560*** (-4.526)	-0.041*** (-3.946)	-	-0.009*** (-20.633)	-0.013*** (-4.136)	-0.001* (-1.971)
Price Momentum	-	-3.136*** (-68.770)	-3.046*** (-8.570)	-0.971*** (-5.932)	-	-2.033*** (-56.020)	-1.977*** (-6.838)	-0.587*** (-8.734)	-	-0.073*** (-33.529)	-0.077*** (-5.843)	-0.019*** (-5.916)
Liquidity (Dollar Vol)	-	3.329*** (100.168)	3.724*** (10.259)	0.475** (2.795)	-	2.473*** (93.560)	2.714*** (11.285)	0.153** (2.663)	-	0.108*** (68.081)	0.095*** (8.428)	0.006*** (3.389)
Cash profit	-	-1.060*** (-44.031)	-1.238*** (-5.864)	-0.438*** (-3.297)	-	-0.228*** (-11.900)	-0.464** (-3.704)	-0.197*** (-5.350)	-	-0.018*** (-15.679)	-0.013** (-2.739)	-0.001 (-1.075)
ROE	-	-1.641*** (-69.569)	-1.647*** (-4.550)	-0.234 (-0.915)	-	-1.040*** (-55.410)	-1.063*** (-6.286)	-0.096 (-1.239)	-	-0.023*** (-20.021)	-0.025*** (-5.498)	-0.001. (-1.705)
Asset Growth	-	3.115*** (63.657)	2.979*** (4.937)	0.475 (1.553)	-	1.710*** (43.920)	1.559*** (4.552)	0.214* (2.184)	-	-0.014*** (-6.077)	-0.009 (-1.079)	0.003* (2.273)
Earnings volatility	-	1.323*** (77.255)	1.018*** (10.280)	0.053* (2.015)	-	1.056*** (77.540)	0.969*** (11.127)	0.003 (0.352)	-	0.044*** (54.167)	0.037*** (7.789)	-0.001 (-1.625)
Debt/EV	-	0.662*** (41.466)	0.632** (3.006)	-0.079 (-0.562)	-	0.644*** (50.730)	0.606*** (5.796)	-0.020 (-0.437)	-	0.001 (0.713)	0.006* (2.313)	0.000 (0.340)
Fixed Effects	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES
Other statistics												
Adj R^2	0.17%	28.13%	35.30%	86.05%	0.63%	30.72%	37.94%	93.95%	0.02%	8.97%	22.94%	93.97%

US universe

Exhibit B-U-1: Regression Specifications Analysing the Relationship Between Risk and ESG for Stocks in the US Universe

	TOTAL RISK				STOCK SPECIFIC RISK				MARKET BETA			
	Spec 1: Simple OLS	*Spec 2: Multi OLS*	*Spec 3: Static FE*	*Spec 4: Dyn FE*	*Spec 5: Simple OLS*	*Spec 6: Multi OLS*	*Spec 7: Static FE*	*Spec 8: Dyn FE*	*Spec 9: Simple OLS*	*Spec 10: Multi OLS*	*Spec 11: Static FE*	*Spec 12: Dyn FE*
Lagged past risk	-	-	-	0.879*** (31.887)	-	-	-	0.917*** (72.249)	-	-	-	0.946*** (62.468)
ESG	-0.079*** (-4.415)	0.107*** (7.409)	0.172* (1.972)	-0.009 (-0.320)	-0.224*** (-17.08)	-0.002 (-0.242)	0.034 (0.604)	-0.013 (-1.048)	-0.017*** (-27.780)	-0.007*** (-12.521)	-0.008* (-2.519)	-0.001* (-2.119)
Size	-	-9.894*** (-172.577)	-9.202*** (-11.219)	-1.312*** (-3.907)	-	-7.716*** (-193.942)	-7.296*** (-17.121)	-0.669*** (-4.308)	-	-0.202*** (-87.939)	-0.171*** (-11.340)	-0.015*** (-3.668)
Dividend Yield	-	-0.573*** (-33.125)	-0.348** (-3.082)	-0.038 (-1.183)	-	-0.805*** (-67.081)	-0.397*** (-4.332)	-0.022 (-1.494)	-	-0.041*** (-59.514)	-0.026*** (-5.638)	0.000 (0.235)
Price Momentum	-	-5.372*** (-91.235)	-5.216*** (-8.910)	-1.671*** (-4.066)	-	-3.087*** (-75.558)	-2.839*** (-9.633)	-1.032*** (-5.356)	-	-0.027*** (-11.328)	-0.037* (-2.116)	-0.012** (-2.26)
Liquidity (Dollar Vol)	-	8.236*** (151.756)	7.334*** (10.363)	1.080*** (3.921)	-	5.782*** (153.524)	5.052*** (14.232)	0.459*** (3.889)	-	0.159*** (73.124)	0.134*** (9.207)	0.012*** (3.581)
Cash profit	-	0.716*** (20.646)	0.616. (1.721)	-0.507* (-2.450)	-	1.164*** (48.339)	0.672*** (3.917)	-0.093 (-1.118)	-	-0.027*** (-19.734)	-0.027*** (-3.426)	0.006** (2.316)
ROE	-	1.449*** (62.076)	1.479*** (3.631)	0.195 (0.870)	-	0.776*** (47.931)	0.796*** (4.083)	0.131 (1.381)	-	-0.008*** (-9.029)	-0.007* (-1.996)	0.006*** (3.905)
Asset Growth	-	1.034*** (15.305)	1.128* (2.380)	0.464* (2.083)	-	0.563*** (11.995)	0.565. (1.915)	0.192* (2.018)	-	-0.016*** (-5.749)	-0.008 (0.703)	0.008** (2.511)
Earnings volatility	-	1.361*** (61.948)	1.091*** (8.116)	0.009 (0.170)	-	1.210*** (79.383)	0.987*** (11.725)	0.009 (0.531)	-	0.040*** (45.551)	0.037*** (7.587)	-0.000 (-0.479)
Debt/EV	-	1.509*** (75.943)	1.518*** (6.581)	-0.215. (-1.935)	-	1.207*** (87.552)	1.174*** (8.135)	-0.126 (-1.689)	-	0.039*** (49.581)	0.041*** (10.640)	0.003** (2.675)
Fixed Effects	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES
Other statistics												
Adj R^2	0.017%	40.660%	43.950%	86.900%	0.274%	46.390%	51.880%	92.260%	0.865%	16.940%	29.270%	92.240%
Durban-Wu-Hausman test				855.2837 *(p=0.00)****				1654.003 *(p=0.00) ****				342.075 *(p=0.00) ****
First stage F-test				1.92×10^{31}				7.50×10^{31}				9.16×10^{29}

Exhibit B-U-2: Regression Specifications Analysing the Relationship Between Risk and Environmental for Stocks in the US Universe

	TOTAL RISK				STOCK SPECIFIC RISK				MARKET BETA			
	Spec 1: Simple OLS	*Spec 2: Multi OLS*	*Spec 3: Static FE*	*Spec 4: Dyn FE*	*Spec 5: Simple OLS*	*Spec 6: Multi OLS*	*Spec 7: Static FE*	*Spec 8: Dyn FE*	*Spec 9: Simple OLS*	*Spec 10: Multi OLS*	*Spec 11: Static FE*	*Spec 12: Dyn FE*
Lagged past risk	-	-	-	0.879*** (31.730)	-	-	-	0.917*** (72.144)	-	-	-	0.947*** (62.802)
Environmental	-0.568*** (-35.950)	-0.130*** (-10.050)	-0.122* (-2.016)	-0.025. (-1.856)	-0.336*** (-29.100)	0.102*** (11.360)	0.019 (0.356)	-0.0002 (-0.032)	-0.016*** (-30.4)	-0.004*** (-7.287)	0.002 (0.677)	0.0002 (0.679)
Size	-	-9.725*** (-166.940)	-9.040*** (-10.768)	-1.299*** (-3.786)		-7.813*** (-193.340)	-7.296*** (-16.684)	-0.675*** (-4.260)		-0.201*** (-86.324)	-0.176*** (-11.248)	-0.015*** (-3.692)
Dividend Yield	-	-0.576*** (-33.300)	-0.335** (-2.997)	-0.037 (-1.181)		-0.804*** (-67.040)	-0.396*** (-4.346)	-0.022 (-1.550)		-0.041*** (-59.385)	-0.026*** (-5.723)	-0.000 (0.151)
Price Momentum	-	-5.420*** (-92.000)	-5.270*** (-8.955)	-1.674*** (-4.086)		-3.062*** (-74.930)	-2.842*** (-9.618)	-1.030*** (-5.367)		-0.026*** (-11.236)	-0.036* (-2.035)	-0.012* (-2.22)
Liquidity (Dollar Vol)	-	8.188*** (150.510)	7.304*** (10.262)	1.077*** (3.889)		5.814*** (154.070)	5.053*** (14.169)	0.460*** (3.881)		0.159*** (73.318)	0.134*** (9.221)	0.012*** (3.583)
Cash profit	-	0.761*** (21.980)	0.651. (1.797)	-0.505* (-2.422)		1.146*** (47.700)	0.675*** (3.898)	-0.095 (-1.127)		-0.028*** (-20.556)	-0.028*** (-3.599)	0.006* (2.250)
ROE	-	1.477*** (63.800)	1.517*** (3.775)	0.194 (0.876)		0.771*** (48.030)	0.803*** (4.187)	0.129 (1.372)		-0.010*** (-11.447)	-0.009* (-2.416)	0.006*** (3.801)
Asset Growth	-	0.989*** (14.670)	1.054* (2.201)	0.462* (2.030)		0.573*** (12.250)	0.550. (1.854)	0.196* (2.006)		-0.014*** (-5.182)	-0.007 (-0.639)	0.008* (2.569)
Earnings volatility	-	1.356*** (61.820)	1.083*** (8.178)	0.010 (0.199)		1.207*** (79.340)	0.984*** (11.756)	0.010 (0.591)		0.040*** (46.135)	0.038*** (7.684)	-0.000 (-0.401)
Debt/EV	-	1.511*** (76.080)	1.518*** (6.597)	-0.216. (-1.951)		1.209*** (87.770)	1.173*** (8.149)	-0.126. (-1.694)		0.039*** (49.368)	0.041*** (10.656)	0.003** (2.676)
Fixed Effects	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES
Other statistics												
Adj R^2	1.21%	40.68%	43.92%	86.90%	0.27%	46.39%	51.88%	92.26%	0.87%	16.94%	29.27%	92.24%

Exhibit B-U-3: Regression Specifications Analysing the Relationship Between Risk and Social for Stocks in the US Universe

