Essays on ESG Investing

Ebtehal Abdelmegeed Youssef Abdelrahman Ramadan

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Abstract

Environmental, Social, and Governance (ESG) investing, also known as Socially Responsible Investment (SRI), seeks to align financial practices with ESG objectives by promoting investment vehicles that deliver financial returns while fostering positive social and environmental outcomes. ESG investment has grown rapidly in recent years, attracting attention from investors, policymakers, business leaders, employees, regulators, and academics alike. This thesis outlines three chapters that contribute to this growth in the literature on ESG investing. A common theme across these chapters is a deeper exploration of investor behaviour in allocating capital to ESG funds.

Chapter 2 investigates how investors and fund managers aligned their actions with the objectives of the EU Sustainable Finance Disclosure Regulation (SFDR). The SFDR requires funds marketed in the EU to classify themselves as Article 9 (Dark Green), Article 8 (Light Green), or Article 6 (Other). Paradoxically, the findings suggest that the regulation may have produced outcomes contrary to its intended purpose. Specifically, there is no evidence that Article 9 funds received higher inflows than Article 8 or Article 6 funds following SFDR's application. However, other fund characteristics, such as lagged flows, past returns, age, size, and four-factor alpha, appear to influence fund flows. Propensity Score Matching (PSM) results show that Article 9 funds still attracted higher mean inflows than their matched Article 8 and Article 6 peers. Overall, while panel, difference-in-differences (DiD), and event study analyses report no significant increase in flows to Article 9 funds, the PSM results indicate that these funds remained the most appealing to investors. Furthermore, only Article 8 fund managers increased their exposure to firms with medium to high Refinitiv ESG scores after the announcement of SFDR in November 2019, whereas Article 9 and Article 6 funds showed no such change.

Chapter 3 examines differences in performance and flow-performance sensitivity between ESG and conventional funds, and whether these differences vary across regions.

The results reveal no significant performance difference between U.S. ESG active funds and their matched conventional active peers, while EU ESG active funds outperform their conventional counterparts. Conversely, US ESG passive funds underperform their matched conventional peers, whereas no significant difference is observed between EU ESG passive funds and their conventional equivalents. These performance disparities are largely attributable to differing portfolio compositions across regions. Further analysis of flow-performance sensitivity shows that EU ESG active investors place greater value on the non-financial attributes of ESG investments compared to their US counterparts. Moreover, US conventional active investors appear to exhibit greater investment sophistication than those in the EU. Overall, the findings suggest that EU ESG investors, both active and passive, emphasize the non-financial dimensions of ESG investing more strongly than their US peers.

Chapter 4 explores how ESG investors respond to ambiguity and compares their behaviour to that of investors focused on conventional funds. The results indicate that both US and EU ESG active investors derive utility primarily from non-financial aspects of their investments, as reflected in their neutral response to ambiguity (i.e., minimal sensitivity to poor performance). This behaviour is also observed among conventional active investors in both regions. In contrast, US ESG passive investors appear more financially motivated, exhibiting aversion to the lowest performance outcomes. Additionally, investors across both ESG and conventional categories assess ambiguity not only in terms of performance but also in relation to other fund characteristics, including flow volatility, fund family size, and strategy changes.

Contents

List of Tables

List of Figures

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Abbreviations

AMS	Accepted-Minus-Shunned factor
AUM	Asset Under Management
C-4	Carhart four-factor model
CAPM	Capital Asset Pricing Model
CRSP	Centre for Research on Security Prices
CSR	Corporate Social Responsibility
DiD	Difference-in-Difference
DNSH	Do No Significant Harm
EMH	Efficient Market Hypothesis
EU CTB	EU Climate Transition Benchmark
EU PAB	EU Paris-aligned Benchmark
EUUP	expected utility with uncertain probabilities
FF5	Fama and French five-factor model
FF6	Fama and French six-factor model
FMP	Financial Market Participants
HML	High-minus-Low
LCD	Low Carbon Designation
MOR	Morningstar Overall Rating
MPT	Modern Portfolio Theory
MSR	Morningstar Sustainability Rating
PAIS	Principal Adverse Impacts
PRI	United Nations Principles for Responsible Investment
RMSE	Root Mean square Error
RTS	Regulatory Technical Standards
SEC	Security and Exchange Commission
SFDR	Sustainable Finance Disclosure Regulation
SRI	Socially responsible investment
TMB	Top-Minus-Bottom factor
TNA	total-net-assets
TSC	Technical Screening Criteria
USD	United States Dollars

Chapter 1: Introduction

1.1 Background

In the last two decades, socially responsible investment (SRI) or Environmental, Social, and Governance (ESG) investing has received significant attention due to increasing concern over environmental issues, social responsibility, and corporate governance issues. According to Morningstar, US sustainable funds experienced outflows of USD 6.5 billion in the first quarter of 2025 (Bioy et al. 2025), which slightly decreased to USD 5.7 billion in the second quarter. Conversely, Europe, which is the largest market for sustainable funds, experienced an outflow of USD 7.3 billion in the first quarter of 2025, which was subsequently offset by an inflow of USD 8.6 billion in the second quarter. The global sustainable assets account for almost USD 3.5 trillion. The largest market is Europe which comprises 85% of global sustainable assets, followed by the US with only 10% (total assets of USD 355 billion).