	TOTAL RISK				STOCK SPECIFIC RISK				MARKET BETA			
	Spec 1: Simple OLS	*Spec 2: Multi OLS*	*Spec 3: Static FE*	*Spec 4: Dyn FE*	*Spec 5: Simple OLS*	*Spec 6: Multi OLS*	*Spec 7: Static FE*	*Spec 8: Dyn FE*	*Spec 9: Simple OLS*	*Spec 10: Multi OLS*	*Spec 11: Static FE*	*Spec 12: Dyn FE*
Lagged past risk	-	-	-	0.878*** (31.748)	-	-	-	0.917*** (72.078)	-	-	-	0.947*** (62.849)
Social	0.359*** (15.050)	0.354*** (19.090)	0.322*** (3.740)	0.045* (2.310)	0.147*** (8.444)	0.174*** (13.490)	0.138* (2.233)	0.012 (1.355)	-0.008*** (-9.699)	-0.005*** (-6.663)	0.000 (0.120)	-0.001 (-1.143)
Size	-	-9.888*** (-173.660)	-9.164*** (-11.128)	-1.325*** (-3.852)	-	-7.737*** (-195.700)	-7.296*** (-17.159)	-0.677*** (-4.287)	-	-0.204*** (-89.515)	-0.175*** (-11.512)	-0.015*** (-3.673)
Dividend Yield	-	-0.561*** (-32.470)	-0.343** (-3.074)	-0.039 (-1.228)	-	-0.799*** (-66.540)	-0.396*** (-4.346)	-0.022 (-1.553)	-	-0.041*** (-59.553)	-0.026*** (-5.723)	0.000 (0.175)
Price Momentum	-	-5.364*** (-91.270)	-5.231*** (-8.928)	-1.669*** (-4.080)	-	-3.075*** (-75.360)	-2.838*** (-9.640)	-1.029*** (-5.367)	-	-0.026*** (-11.003)	-0.036* (-2.035)	-0.012* (-2.228)
Liquidity (Dollar Vol)	-	8.229*** (151.880)	7.335*** (10.374)	1.085*** (3.917)	-	5.782*** (153.690)	5.054*** (14.261)	0.461*** (3.892)	-	0.159*** (73.318)	0.134*** (9.221)	0.012*** (3.580)
Cash profit	-	0.707*** (20.480)	0.621. (1.725)	-0.51* (-2.441)	-	1.148*** (47.850)	0.669*** (3.889)	-0.095 (-1.135)	-	-0.028*** (-20.556)	-0.028*** (-3.569)	0.006* (2.274)
ROE	-	1.442*** (62.280)	1.486*** (3.708)	0.190 (0.860)	-	0.762*** (47.370)	0.791*** (4.132)	0.128 (1.362)	-	-0.010*** (-10.272)	-0.009* (-2.416)	0.005*** (3.810)
Asset Growth	-	1.052*** (15.610)	1.120* (2.344)	0.473* (2.076)	-	0.588*** (12.570)	0.574. (1.935)	0.198* (2.027)	-	-0.014*** (-5.182)	-0.006 (-0.501)	0.008* (2.566)
Earnings volatility	-	1.362*** (62.200)	1.093*** (8.217)	0.012 (0.230)	-	1.216*** (79.930)	0.990*** (11.784)	0.011 (0.622)	-	0.040*** (46.135)	0.038*** (7.684)	-0.000 (-0.426)
Debt/EV	-	1.503*** (75.760)	1.514*** (6.583)	-0.216. (-1.946)	-	1.202*** (87.260)	1.171*** (8.120)	-0.126. (-1.698)	-	0.039*** (49.368)	0.041*** (10.548)	0.003** (2.666)
Fixed Effects	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES
Other statistics												
Adj R^2	0.21%	40.83%	44.03%	86.90%	0.07%	46.48%	51.93%	92.26%	0.09%	16.93%	29.26%	92.24%

Exhibit B-U-4: Regression Specifications Analysing the Relationship Between Risk and Governance for Stocks in the US Universe

	TOTAL RISK				STOCK SPECIFIC RISK				MARKET BETA			
	Spec 1: Simple OLS	*Spec 2: Multi OLS*	*Spec 3: Static FE*	*Spec 4: Dyn FE*	*Spec 5: Simple OLS*	*Spec 6: Multi OLS*	*Spec 7: Static FE*	*Spec 8: Dyn FE*	*Spec 9: Simple OLS*	*Spec 10: Multi OLS*	*Spec 11: Static FE*	*Spec 12: Dyn FE*
Lagged past risk	-	-	-	0.879*** (31.758)	-	-	-	0.917*** (72.145)	-	-	-	0.947*** (62.792)
Governance	-0.267*** (-11.180)	-0.075*** (-4.007)	0.061 (0.602)	0.010 (0.213)	-0.339*** (-19.450)	-0.238*** (-18.380)	-0.032 (0.504)	-0.013 (-0.683)	-0.008*** (-10.500)	-0.007*** (-9.340)	-0.010** (-2.816)	-0.001 (-0.923)
Size	-	-9.859*** (-172.775)	-9.119*** (-11.106)	-1.315*** (-3.849)	-	-7.753*** (-196.140)	-7.288*** (-17.169)	-0.678*** (-4.330)	-	-0.206*** (-90.195)	-0.176*** (-11.539)	-0.015*** (-3.687)
Dividend Yield	-	-0.571*** (-33.004)	-0.342** (-3.052)	-0.039 (-1.224)	-	-0.795*** (-66.310)	-0.395*** (-4.334)	-0.022 (-1.547)	-	-0.041*** (-58.872)	-0.026*** (-5.703)	0.000 (0.172)
Price Momentum	-	-5.383*** (-91.454)	-5.249*** (-8.914)	-1.669*** (-4.076)	-	-3.071*** (-75.320)	-2.845*** (-9.629)	-1.030*** (-5.364)	-	-0.025*** (-10.663)	-0.036* (-2.036)	-0.012* (-2.226)
Liquidity (Dollar Vol)	-	8.230*** (151.639)	7.320*** (10.364)	1.080*** (3.914)	-	5.786*** (153.890)	5.053*** (14.264)	0.461*** (3.915)	-	0.159*** (73.383)	0.135*** (9.274)	0.012*** (3.591)
Cash profit	-	0.736*** (21.296)	0.639. (1.767)	-0.508* (-2.43)	-	1.155*** (48.250)	0.677*** (3.918)	-0.095 (-1.135)	-	-0.029*** (-21.060)	-0.028*** (-3.599)	0.006* (2.260)
ROE	-	1.463*** (63.016)	1.521*** (3.796)	0.195 (0.870)	-	0.752*** (46.740)	0.800*** (4.171)	0.128 (1.362)	-	-0.011*** (-11.447)	-0.010** (-2.638)	0.005*** (3.770)
Asset Growth	-	0.988*** (14.633)	1.087* (2.267)	0.468* (2.041)	-	0.522*** (11.170)	0.550. (1.854)	0.194* (1.968)	-	-0.014*** (-5.363)	-0.007 (-0.639)	0.008* (2.553)
Earnings volatility	-	1.347*** (61.366)	1.082*** (8.155)	0.012 (0.230)	-	1.198*** (78.740)	0.984*** (11.757)	0.011 (0.622)	-	0.040*** (45.868)	0.037*** (7.675)	-0.000 (-0.411)
Debt/EV	-	1.509*** (75.795)	1.528*** (6.656)	-0.215. (-1.925)	-	1.192*** (86.440)	1.173*** (8.149)	-0.126. (-1.705)	-	0.039*** (48.551)	0.040*** (10.657)	0.003** (2.655)
Fixed Effects	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES
Other statistics												
Adj R^2	0.12%	40.63%	43.88%	86.90%	0.36%	46.56%	51.87%	92.26%	0.10%	16.97%	29.38%	92.24%

Exhibit B-U-5: Regression Specifications Analysing the Relationship Between Risk and Carbon for Stocks in the US Universe

	TOTAL RISK				STOCK SPECIFIC RISK				MARKET BETA			
	Spec 1: Simple OLS	*Spec 2: Multi OLS*	*Spec 3: Static FE*	*Spec 4: Dyn FE*	*Spec 5: Simple OLS*	*Spec 6: Multi OLS*	*Spec 7: Static FE*	*Spec 8: Dyn FE*	*Spec 9: Simple OLS*	*Spec 10: Multi OLS*	*Spec 11: Static FE*	*Spec 12: Dyn FE*
Lagged past risk	-	-	-	0.879*** (31.775)	-	-	-	0.917*** (72.178)	-	-	-	0.947*** (62.786)
Carbon	-0.485*** (-36.490)	-0.074*** (-6.573)	-0.011 (0.198)	-0.020. (-1.827)	-0.341*** (-35.130)	0.071*** (9.151)	0.032 (0.698)	-0.004 (-0.633)	-0.010*** (-21.460)	0.003*** (6.798)	0.004 (1.502)	0.000 (-0.015)
Size	-	-9.753*** (-165.955)	-9.118*** (-10.740)	-1.294*** (-3.769)	-	-7.809*** (-191.554)	-7.319*** (-16.705)	-0.671*** (-4.251)	-	-0.209*** (-88.764)	-0.179*** (-11.278)	-0.015*** (-3.666)
Dividend Yield	-	-0.575*** (-33.253)	-0.340** (-3.075)	-0.035 (-1.122)	-	-0.805*** (-67.058)	-0.401*** (-4.407)	-0.022 (-1.494)	-	-0.041*** (-59.294)	-0.027*** (-5.896)	0.000 (0.171)
Price Momentum	-	-5.404*** (-91.761)	-5.251*** (-8.948)	-1.674*** (-4.087)	-	-3.072*** (-75.204)	-2.837*** (-9.634)	-1.031*** (-5.367)	-	-0.025*** (-10.580)	-0.035* (-1.977)	-0.012* (-2.224)
Liquidity (Dollar Vol)	-	8.200*** (150.658)	7.322*** (10.270)	1.075*** (3.880)	-	5.809*** (153.859)	5.059*** (14.203)	0.459*** (3.872)	-	0.160*** (73.628)	0.135*** (9.227)	0.012*** (3.569)
Cash profit	-	0.761*** (21.912)	0.640. (1.774)	-0.506* (-2.430)	-	1.142*** (47.397)	0.675*** (3.910)	-0.095 (-1.126)	-	-0.030*** (-21.458)	-0.028*** (-3.594)	0.006* (2.261)
ROE	-	1.478*** (63.782)	1.516*** (3.773)	0.195 (0.878)	-	0.769*** (47.877)	0.801*** (4.182)	0.129 (1.373)	-	-0.010*** (-11.011)	-0.009* (-2.436)	0.005*** (3.810)
Asset Growth	-	0.985*** (14.598)	1.074* (2.237)	0.461* (2.027)	-	0.579*** (12.363)	0.565. (1.895)	0.195* (2.004)	-	-0.013*** (-4.675)	-0.005 (-0.402)	0.008* (2.548)
Earnings volatility	-	1.357*** (61.825)	1.081*** (8.111)	0.011 (0.227)	-	1.205*** (79.154)	0.982*** (11.668)	0.010 (0.609)	-	0.040*** (46.036)	0.037*** (7.555)	-0.000 (-0.397)
Debt/EV	-	1.513*** (76.192)	1.524*** (6.630)	-0.216. (-1.951)	-	1.207*** (87.619)	1.177*** (8.153)	-0.126. (-1.698)	-	0.039*** (49.205)	0.041*** (10.635)	0.003** (2.670)
Fixed Effects	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES
Other statistics												
Adj R^2	1.24%	40.65%	43.88%	86.90%	1.15%	46.43%	51.88%	92.26%	0.43%	16.94%	29.31%	92.24%

Appendix 6-C: Robustness Testing With Additional Lags As Different Instrumental Variables

Exhibit C-1: Sensitivity Analysis of Lagged Risk and Sustainability Coefficients Using Various Lags as Instrumental Variables for World Stocks

	Lag 3 of the risk variables as IV			Lag 4 of the risk variables as IV			Lag 5 of the risk variables as IV		
Combinations	*Lagged Risk*	*Sustainability*	*Adj. R^2*	*Lagged Risk*	*Sustainability*	*Adj. R^2*	*Lagged Risk*	*Sustainability*	*Adj. R^2*
ESG and total risk	0.79453***	-0.0428	*80.788%*	0.72825***	-0.04767	*75.070%*	0.67589***	-0.04447	*70.610%*
Environmental and total risk	0.79464***	-0.03889*	*80.786%*	0.72833***	-0.04699*	*75.070%*	0.67587***	-0.05275*	*70.610%*
Social and total risk	0.79511***	0.02316	*80.782%*	0.72891***	0.03637	*75.060%*	0.67655***	0.05160.	*70.600%*
Governance and total risk	0.79413***	-0.06111	*80.789%*	0.72771***	-0.07455	*75.070%*	0.67532***	-0.07192	*70.610%*
Carbon and total risk	0.79507***	-0.00787	*80.781%*	0.72888***	-0.00268	*75.060%*	0.67652***	0.00314	*70.600%*
ESG and specific risk	0.89747***	-0.03047**	*92.007%*	0.86411***	-0.03838**	*89.430%*	0.83589***	-0.04272**	*87.090%*
Environmental and specific risk	0.89791***	-0.02224*	*92.004%*	0.86463***	-0.02833**	*89.420%*	0.83639***	-0.03379**	*87.080%*
Social and specific risk	0.89849***	-0.00234	*92.001%*	0.86537***	-0.00082	*89.420%*	0.83729***	0.00144	*87.070%*
Governance and specific risk	0.89716***	-0.05355***	*92.012%*	0.86366***	-0.07158***	*89.440%*	0.83535***	-0.08343***	*87.100%*
Carbon and specific risk	0.89830***	-0.00984	*92.002%*	0.86515***	-0.01092	*89.420%*	0.83703***	-0.01235	*87.080%*
ESG and market beta	0.93058***	-0.00145***	*89.892%*	0.90526***	-0.00191***	*86.410%*	0.87967***	-0.00236***	*82.960%*
Environmental and market beta	0.93098***	-0.00006	*89.886%*	0.90577***	-0.00005	*86.400%*	0.88027***	-0.00006	*82.950%*
Social and market beta	0.93102***	-0.00049	*89.886%*	0.90582***	-0.00065	*86.400%*	0.88034***	-0.0008	*82.950%*
Governance and market beta	0.93055***	-0.00126*	*89.888%*	0.90517***	-0.00182*	*86.400%*	0.87948***	-0.00247*	*82.960%*
Carbon and market beta	0.93103***	-0.00033	*89.886%*	0.90582***	-0.00037	*86.400%*	0.88032***	-0.00035	*82.950%*

Exhibit C-2: Sensitivity Analysis of Lagged Risk and Sustainability Coefficients Using Various Lags as Instrumental Variables for World ex US Stocks

	Lag 3 of the risk variables as IV			Lag 4 of the risk variables as IV			Lag 5 of the risk variables as IV		
Combinations	*Lagged Risk*	*Sustainability*	*Adj. R^2*	*Lagged Risk*	*Sustainability*	*Adj. R^2*	*Lagged Risk*	*Sustainability*	*Adj. R^2*
ESG and total risk	0.79219***	-0.07887.	*78.572%*	0.72196***	-0.09788.	*72.134%*	0.66335***	-0.10872.	*66.890%*
Environmental and total risk	0.79296***	-0.06651**	*78.561%*	0.72287***	-0.08331**	*72.118%*	0.66433***	-0.09614**	*66.873%*
Social and total risk	0.79395***	0.01171	*78.543%*	0.72408***	0.01586	*72.090%*	0.66573***	0.022	*66.836%*
Governance and total risk	0.79331***	-0.04241	*78.548%*	0.72321***	-0.05751	*72.098%*	0.66476***	-0.05871	*66.844%*
Carbon and total risk	0.79386***	-0.00918	*78.543%*	0.72398***	-0.00505	*72.089%*	0.66561***	0.00002	*66.834%*
ESG and specific risk	0.89663***	-0.04050*	*90.815%*	0.86134***	-0.05302*	*87.744%*	0.83000***	-0.06154*	*84.909%*
Environmental and specific risk	0.89748***	-0.03327**	*90.810%*	0.86242***	-0.04296**	*87.735%*	0.83119***	-0.05109***	*84.898%*
Social and specific risk	0.89844***	0.00089	*90.803%*	0.86364***	0.00105	*87.723%*	0.83265***	0.00253	*84.881%*
Governance and specific risk	0.89732***	-0.04869*	*90.814%*	0.86217***	-0.06848*	*87.743%*	0.83094***	-0.08253*	*84.910%*
Carbon and specific risk	0.89829***	-0.00838	*90.804%*	0.86347***	-0.00944	*87.724%*	0.83245***	-0.0105	*84.882%*
ESG and market beta	0.93659***	-0.00128**	*90.626%*	0.91305***	-0.00163**	*87.324%*	0.88931***	-0.00196**	*84.045%*
Environmental and market beta	0.93690***	-0.00049	*90.623%*	0.91343***	-0.00061	*87.318%*	0.88975***	-0.00072	*84.036%*
Social and market beta	0.93700***	-0.00051	*90.622%*	0.91355***	-0.00067	*87.318%*	0.88991***	-0.00083	*84.036%*
Governance and market beta	0.93669***	-0.00087	*90.623%*	0.91315***	-0.00116	*87.319%*	0.88941***	-0.00145	*84.038%*
Carbon and market beta	0.93708***	-0.0005	*90.623%*	0.91365***	-0.0006	*87.318%*	0.89001***	-0.0006	*84.036%*

Exhibit C-3: Sensitivity Analysis of Lagged Risk and Sustainability Coefficients Using Various Lags as Instrumental Variables for US Stocks

	Lag 3 of the risk variables as IV				Lag 4 of the risk variables as IV				Lag 5 of the risk variables as IV		
Combinations	*Lagged Risk*	*Sustainability*	*Adj. R^2*		*Lagged Risk*	*Sustainability*	*Adj. R^2*		*Lagged Risk*	*Sustainability*	*Adj. R^2*
ESG and total risk	0.78959***	0.02999	*81.088%*		0.71823***	0.04625	*75.264%*		0.66099***	0.05529	*70.453%*
Environmental and total risk	0.78966***	-0.02337*	*81.087%*		0.71838***	-0.02866*	*75.260%*		0.66112***	-0.04091*	*70.449%*
Social and total risk	0.78919***	0.09544**	*81.100%*		0.71780***	0.12726**	*75.283%*		0.66052***	0.15455**	*70.481%*
Governance and total risk	0.78981***	0.01918	*81.087%*		0.71855***	0.03616	*75.260%*		0.66136***	0.05775	*70.450%*
Carbon and total risk	0.78990***	0.01297	*81.087%*		0.71873***	0.02131	*75.260%*		0.66159***	0.0214	*70.447%*
ESG and specific risk	0.85352***	-0.00374	*88.631%*		0.80492***	-0.0042	*85.013%*		0.76443***	-0.00657	*81.726%*
Environmental and specific risk	0.85333***	-0.00995	*88.632%*		0.80466***	-0.01317	*85.014%*		0.76401***	-0.02038	*81.727%*
Social and specific risk	0.85335***	0.02641	*88.633%*		0.80470***	0.03511	*85.016%*		0.76415***	0.04212.	*81.731%*
Governance and specific risk	0.85357***	-0.0215	*88.632%*		0.80499***	-0.02615	*85.015%*		0.76450***	-0.02667	*81.727%*
Carbon and specific risk	0.85352***	0.00143	*88.631%*		0.80493***	0.00214	*85.013%*		0.76436***	-0.00168	*81.726%*
ESG and market beta	0.91097***	-0.00158*	*88.675%*		0.88046***	-0.00218*	*84.947%*		0.84966***	-0.00280*	*81.343%*
Environmental and market beta	0.91148***	0.0002	*88.669%*		0.88115***	0.00026	*84.937%*		0.85050***	0.00026	*81.326%*
Social and market beta	0.91137***	-0.00113	*88.671%*		0.88101***	-0.00162	*84.940%*		0.85034***	-0.00208.	*81.331%*
Governance and market beta	0.91127***	-0.00112	*88.671%*		0.88080***	-0.00189	*84.941%*		0.85001***	-0.00286.	*81.335%*
Carbon and market beta	0.91146***	-0.00019	*88.669%*		0.88112***	-0.00023	*84.937%*		0.85047***	-0.00027	*81.326%*

Appendix 6-D: Sustainability and Risk Across Sustainability Dimensions

Exhibit D-1: Quantile Regression Specifications Analysing the Relationship Between Risk and Environmental Scores Across The Risk Spectrum

	TOTAL RISK			STOCK SPECIFIC RISK			MARKET BETA		
	Spec 1: 25% Percentile	*Spec 2: 50% Percentile*	*Spec 3: 75% Percentile*	*Spec 4: 25% Percentile*	*Spec 5: 50% Percentile*	*Spec 6: 75% Percentile*	*Spec 7: 25% Percentile*	*Spec 8: 50% Percentile*	*Spec 9: 75% Percentile*
World Universe									
Lagged past risk	0.747*** (478.600)	0.749*** (393.657)	0.752*** (259.357)	0.860*** (495.934)	0.874*** (508.139)	0.897*** (397.484)	0.922*** (655.103)	0.931 *** (809.604)	0.940 *** (544.034)
Environmental	-0.008** (-2.011)	-0.023*** (-4.703)	-0.050*** (-6.085)	-0.001 (-0.491)	-0.010 *** (-3.934)	-0.025*** (-5.751)	0.001*** (-3.053)	-0.000 (0.932)	-0.001*** (-4.158)
Fixed E}ects	YES	YES	YES	YES	YES	YES	YES	YES	YES
World ex-US Universe									
Lagged past risk	0.734*** (431.857)	0.732*** (368.498)	0.730*** (236.369)	0.839*** (332.442)	0.852*** (357.109)	0.874*** (313.136)	0.967*** (519.661)	0.977*** (663.335)	0.987*** (415.708)
Environmental	-0.011* (-2.341)	-0.032*** (-5.228)	-0.066*** (-6.286)	-0.003 (-1.012)	-0.014*** (-3.870)	-0.030*** (-5.192)	0.000 (1.129)	-0.001* (-2.506)	-0.001*** (-4.811)
Fixed E}ects	YES	YES	YES	YES	YES	YES	YES	YES	YES
US Universe									
Lagged past risk	0.760*** (380.176)	0.771*** (353.401)	0.789*** (253.814)	0.810*** (190.315)	0.830*** (215.991)	0.862*** (211.639)	0.787*** (441.141)	0.800*** (579.981)	0.814*** (470.458)
Environmental	-0.0076 (-0.232)	-0.0181* (-2.424)	-0.0361** (-2.889)	0.0045 (0.240)	0.0018 (0.386)	-0.0024 (-0.344)	0.0008* (-2.883)	0.0002 (0.974)	-0.0003 (-0.704)
Fixed E}ects	YES	YES	YES	YES	YES	YES	YES	YES	YES

Exhibit D-2: Quantile Regression Specifications Analysing the Relationship Between Risk and Social Scores Across The Risk Spectrum

	TOTAL RISK			STOCK SPECIFIC RISK			MARKET BETA		
	Spec 1: 25% Percentile	*Spec 2: 50% Percentile*	*Spec 3: 75% Percentile*	*Spec 4: 25% Percentile*	*Spec 5: 50% Percentile*	*Spec 6: 75% Percentile*	*Spec 7: 25% Percentile*	*Spec 8: 50% Percentile*	*Spec 9: 75% Percentile*
World Universe									
Lagged past risk	0.760*** (380.176)	0.771*** (353.401)	0.789*** (253.814)	0.810*** (190.315)	0.830*** (215.991)	0.862*** (211.639)	0.787*** (441.141)	0.800*** (579.981)	0.814*** (470.458)
Social	-0.0076 (0.232)	-0.0181* (-2.424)	-0.0361** (-2.889)	0.0045 (0.240)	0.0018 (0.386)	-0.0024 (0.344)	0.0008 * (2.883)	0.0002 (0.974)	-0.0003 (0.704)
Fixed E}ects	YES	YES	YES	YES	YES	YES	YES	YES	YES
World ex-US Universe									
Lagged past risk	0.734*** (435.400)	0.732*** (362.214)	0.731*** (230.005)	0.839*** (335.166)	0.853*** (358.844)	0.875*** (312.815)	0.967*** (518.466)	0.977*** (659.784)	0.987*** (410.239)
Social	0.026*** (4.527)	0.014. (1.912)	-0.005 (0.430)	0.013*** (3.761)	0.006 (1.558)	-0.005 (-0.733)	-0.000 (0.446)	-0.000 (-0.908)	-0.000 (-1.033)
Fixed E}ects	YES	YES	YES	YES	YES	YES	YES	YES	YES
US Universe									
Lagged past risk	0.760*** (378.237)	0.771*** (353.263)	0.789*** (254.577)	0.810 *** (190.229)	0.831*** (216.164)	0.862*** (212.216)	0.786*** (439.592)	0.800*** (580.589)	0.814*** (470.928)
Social	0.054 *** (6.529)	0.045*** (4.543)	0.029. (1.773)	0.015** (3.068)	0.011* (2.043)	0.007 (0.753)	-0.000 (0.667)	-0.001* (-2.01)	-0.001** (-2.782)
Fixed E}ects	YES	YES	YES	YES	YES	YES	YES	YES	YES

Exhibit D-3: Quantile Regression Specifications Analysing the Relationship Between Risk and Governance Scores Across The Risk Spectrum

	TOTAL RISK			STOCK SPECIFIC RISK			MARKET BETA		
	Spec 1: 25% Percentile	*Spec 2: 50% Percentile*	*Spec 3: 75% Percentile*	*Spec 4: 25% Percentile*	*Spec 5: 50% Percentile*	*Spec 6: 75% Percentile*	*Spec 7: 25% Percentile*	*Spec 8: 50% Percentile*	*Spec 9: 75% Percentile*
World Universe									
Lagged past risk	0.747 ** (476.872)	0.749*** (394.492)	0.752*** (261.156)	0.859*** (493.919)	0.874*** (507.423)	0.897*** (400.073)	0.922*** (646.328)	0.931*** (813.293)	0.940*** (548.698)
Governance	-0.011** (-2.654)	-0.019*** (-3.550)	-0.032*** (-3.649)	-0.010*** (-3.292)	-0.017*** (-5.278)	-0.028*** (-5.735)	-0.000 (-1.108)	-0.001* (-2.444)	-0.001*** (-3.045)
Fixed E}ects	YES	YES	YES	YES	YES	YES	YES	YES	YES
World ex-US Universe									
Lagged past risk	0.734*** (429.788)	0.732*** (367.548)	0.730*** (236.624)	0.839*** (332.581)	0.853*** (357.401)	0.874*** (314.719)	0.967*** (515.320)	0.977*** (665.332)	0.987*** (417.101)
Governance	0.001 (0.270)	-0.007 (-1.011)	-0.020. (-1.775)	-0.004 (-1.000)	-0.012** (-2.771)	-0.024*** (-3.693)	0.000 (0.569)	-0.000 (-1.244)	-0.001** (-2.740)
Fixed E}ects	YES	YES	YES	YES	YES	YES	YES	YES	YES
US Universe									
Lagged past risk	0.760*** (378.237)	0.771*** (353.263)	0.789*** (254.577)	0.810*** (190.229)	0.831*** (216.164)	0.862*** (212.216)	0.786*** (439.592)	0.800*** (580.589)	0.814*** (470.928)
Governance	0.002 (0.324)	0.005 (0.589)	0.011 (0.675)	-0.014** (-2.923)	-0.013* (-2.352)	-0.012 (-1.416)	-0.000 (-0.114)	-0.000 (-1.335)	-0.001* (-2.173)
Fixed E}ects	YES	YES	YES	YES	YES	YES	YES	YES	YES

Exhibit D-4: Quantile Regression Specifications Analysing the Relationship Between Risk and Carbon Scores Across The Risk Spectrum

	TOTAL RISK			STOCK SPECIFIC RISK			MARKET BETA		
	Spec 1: 25% Percentile	*Spec 2: 50% Percentile*	*Spec 3: 75% Percentile*	*Spec 4: 25% Percentile*	*Spec 5: 50% Percentile*	*Spec 6: 75% Percentile*	*Spec 7: 25% Percentile*	*Spec 8: 50% Percentile*	*Spec 9: 75% Percentile*
World Universe									
Lagged past risk	0.747*** (476.951)	0.749*** (393.214)	0.752*** (259.503)	0.860*** (493.886)	0.874*** (506.833)	0.897*** (396.022)	0.922*** (651.976)	0.931*** (807.239)	0.940*** (539.303)
Carbon	-0.002 (-0.524)	-0.013** (-2.862)	-0.033*** (-4.342)	0.001 (0.607)	-0.007** (-2.745)	-0.020*** (-4.796)	0.000 (1.399)	-0.000** (-2.606)	-0.001*** (-5.228)
Fixed E}ects	YES	YES	YES	YES	YES	YES	YES	YES	YES
World ex-US Universe									
Lagged past risk	0.734*** (435.069)	0.732*** (362.844)	0.730*** (230.262)	0.839*** (331.443)	0.853*** (356.031)	0.874*** (310.598)	0.967*** (518.145)	0.977*** (657.466)	0.987*** (408.838)
Carbon	0.003 (0.593)	-0.010 (-1.650)	-0.029** (-2.916)	0.004 (1.429)	-0.004 (-1.105)	-0.016** (-2.760)	0.000 (0.362)	-0.001* (-2.409)	-0.001*** (-3.917)
Fixed E}ects	YES	YES	YES	YES	YES	YES	YES	YES	YES
US Universe									
Lagged past risk	0.760*** (378.237)	0.771*** (353.263)	0.789*** (254.577)	0.810*** (190.229)	0.831*** (216.164)	0.862*** (212.216)	0.786*** (439.592)	0.800*** (580.589)	0.814*** (470.928)
Carbon	-0.003 (-0.468)	-0.014* (-2.113)	-0.032** (-3.050)	0.005 (1.321)	-0.000 (-0.068)	-0.008 (-1.331)	0.001** (2.787)	0.000 (0.058)	-0.001** (-2.620)
Fixed E}ects	YES	YES	YES	YES	YES	YES	YES	YES	YES

Appendix 6-E: Sustainability and Risk in the Context of COVID-19

Exhibit E-1: Dynamic Fixed E}ects Regression Speci%cations Analysing the Relationship Between Risk and E Scores during COVID

	TOTAL RISK		STOCK SPECIFIC RISK		MARKET BETA	
	Spec 1: All Period	*Spec 2: With COVID Binary Variable*	*Spec 3: All Period*	*Spec 4: With COVID Binary Variable*	*Spec 5: All Period*	*Spec 6: With COVID Binary Variable*
World Universe						
Lagged past risk	0.873*** (27.697)	0.828*** (17.900)	0.939*** (106.716)	0.932*** (77.003)	0.954*** (89.772)	0.956*** (93.963)
COVID		2.990* (2.219)		0.778. (1.877)		0.003 (0.351)
COVID × Environmental		-0.088 (-1.449)		-0.030 (-1.223)		-0.001 (-1.068)
Environmental	-0.030. (1.969)	-0.028* (-2.190)	-0.016* (2.289)	-0.013* (-2.376)	-0.000 (-0.309)	0.000 (0.224)
Adj R^2	*87.32%*	*88.13%*	*94.51%*	*94.69%*	*93.22%*	*93.38%*
World ex US Universe						
Lagged past risk	0.880*** (31.175)	0.823*** (18.121)	0.941*** (119.129)	0.930*** (83.228)	0.961*** (114.462)	0.961*** (114.308)
COVID		3.339* (2.393)		0.981* (2.375)		-0.007 (-1.614)
COVID × Environmental		-0.059 (1.374)		-0.032. (-1.881)		0.001 (0.702)
Environmental	-0.044* (-2.400)	-0.072** (3.099)	-0.021** (-2.646)	-0.023** (2.779)	-0.000 (1.547)	-0.001. (-1.717)
Adj R^2	*86.06%*	*87.16%*	*93.95%*	*94.09%*	*93.97%*	*93.97%*
US Universe						
Lagged past risk	0.879*** (31.730)	0.772*** (13.249)	0.917*** (72.144)	0.885*** (39.650)	0.947*** (62.802)	0.947*** (62.903)
COVID		5.322* (2.393)		1.510. (1.874)		0.003 (0.153)
COVID × Environmental		-0.092 (1.345)		-0.004 (0.125)		-0.000 (0.461)
Environmental	-0.025* (-2.056)	-0.024 (1.311)	0.034 (0.604)	-0.002 (0.231)	0.002 (0.677)	0.000 (0.737)
Adj R^2	*88.51%*	*88.60%*	*92.61%*	*92.26%*	*92.24%*	*92.24%*

Exhibit E-2: Dynamic Fixed Effects Regression Specifications Analysing the Relationship Between Risk and S Scores during COVID

	TOTAL RISK		STOCK SPECIFIC RISK		MARKET BETA	
	Spec 1: All Period	*Spec 2: With COVID Binary Variable*	*Spec 3: All Period*	*Spec 4: With COVID Binary Variable*	*Spec 5: All Period*	*Spec 6: With COVID Binary Variable*
World Universe						
Lagged past risk	0.873*** (27.840)	0.829*** (0.046)	0.939*** (108.046)	0.932*** (77.189)	0.954*** (89.835)	0.956*** (93.439)
COVID		3.164* (2.196)		0.819* (1.986)		0.015 (1.330)
COVID × Social		-0.141 (-1.560)		-0.044 (-1.549)		-0.003* (-2.156)
Social	0.011 (0.692)	0.004 (0.307)	-0.003 (0.500)	-0.003 (0.545)	-0.000 (1.093)	0.000 (1.220)
Adj R^2	*87.30%*	*88.10%*	*94.50%*	*94.70%*	*93.20%*	*93.40%*
World ex US Universe						
Lagged past risk	0.880*** (31.412)	0.825*** (18.250)	0.941*** (120.944)	0.931*** (83.228)	0.961*** (114.315)	0.961*** (114.334)
COVID		3.356* (2.409)		0.950* (2.366)		0.003 (0.510)
COVID × Social		-0.076 (-1.510)		-0.033. (-1.817)		-0.001 (-1.199)
Social	0.009 (0.618)	-0.029 (-1.365)	0.002 (0.261)	-0.005 (-0.632)	-0.000 (-0.475)	0.000 (0.536)
Adj R^2	*86.05%*	*87.14%*	*93.95%*	*94.08%*	*93.97%*	*93.97%*
US Universe						
Lagged past risk	0.878*** (31.748)	0.772*** (13.229)	0.917*** (72.078)	0.884*** (39.521)	0.947*** (62.849)	0.946*** (62.006)
COVID		5.732* (2.327)		1.712* (2.074)		0.022 (0.831)
COVID × Social		-0.196. (1.497)		-0.047 (1.247)		-0.005. (1.570)
Social	0.045* (2.310)	0.019 (0.845)	0.012 (1.355)	-0.006 (0.554)	-0.001 (-1.143)	0.001 (1.172)
Adj R^2	*86.90%*	*88.51%*	*92.30%*	*92.61%*	*92.20%*	*92.24%*

Exhibit E-3: Dynamic Fixed Eﬀects Regression Speciﬁcations Analysing the Relationship Between Risk and G Scores during COVID

	TOTAL RISK		STOCK SPECIFIC RISK		MARKET BETA	
	Spec 1: All Period	*Spec 2: With COVID Binary Variable*	*Spec 3: All Period*	*Spec 4: With COVID Binary Variable*	*Spec 5: All Period*	*Spec 6: With COVID Binary Variable*
World Universe						
Lagged past risk	0.873*** (27.846)	0.828*** (18.125)	0.939*** (109.000)	0.932*** (79.271)	0.954*** (89.475)	0.956*** (93.802)
COVID		1.579** (2.707)		0.419** (2.702)		-0.004 (0.707)
COVID × Governance		0.155 (1.572)		0.031 (0.928)		0.001 (0.420)
Governance	-0.015 (-0.573)	-0.056. (-1.843)	-0.019* (-1.977)	-0.027* (-2.525)	-0.001. (-1.655)	-0.001. (1.769)
Adj R^2	*87.31%*	*88.12%*	*94.51%*	*94.69%*	*93.22%*	*93.38%*
World ex US Universe						
Lagged past risk	0.880*** (31.464)	0.823*** (18.124)	0.941*** (121.697)	0.930*** (83.229)	0.961*** (113.994)	0.961*** (114.026)
COVID		2.108** (2.887)		0.744** (3.357)		-0.011. (-1.954)
COVID × Governance		0.154 (1.643)		0.007 (0.243)		0.001 (1.106)
Governance	-0.012 (0.592)	-0.098* (-2.493)	-0.018* (-2.135)	-0.033** (-2.730)	-0.001 (1.305)	-0.001 (1.384)
Adj R^2	*86.05%*	*87.16%*	*93.95%*	*94.09%*	*93.97%*	*93.97%*
US Universe						
Lagged past risk	0.879*** (31.758)	0.773*** (13.386)	0.917*** (72.145)	0.885*** (39.875)	0.947*** (62.849)	0.947*** (62.933)
COVID		4.648* (2.505)		1.225. (1.958)		-0.000 (0.016)
COVID × Governance		0.029 (0.325)		0.047 (1.218)		0.000 (0.048)
Governance	0.010 (0.213)	-0.027 (-0.698)	-0.013 (-0.683)	-0.033* (2.187)	-0.001 (-1.143)	-0.000 (0.898)
Adj R^2	*88.50%*	*88.58%*	*92.26%*	*92.61%*	*92.24%*	*92.24%*

Exhibit E-4: Dynamic Fixed Effects Regression Specifications Analysing the Relationship Between Risk and Carbon Scores during COVID

	TOTAL RISK		STOCK SPECIFIC RISK		MARKET BETA	
	Spec 1: All Period	*Spec 2: With COVID Binary Variable*	*Spec 3: All Period*	*Spec 4: With COVID Binary Variable*	*Spec 5: All Period*	*Spec 6: With COVID Binary Variable*
World Universe						
Lagged past risk	0.873*** (27.813)	0.828*** (17.846)	0.939*** (107.362)	0.932*** (76.558)	0.954*** (89.757)	0.956*** (94.028)
COVID		3.500* (2.260)		0.995. (1.976)		0.010 (0.986)
COVID × Carbon		-0.134. (-1.828)		-0.052. (-1.667)		-0.001. (1.778)
Carbon	-0.016 (1.581)	-0.002 (0.167)	-0.011. (1.776)	-0.003 (0.649)	-0.000 (1.312)	0.000 (0.006)
Adj R^2	*87.31%*	*88.14%*	*94.51%*	*94.69%*	*93.22%*	*93.38%*
World ex US Universe						
Lagged past risk	0.880*** (31.428)	0.824*** (18.255)	0.941*** (120.552)	0.930*** (82.881)	0.961*** (114.247)	0.961*** (114.308)
COVID		3.653* (2.386)		1.097* (2.275)		-0.002 (-0.386)
COVID × Carbon		-0.087. (1.718)		-0.040. (1.815)		-0.000 (-0.446)
Carbon	-0.016 (-1.417)	-0.034* (-2.437)	-0.009 (1.301)	-0.010 (-1.539)	-0.000 (-1.610)	-0.000 (-1.055)
Adj R^2	*86.05%*	*87.15%*	*93.95%*	*94.09%*	*93.97%*	*93.97%*
US Universe						
Lagged past risk	0.879*** (31.775)	0.771*** (13.097)	0.917*** (72.178)	0.884*** (39.093)	0.947*** (62.786)	0.947*** (62.834)
COVID		5.887* (2.370)		1.781. (1.905)		0.008 (0.396)
COVID × Carbon		-0.153. (-1.677)		-0.042 (1.000)		-0.001 (0.983)
Carbon	-0.020. (-1.827)	-0.006 (-0.287)	-0.004 (-0.633)	0.000 (0.022)	0.000 (-0.015)	0.000 (0.661)
Adj R^2	*86.90%*	*88.53%*	*92.26%*	*92.61%*	*92.24%*	*92.24%*

Appendix 6-F: Sustainability and Forward Risk

Exhibit F-1: Dynamic Fixed E}ects Regression Speci%cations Analysing the Relationship Between Forward Risk and E Scores

	TOTAL RISK		STOCK SPECIFIC RISK		MARKET BETA	
	Spec 1: 6 month forward risk	*Spec 2: 1 year forward risk*	*Spec 3: 6 month forward risk*	*Spec 4: 12 month forward risk*	*Spec 5: 6 month forward risk*	*Spec 6: 12 month forward risk*
World Universe						
Lagged past risk	0.895*** (21.706)	0.666*** (21.555)	0.942*** (72.579)	0.821*** (61.885)	0.409*** (33.118)	0.380*** (31.030)
Environmental	-0.043. (-1.825)	-0.092*** (-3.545)	-0.020* (-2.027)	-0.054*** (-3.880)	-0.004*** (-4.973)	-0.005*** (-4.723)
Adj R^2	*76.10%*	*70.00%*	*89.40%*	*80.70%*	*69.00%*	*62.20%*
World ex US Universe						
Lagged past risk	0.883*** (21.14)	0.675*** (21.71)	0.929*** (75.64)	0.675*** (21.71)	0.377*** (34.43)	0.349*** (28.60)
Environmental	-0.039 (-1.43)	-0.109*** (-3.57)	-0.016 (-1.43)	-0.063*** (-3.53)	-0.006*** (-5.74)	-0.007*** (-5.95)
Adj R^2	*73.10%*	*65.80%*	*88.40%*	*65.80%*	*68.90%*	*59.70%*
US Universe						
Lagged past risk	0.940*** (22.654)	0.635*** (23.086)	0.919*** (37.889)	0.755*** (32.734)	0.433*** (21.826)	0.376*** (22.232)
Environmental	-0.063* (-2.169)	-0.108** (-2.812)	-0.040** (-2.750)	-0.057* (-2.237)	-0.004** (-2.575)	-0.005** (-2.760)
Adj R^2	*74.20%*	*71.90%*	*83.90%*	*77.30%*	*67.00%*	*64.00%*

Exhibit F-2: Dynamic Fixed E}ects Regression Speci%cations Analysing the Relationship Between Forward Risk and S Scores

	TOTAL RISK		STOCK SPECIFIC RISK		MARKET BETA	
	Spec 1: 6 month forward risk	*Spec 2: 1 year forward risk*	*Spec 3: 6 month forward risk*	*Spec 4: 12 month forward risk*	*Spec 5: 6 month forward risk*	*Spec 6: 12 month forward risk*
World Universe						
Lagged past risk	0.896*** (21.835)	0.667*** (21.702)	0.943*** (73.250)	0.822*** (62.210)	0.410*** (33.138)	0.381*** (31.085)
Social	0.037 (1.642)	0.009 (0.313)	0.004 (0.431)	-0.021 (-1.454)	-0.001 (-0.840)	-0.000 (-0.224)
Adj R^2	*76.10%*	*69.90%*	*89.40%*	*80.70%*	*68.90%*	*62.10%*
World ex US Universe						
Lagged past risk	0.883*** (21.31)	0.676*** (22.08)	0.929*** (76.55)	0.676*** (22.08)	0.378*** (34.26)	0.351*** (28.50)
Social	0.009 (0.47)	0.013 (0.38)	-0.005 (-0.51)	-0.012 (-0.66)	-0.001 (-0.64)	-0.001 (-0.53)
Adj R^2	*73.10%*	*65.80%*	*88.40%*	*65.80%*	*68.70%*	*59.50%*
US Universe						
Lagged past risk	0.940*** (22.720)	0.635*** (23.238)	0.920*** (38.014)	0.755*** (32.946)	0.433*** (21.822)	0.377*** (22.275)
Social	0.086. (1.901)	0.148** (3.022)	0.021 (1.071)	0.038 (1.364)	0.001 (0.937)	0.001 (0.589)
Adj R^2	*74.20%*	*71.90%*	*83.90%*	*77.30%*	*67.00%*	*64.00%*

Exhibit F-3: Dynamic Fixed E}ects Regression Speci%cations Analysing the Relationship Between Forward Risk and G Scores

	TOTAL RISK		STOCK SPECIFIC RISK		MARKET BETA	
	Spec 1: 6 month forward risk	*Spec 2: 1 year forward risk*	*Spec 3: 6 month forward risk*	*Spec 4: 12 month forward risk*	*Spec 5: 6 month forward risk*	*Spec 6: 12 month forward risk*
World Universe						
Lagged past risk	0.896*** (21.945)	0.667*** (21.677)	0.943*** (74.244)	0.821*** (62.823)	0.408*** (33.088)	0.379*** (30.985)
Governance	0.004 (0.101)	0.011 (0.261)	0.005 (0.334)	-0.032. (-1.714)	-0.006*** (-6.170)	-0.005*** (-5.026)
Adj R^2	*76.10%*	*69.90%*	*89.40%*	*80.70%*	*69.10%*	*62.30%*
World ex US Universe						
Lagged past risk	0.884*** (21.39)	0.676*** (22.04)	0.930*** (77.45)	0.676*** (22.04)	0.376*** (34.23)	0.349*** (28.37)
Governance	0.046 (1.35)	-0.019 (-0.47)	0.022 (1.58)	-0.039. (-1.73)	-0.005*** (-4.11)	-0.005*** (-3.67)
Adj R^2	*73.10%*	*65.80%*	*88.40%*	*65.80%*	*68.70%*	*59.60%*
US Universe						
Lagged past risk	0.941*** (22.748)	0.636*** (23.183)	0.920*** (38.073)	0.756*** (32.920)	0.432*** (21.944)	0.376*** (22.332)
Governance	0.083 (1.073)	-0.016 (-0.237)	0.040 (1.200)	-0.062 (-1.551)	-0.007*** (-3.395)	-0.006** (3.107)
Adj R^2	*74.20%*	*71.90%*	*83.90%*	*77.30%*	*67.00%*	*64.00%*

Exhibit F-4 Dynamic Fixed Effects Regression Specifications Analysing the Relationship Between Forward Risk and Carbon Scores

	TOTAL RISK		STOCK SPECIFIC RISK		MARKET BETA	
	Spec 1: 6 month forward risk	*Spec 2: 1 year forward risk*	*Spec 3: 6 month forward risk*	*Spec 4: 12 month forward risk*	*Spec 5: 6 month forward risk*	*Spec 6: 12 month forward risk*
World Universe						
Lagged past risk	0.896*** (21.807)	0.667*** (21.681)	0.942*** (72.873)	0.821*** (62.132)	0.410*** (33.185)	0.381*** (31.119)
Carbon	-0.031. (-1.898)	-0.071** (-3.138)	-0.021* (-2.344)	-0.052*** (-3.801)	-0.003*** (-4.028)	-0.003*** (-3.723)
Adj R^2	*76.10%*	*69.90%*	*89.40%*	*80.70%*	*69.00%*	*62.20%*
World ex US Universe						
Lagged past risk	0.883*** (21.31)	0.674*** (21.71)	0.929*** (76.55)	0.676*** (22.09)	0.378*** (28.56)	0.351*** (28.56)
Carbon	-0.021 (-1.33)	-0.052* (-2.61)	-0.016 (-0.80)	-0.051. (-1.95)	-0.004*** (-3.79)	-0.004*** (-3.79)
Adj R^2	*73.10%*	*65.80%*	*88.40%*	*65.80%*	*59.80%*	*59.50%*
US Universe						
Lagged past risk	0.941*** (22.751)	0.636*** (23.202)	0.920*** (38.008)	0.755*** (32.849)	0.433*** (21.837)	0.377*** (22.225)
Carbon	-0.022 (0.963)	-0.079** (2.647)	-0.017 (1.269)	-0.061** (2.978)	-0.004** (3.199)	-0.005** (3.330)
Adj R^2	*74.20%*	*71.90%*	*83.90%*	*77.30%*	*67.00%*	*64.00%*

Exhibit F-3: Dynamic Fixed Effects Regression Specifications Analysing the Relationship Between Forward Risk and G Scores

	TOTAL RISK		STOCK SPECIFIC RISK		MARKET BETA	
	Spec 1: 6 month forward risk	*Spec 2: 1 year forward risk*	*Spec 3: 6 month forward risk*	*Spec 4: 12 month forward risk*	*Spec 5: 6 month forward risk*	*Spec 6: 12 month forward risk*
World Universe						
Lagged past risk	0.896*** (21.945)	0.667*** (21.677)	0.943*** (74.244)	0.821*** (62.823)	0.408*** (33.088)	0.379*** (30.985)
Governance	0.004 (0.101)	0.011 (0.261)	0.005 (0.334)	-0.032. (-1.714)	-0.006*** (-6.170)	-0.005*** (-5.026)
Adj R^2	*76.10%*	*69.90%*	*89.40%*	*80.70%*	*69.10%*	*62.30%*
World ex US Universe						
Lagged past risk	0.884*** (21.39)	0.676*** (22.04)	0.930*** (77.45)	0.676*** (22.04)	0.376*** (34.23)	0.349*** (28.37)
Governance	0.046 (1.35)	-0.019 (-0.47)	0.022 (1.58)	-0.039. (-1.73)	-0.005*** (-4.11)	-0.005*** (-3.67)
Adj R^2	*73.10%*	*65.80%*	*88.40%*	*65.80%*	*68.70%*	*59.60%*
US Universe						
Lagged past risk	0.941*** (22.748)	0.636*** (23.183)	0.920*** (38.073)	0.756*** (32.920)	0.432*** (21.944)	0.376*** (22.332)
Governance	0.083 (1.073)	-0.016 (-0.237)	0.040 (1.200)	-0.062 (-1.551)	-0.007*** (-3.395)	-0.006** (3.107)
Adj R^2	*74.20%*	*71.90%*	*83.90%*	*77.30%*	*67.00%*	*64.00%*

Exhibit F-4 Dynamic Fixed Effects Regression Specifications Analysing the Relationship Between Forward Risk and Carbon Scores

	TOTAL RISK		STOCK SPECIFIC RISK		MARKET BETA	
	Spec 1: 6 month forward risk	*Spec 2: 1 year forward risk*	*Spec 3: 6 month forward risk*	*Spec 4: 12 month forward risk*	*Spec 5: 6 month forward risk*	*Spec 6: 12 month forward risk*
World Universe						
Lagged past risk	0.896*** (21.807)	0.667*** (21.681)	0.942*** (72.873)	0.821*** (62.132)	0.410*** (33.185)	0.381*** (31.119)
Carbon	-0.031. (-1.898)	-0.071** (-3.138)	-0.021* (-2.344)	-0.052*** (-3.801)	-0.003*** (-4.028)	-0.003*** (-3.723)
Adj R^2	*76.10%*	*69.90%*	*89.40%*	*80.70%*	*69.00%*	*62.20%*
World ex US Universe						
Lagged past risk	0.883*** (21.31)	0.674*** (21.71)	0.929*** (76.55)	0.676*** (22.09)	0.378*** (28.56)	0.351*** (28.56)
Carbon	-0.021 (-1.33)	-0.052* (-2.61)	-0.016 (-0.80)	-0.051. (-1.95)	-0.004*** (-3.79)	-0.004*** (-3.79)
Adj R^2	*73.10%*	*65.80%*	*88.40%*	*65.80%*	*59.80%*	*59.50%*
US Universe						
Lagged past risk	0.941*** (22.751)	0.636*** (23.202)	0.920*** (38.008)	0.755*** (32.849)	0.433*** (21.837)	0.377*** (22.225)
Carbon	-0.022 (0.963)	-0.079** (2.647)	-0.017 (1.269)	-0.061** (2.978)	-0.004** (3.199)	-0.005** (3.330)
Adj R^2	*74.20%*	*71.90%*	*83.90%*	*77.30%*	*67.00%*	*64.00%*

7 Concluding Remarks

7.1 Conclusion

This thesis set out to examine the interplay between sustainability metrics and both fund performance and financial risk, contributing to a rapidly evolving literature on ESG investing. Two complementary strands of analysis were pursued. First, Chapter 1 explored whether sustainability systematically aligns with established equity risk factors and whether ESG characteristics enhance fund returns. Second, Chapter 2 scrutinised the relationship between ESG and financial risk at the stock level, employing robust econometric techniques, including a two-stage least squares (2SLS) framework, to address endogeneity concerns.

Although at first sight the conclusions of Chapters 1 and 2 might appear contradictory, they are not. Chapter 1 demonstrates that high governance scores correlate with enhanced fund-level alpha, whereas the overall ESG profile exhibits minimal or inconsistent links to defensive factor exposures. Chapter 2, by contrast, does not find a robust relationship between governance and financial risk once rigorous controls for endogeneity are applied.

In reconciling these findings, several factors emerge: (1) The governance dimensions that drive fund-level alpha may capture aspects of corporate oversight and managerial decisions that go beyond the passive 'building blocks' employed in standard risk models. By contrast, in the stock-level risk analysis of Chapter 2, some governance effects may already be subsumed in fundamental controls—such as earnings quality or firm size—thus reducing governance's direct explanatory power. (2) The contrast between fund-level and stock-level analyses is equally important. Fund managers, through active selection and weighting of companies, may exploit governance characteristics to generate alpha in a way that is not reflected in a straightforward regression of stock-level risk on governance scores, in which the weights of stocks are not adjusted dynamically. In such a setting, systemic or macroeconomic factors could overshadow firm-specific governance effects, especially during highly volatile periods. Consequently, the governance elements that contribute to alpha in Chapter 1 need not necessarily manifest as a significant reduction in total or idiosyncratic risk at the stock level in Chapter 2. (3) Far from being contradictory, these results highlight the dimension-specific impacts of ESG: governance can matter for alpha generation without functioning as a universal hedge against broader financial risk.

7.2 Key Findings

The findings across the two chapters collectively challenge several widespread assumptions in both academic and practitioner circles:

1. Defensive Factor Alignment: Contrary to earlier studies suggesting that ESG—particularly environmental and social dimensions—aligns with so-called 'defensive' factors (e.g., low-volatility or quality), this thesis demonstrates that once factor exposures and methodological rigour are accounted for, ESG scores do not exhibit consistent defensive properties. At the fund level, market beta emerges as the dominant driver of returns; moreover, disaggregated analysis reveals that funds with higher environmental or social scores tilt more towards momentum, rather than low volatility.

2. Governance and Fund Performance: Governance shows a nuanced but meaningful effect on performance, particularly through alpha generation in the mid-to-upper percentiles of fund returns. This contrasts with much of the literature that treats ESG as a monolithic construct. The results here underscore the specificity of governance as the most influential dimension for

3. fund-level outperformance, consistent with prior research highlighting governance's critical role in reducing agency conflicts (Gompers, Ishii, and Metrick 2003).

4. ESG and Financial Risk at the Firm Level: The more rigorous 2SLS approach employed in Chapter 2 dramatically diminishes previously observed correlations between ESG and reduced financial risk. Once endogeneity is accounted for, broad ESG scores largely lose their statistical significance in explaining total, idiosyncratic, or market risk, with coefficients often shrinking by orders of magnitude. The study's results do not discount the possibility that ESG, particularly governance, may have a latent long-term effect on corporate resilience, but they do caution against interpreting short-to-medium-term correlations as evidence of strong risk mitigation.

7.3 Policy Implications

From a policy perspective, these findings offer several insights:

1. Refinement of Regulatory Focus: Given that aggregate ESG scores do not reliably mitigate financial risk, regulators might consider placing greater emphasis on corporate governance standards. This thesis highlights governance as the most influential dimension for enhancing fund-level alpha and potentially improving long-term operational stability. Further strengthening mandatory disclosures around board composition, executive remuneration, and shareholder rights could be more impactful than broad ESG reporting requirements.

2. Caution in Obligating ESG Disclosure as a Risk Tool: Policymakers and industry bodies, such as the Task Force on Climate-related Financial Disclosures (TCFD) and under the EU Sustainable Finance Disclosure Regulation (SFDR), have often promoted ESG disclosure as a

means to reduce systemic and idiosyncratic risk. However, while greater transparency can improve stakeholder trust, the empirical evidence suggests that these disclosures do not necessarily translate into significant near-term risk mitigation. Factors such as macroeconomic conditions or firm-specific shocks may overshadow any immediate risk-reduction benefits, particularly in volatile periods. Consequently, policymakers should be circumspect in framing ESG policies primarily as tools for immediate risk reduction, focusing instead on transparency, stakeholder accountability, and longer-horizon benefits of robust governance and environmental initiatives.

3. Supporting Standardisation: Persistent divergences in ESG scoring methodologies underscore the challenges faced by both investors and regulators in drawing reliable conclusions from sustainability ratings. Notably, the European Commission has taken steps to regulate ESG rating agencies, aiming to increase the reliability and comparability of ESG data and reduce the "noise" that arises from divergent assessment methods[16]. While greater standardisation alone may not transform ESG into a powerful short-term risk-mitigation mechanism, it could enhance the overall utility of ESG data—particularly governance information—which has shown more tangible performance implications in the long run.

4. Longer-Term Horizons: The nuanced role of environmental and carbon-transition initiatives suggests that any material risk or return benefits may only manifest over extended periods. Policymakers might consider aligning disclosure and reporting standards with longer-term objectives, acknowledging that short-term analyses may underestimate the ultimate effects of sustainability practices, particularly in the environmental domain. Although the short- to medium-term impact of ESG on risk and return appears limited, future research and policy initiatives could explore whether these relationships strengthen over extended time horizons.

7.4 Overall Contribution

Overall, this thesis contributes to the ESG literature by employing a more comprehensive analytical toolkit—spanning holdings-based factor attribution, dynamic return analysis, and more advanced econometric methods—to attempt to isolate the genuine effect of sustainability on both performance and risk. It finds that the often-touted defensive qualities of ESG are neither as universal nor as robust as previously claimed. Governance emerges as a notable exception, exhibiting a measurable and statistically significant relationship with alpha generation, especially for mid-to-high-performing funds.

[16] https://www.consilium.europa.eu/en/press/press-releases/2024/11/19/environmental-social-and-governance-esg-ratings-council-greenlights-new-regulation/

Yet, these findings do not entirely discount the potential of sustainability to foster long-term corporate resilience; rather, they caution against overreliance on broad ESG scores as immediate, systematic determinants of either excess returns or reduced volatility.

Future research should explore longer time horizons, different rating providers, and varying regional contexts to gain further clarity on the subtle, and potentially slow-burn, impact of environmental and social dimensions. Likewise, as disclosure standards evolve, it will be instructive to re-examine whether improved data quality and standardisation alter the conclusions drawn here. By laying bare the complexities and conditionalities of ESG's role in financial performance and risk mitigation, this thesis provides a foundation for both policymakers and investors seeking to integrate sustainability considerations in a more targeted and empirically grounded manner.

References

Achen, C. (2000) *Why Lagged Dependent Variables Can Suppress the Explanatory Power of Other Independent Variables*. University of Michigan.

Albuquerque, R., Koskinen, Y., Yang, S. and Zhang, C. (2020) *Resiliency of Environmental and Social Stocks: An Analysis of the Exogenous COVID-19 Market Crash*. The Review of Corporate Finance Studies, 9(3), pp. 593–621. doi:10.1093/rcfs/cfaa011.

Alzayed, N., Eskandari, R., Eshraghi, A. and Yazdifar, H. (2024) *Revisiting Corporate Governance and Financial Risk-Taking*. International Journal of Finance & Economics, 29(4), pp. 4787–4812. doi:10.1002/ijfe.2896.

Arellano, M. and Bond, S. (1991) *Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations*. The Review of Economic Studies, 58(2), pp. 277–297. doi:10.2307/2297968.

Baker McKenzie, Principles for Responsible Investment. (2017) *Recommendations of the Task Force on Climate-Related Financial Disclosures*. Available at: https://www.unpri.org/download?ac=4308.

Barber, B. M., Morse, A. and Yasuda, A. (2021) *Impact Investing*. Journal of Financial Economics, 139(1), pp. 162–185. doi:10.1016/j.jfineco.2020.07.008.

Bax, K., Sahin, Ö., Czado, C. and Paterlini, S. (2023) *ESG, Risk, and (Tail) Dependence*. International Review of Financial Analysis, 87(May), p. 102513. doi:10.1016/j.irfa.2023.102513.

Beasley, M. S., Clune, R. and Hermanson, D. R. (2005) *Enterprise Risk Management: An Empirical Analysis of Factors Associated with the Extent of Implementation*. Journal of Accounting and Public Policy, 24(6), pp. 521–531. doi:10.1016/j.jaccpubpol.2005.10.001.

Bebchuk, L. A., Cohen, A. and Wang, C. C. Y. (2013) *Learning and the Disappearing Association between Governance and Returns*. Journal of Financial Economics, 108(2), pp. 323–348. doi:10.1016/j.jfineco.2012.10.004.

Berg, F., Heeb, F. and Kölbel, J. (2022) *The Economic Impact of ESG Ratings*. SSRN Electronic Journal. doi:10.2139/ssrn.4088545.

Berg, F., Kolbel, J. F. and Rigobon, R. (2022) *Aggregate Confusion: The Divergence of ESG Ratings*. Review of Finance, May, rfac033. doi:10.1093/rof/rfac033.

Bernow, S., Klempner, B. and Magnin, C. (2017) *From Why to Why Not: Sustainable Investing as the New Normal*. McKinsey.

Bhagat, S. and Bolton, B. (2008) *Corporate Governance and Firm Performance*. Journal of Corporate Finance, 14(3), pp. 257–273. doi:10.1016/j.jcorpfin.2008.03.006.

Blundell, R. and Bond, S. (1998) *Initial Conditions and Moment Restrictions in Dynamic Panel Data Models*. Journal of Econometrics, 87(1), pp. 115–143. doi:10.1016/S0304-4076(98)00009-8.

Blundell, R. and Bond, S. (2023) *Initial Conditions and Blundell–Bond Estimators*. Journal of Econometrics, 234(March), pp. 101–110. doi:10.1016/j.jeconom.2023.01.020.

Brennan, M. J., Chordia, T. and Subrahmanyam, A. (1998) *Alternative Factor Specifications, Security Characteristics, and the Cross-Section of Expected Stock Returns*. Journal of Financial Economics, 49(3), pp. 345–373. doi:10.1016/S0304-405X(98)00028-2.

Broadstock, D. C., Chan, K., Cheng, L. T. W. and Wang, X. (2021) *The Role of ESG Performance during Times of Financial Crisis: Evidence from COVID-19 in China*. Finance Research Letters, 38, p. 101716. doi:10.1016/j.frl.2020.101716.

Capelle-Blancard, G. and Petit, A. (2019) *Every Little Helps? ESG News and Stock Market Reaction*. Journal of Business Ethics, 157(2), pp. 543–565. doi:10.1007/s10551-017-3667-3.

Carhart, M. M. (1997) *On Persistence in Mutual Fund Performance*. The Journal of Finance, 52(1), pp. 57–82. doi:10.1111/j.1540-6261.1997.tb03808.x.

Cremers, K. J. M. and Nair, V. B. (2005) *Governance Mechanisms and Equity Prices*. The Journal of Finance, 60(6), pp. 2859–2894. doi:10.1111/j.1540-6261.2005.00819.x.

Clarke, R., de Silva, H. and Thorley, S. (2005) *Performance Attribution and the Fundamental Law*. Financial Analysts Journal, 61(5), pp. 70–83. doi:10.2469/faj.v61.n5.2758.

Clubb, R., Takahashi, Y. and Tiburzio, P. (2016) *Evaluating the Relationship Between ESG and Corporate Quality*. MIT Management Sloan School.

Dekhayser, J. and Lawrence, E. (2020) *Using-Quality-and-Esg-to-Enhance-Returns*. Northern Trust Asset Management.

Devalle, A., Fiandrino, S. and Cantino, V. (2017) *The Linkage between ESG Performance and Credit Ratings: A Firm-Level Perspective Analysis*. International Journal of Business and Management, 12(9), p. 53. doi:10.5539/ijbm.v12n9p53.

Dunn, J., Fitzgibbons, S. and Pomorski, L. (2018) *Assessing Risk Through Environmental, Social and Governance Exposures*. Journal of Investment Management, 16(1).

Eccles, R. G., Ioannou, I. and Serafeim, G. (2014) *The Impact of Corporate Sustainability on Organizational Processes and Performance*. Management Science, 60(11), pp. 2835–2857. doi:10.1287/mnsc.2014.1984.

El Ghoul, S. and Karoui, A. (2017) *Does Corporate Social Responsibility Affect Mutual Fund Performance and Flows?* Journal of Banking & Finance, 77(April), pp. 53–63. doi:10.1016/j.jbankfin.2016.10.009.

Engle, R. F. (1982) *Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation*. Econometrica, 50(4), p. 987. doi:10.2307/1912773.

Fama, E. F. and French, K. R. (1993) *Common Risk Factors in the Returns on Stocks and Bonds*. Journal of Financial Economics, 33(1), pp. 3–56. doi:10.1016/0304-405X(93)90023-5.

Ferson, W. E. and Harvey, C. R. (1991) *The Variation of Economic Risk Premiums*. Journal of Political Economy, 99(2), pp. 385–415. doi:10.1086/261755.

Filbeck, A., Filbeck, G. and Zhao, X. (2019) *Performance Assessment of Firms Following Sustainalytics ESG Principles*. The Journal of Investing, 28(2), pp. 7–20. doi:10.3905/joi.2019.28.2.007.

Friede, G., Busch, T. and Bassen, A. (2015) *ESG and Financial Performance: Aggregated Evidence from More than 2000 Empirical Studies*. Journal of Sustainable Finance & Investment, 5(4), pp. 210–233. doi:10.1080/20430795.2015.1118917.

Giese, G., Lee, L. E., Melas, D., Nagy, Z. and Nishikawa, L. (2019) *Foundations of ESG Investing: How ESG Affects Equity Valuation, Risk, and Performance*. The Journal of Portfolio Management, 45(5), pp. 69–83. doi:10.3905/jpm.2019.45.5.069.

Gompers, P., Ishii, J. and Metrick, A. (2003) *Corporate Governance and Equity Prices*. The Quarterly Journal of Economics, 118(1), pp. 107–156. doi:10.1162/00335530360535162.

Grinold, R. C. and Kahn, R. N. (2000) *Active Portfolio Management: A Quantitative Approach for Producing Superior Returns and Controlling Risk*. 2nd ed. New York: McGraw-Hill.

Hartzmark, S. M. and Sussman, A. B. (2019) *Do Investors Value Sustainability? A Natural Experiment Examining Ranking Changes in ESG Ratings*. Working Paper. University of Chicago. doi:10.2139/ssrn.3016092.

Hermalin, B. E. and Weisbach, M. S. (2003) *Boards of Directors as an Endogenously Determined Institution: A Survey of the Economic Literature*. Economic Policy Review, 9(1), pp. 7–26.

Hoepner, A. G. F. (2010) *Portfolio Diversification and Environmental, Social or Governance Criteria: Must Responsible Investments Really Be Poorly Diversified?* SSRN Electronic Journal. doi:10.2139/ssrn.1599334.

Huang, Y. (2024) *Do ESG ETFs Provide Downside Risk Protection during Covid-19? Evidence from Forecast Combination Models*. International Review of Financial Analysis, 94(July), p. 103320. doi:10.1016/j.irfa.2024.103320.

IEMA. (2020) *ESG Factors Now Top Priority for Millennial Investors - IEMA*. Available at: https://www.iema.net/articles/esg-factors-now-top-priority-for-millennial-investors.

Jensen, M. C. and Meckling, W. H. (1976) *Theory of the Firm: Managerial Behavior, Agency Costs and Ownership Structure*. Journal of Financial Economics, 3(4), pp. 305–360. doi:10.1016/0304-405X(76)90026-X.

Judson, R. A. and Owen, A. L. (1999) *Estimating Dynamic Panel Data Models: A Guide for Macroeconomists*. Economics Letters, 65(1), pp. 9–15. doi:10.1016/S0165-1765(99)00130-5.

Khan, M., Serafeim, G. and Yoon, A. (2016) *Corporate Sustainability: First Evidence on Materiality*. The Accounting Review, 91(6), pp. 1697–1724. doi:10.2308/accr-51383.

Kishan, S. (2022) *ESG by the Numbers: Sustainable Investing Set Records in 2021*. Bloomberg.com, February 3. Available at: https://www.bloomberg.com/news/articles/2022-02-03/esg-by-the-numbers-sustainable-investing-set-records-in-2021.

Klapper, L. F. and Love, I. (2004) *Corporate Governance, Investor Protection, and Performance in Emerging Markets*. Journal of Corporate Finance, 10(5), pp. 703–728. doi:10.1016/S0929-1199(03)00046-4.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A. and Vishny, R. W. (1998) *Law and Finance*. Journal of Political Economy, 106(6), pp. 1113–1155. doi:10.1086/250042.

Le Sourd, V. (2024) *Does ESG Investing Improve Risk-Adjusted Return?* EDHEC Risk Climate Impact Institute. Available at: https://climateimpact.edhec.edu/does-esg-investing-improve-risk-adjusted-performance.

Liu, W., Shao, X., De Sisto, M. and Li, W. H. (2021) *A New Approach for Addressing Endogeneity Issues in the Relationship Between Corporate Social Responsibility and Corporate Financial Performance*. Finance Research Letters, 39(March), p. 101623. doi:10.1016/j.frl.2020.101623.

Lo, A. (2008) *Where Do Alphas Come From?: A Measure of the Value of Active Investment Management*. Journal of Investment Management, 6(2), pp. 1–29.

Lööf, H. and Stephan, A. (2019) *The Impact of ESG on Stocks' Downside Risk and Risk-Adjusted Return*. CESIS Electronic Working Paper Series, 477(March).

Machado, J. A. F. and Santos Silva, J. M. C. (2019) *Quantiles via Moments*. Journal of Econometrics, 213(1), pp. 145–173. doi:10.1016/j.jeconom.2019.04.009.

Madhavan, A., Sobczyk, A. and Ang, A. (2018) *What's in Your Benchmark? A Factor Analysis of Major Market Indexes*. The Journal of Portfolio Management, 44(4), pp. 46–59. doi:10.3905/jpm.2018.44.4.046.

Madhavan, A., Sobczyk, A. and Ang, A. (2021) *Toward ESG Alpha: Analyzing ESG Exposures Through a Factor Lens*. Financial Analysts Journal, 77(1), pp. 69–88. doi:10.1080/0015198X.2020.1816366.

Milonas, N., Rompotis, G. and Moutzouris, C. (2022) *The Performance of ESG Funds Vis-à-Vis Non-ESG Funds*. The Journal of Impact and ESG Investing, 2(4), pp. 96–115. doi:10.3905/jesg.2022.1.041.

Nofsinger, J. and Varma, A. (2014) *Socially Responsible Funds and Market Crises*. Journal of Banking & Finance, 48(November), pp. 180–193. doi:10.1016/j.jbankfin.2013.12.016.

Pedersen, L. H., Fitzgibbons, S. and Pomorski, L. (2021) *Responsible Investing: The ESG-Efficient Frontier*. Journal of Financial Economics, 142(2), pp. 572–597. doi:10.1016/j.jfineco.2020.11.001.

Raghunandan, A. and Rajgopal, S. (2022a) *Do ESG Funds Make Stakeholder-Friendly Investments?* Review of Accounting Studies, June. doi:10.1007/s11142-022-09693-1.

Raghunandan, A. and Rajgopal, S. (2022b) *Do ESG Funds Make Stakeholder-Friendly Investments?* Review of Accounting Studies, 27(3), pp. 822–863. doi:10.1007/s11142-022-09693-1.

Renneboog, L., Ter Horst, J. and Zhang, C. (2008) *The Price of Ethics and Stakeholder Governance: The Performance of Socially Responsible Mutual Funds*. Journal of Corporate Finance, 14(3), pp. 302–322.

Roberts, M. R. and Whited, T. M. (2013) *Endogeneity in Empirical Corporate Finance*. In: *Handbook of the Economics of Finance*, 2, pp. 493–572. Elsevier. doi:10.1016/B978-0-44-453594-8.00007-0.

Shleifer, A. and Vishny, R. W. (1997) *A Survey of Corporate Governance*. The Journal of Finance, 52(2), pp. 737–783. doi:10.1111/j.1540-6261.1997.tb04820.x.

Statman, M. (2000) *Socially Responsible Mutual Funds (Corrected)*. Financial Analysts Journal, 56(3), pp. 30–39. doi:10.2469/faj.v56.n3.2358.

Treynor, J. and Mazuy, K. (1966) *Can Mutual Funds Outguess the Market?* Harvard Business Review, 44(4), pp. 131–136.

Wintoki, M. B., Linck, J. S. and Netter, J. M. (2012) *Endogeneity and the Dynamics of Internal Corporate Governance*. Journal of Financial Economics, 105(3), pp. 581–606. doi:10.1016/j.jfineco.2012.03.005.

Zhang, J., De Spiegeleer, J. and Schoutens, W. (2021) *Implied Tail Risk and ESG Ratings*. Mathematics, 9(14), p. 1611. doi:10.3390/math9141611.

Zou, X., Jiang, J., Zhang, H. and He, H. (2024) *ESG Performance, Media Coverage and Brand Value*. Asia Pacific