With the growing prominence of ESG investment, concerns have emerged regarding the measurement, comparability, and marketing of ESG portfolios. For example, a study by Berg et al. (2022a) finds a divergence between ESG ratings issued by different ESG rating agencies, while Brandon et al. (2022) highlight inconsistencies between funds marketed as ESG and the quantifiable sustainability factors they actually incorporate. Such discrepancies raise concerns about the credibility and reliability of ESG-labelled funds, potentially affecting investors' abilities to assess their risk-return propositions.

In response to these concerns, the European Commission introduced two major regulatory initiatives: the EU Taxonomy and the Sustainable Financial Disclosure Regulation (SFDR). These frameworks aim to direct capital flows toward genuinely sustainable investment and to mitigate risks associated with environmental and social issues (ESMA 2021). Under the SFDR, funds offered in the EU are required to classify themselves as either Article 9 (Dark green), Article 8 (Light green), or Article 6 (other) in their prospectus, thereby improving transparency and comparability across investment products.

This rise of sustainable finance has fundamentally reshaped global investment, yet uncertainty remains regarding its implications for both investors and fund managers. Earlier empirical studies have compared ESG and conventional fund performance, as well as their flow-performance sensitivity. However, these studies typically use quarterly or annual data and focus primarily on actively manage funds. This thesis revisits this literature by analysing the flow-performance relationship at a monthly frequency, which captures short-term investor reactions to past performance in rapidly changing financial markets. It also extends the scope to include both active and passive mutual funds, providing a more comprehensive understanding of ESG investing.

Furthermore, the rapid growth of ESG investing generated a large number of new resources from multiple ESG rating providers. This overload of information combined with challenges in assessing its quality, has introduced significant ambiguity for investors (Tuttle and Burton 1999). The lack of standardised ESG disclosures and the persistent divergence among rating providers adds to the difficulty of analysing ESG data. As a result, ESG investors may experience greater ambiguity and decision uncertainty compared to conventional investors (Luo et al. 2023). Despite the growing importance of this topic, the behavioural responses of ESG investors under ambiguity remain underexplored. Addressing this gap, this thesis investigates how ESG investors respond to ambiguity relative to their conventional peers.

Hence, the main objective of this thesis is to study responsible investor behaviour in choosing to allocate their capital into ESG funds. Chapter 2 examines the effect of the SFDR on investors and fund managers by answering two main research questions. (1) Did investors respond to the application of the SFDR in March 2021? (2) Did fund managers respond to the announcement of the SFDR in November 2019? To address these questions, this chapter uses different methodological approaches such as fixed effect panel regression, event study of flows, fixed effect panel DiD regression, and PSM. It also uses funds' monthly holdings to examine fund managers response to the announcement of the SFDR.

Chapter three revisits the earlier literature on ESG fund performance and flow-performance sensitivity by comparing ESG and conventional funds in the US and EU, focusing on two main research questions. (1) Did ESG investing command a premium and did this premium vary across regions? (2) Did ESG investors behave differently than conventional investors, across investment styles and regions? To answer these questions, the chapter employs a sample of monthly observations to examine the flow sensitivity to the past 36-months of monthly raw returns and Carhart (1997) four-factor alpha for both ESG and conventional funds. Finally, the chapter implements a piecewise regression methodology to capture the flow-performance sensitivity at different performance levels. Funds are ranked within their investment objective (Growth, Value, or Blend) from worst (0) to best (1) based on 12-, 24-, and 36- monthly raw returns and Carhart (1997) four-factor alpha. They are then grouped into three portfolios: Low (bottom 20%), Mid (20th–80th percentiles), and High (top 20%).

Chapter four examines the behaviour of ESG investors when faced with ambiguity and compares this to conventional investors through answering the following research question. Did ESG investors respond differently than conventional investors to ambiguity signalled by the worst performance? The chapter answers this question using a panel OLS regression model that estimates the relationship between fund flows and the minimum performance over multiple horizons. A fund's minimum historical performance is used as a measure of ambiguity given that it reflects the worst-case realisation of funds returns. Ambiguity is also proxied by flow volatility, family size and strategy change.

1.2 Summary of the chapters

Chapter 2 contributes to the literature on the effect of external sustainability rating and policy intervention on investor and fund manager behaviour (Ammann et al. 2019; Hartzmark and Sussman 2019; Ben-David et al. 2022; Becker et al. 2022; Ferriani 2023; Nishi et al. 2024) by studying investors' and fund managers' responses to the EU SFDR regulation. Hence, this chapter answers two main research questions: (1) Did investors respond to the application of the SFDR in March 2021? (2) Did fund managers respond to the announcement of the SFDR in November 2019? The chapter employs different methodological approaches such as fixed effect panel regression, event study of flows, fixed effect panel DiD regression, and PSM. The fund-level sample includes 650 for Article 9 funds, 4,255 firms for Article 8 funds, and 4,379 firms for Article 6 funds, domiciled in Europe excluding the UK, as identified by Refinitiv Lipper. The findings show that SFDR effect on fund flow varies depending on the methodological approach. While the panel regression and the event study of flows suggest a significant inflow into Article 6 and 8 funds, particularly in the short-term, the DiD and the PSM provide mixed evidence.

The panel regression shows that investors did not necessarily prefer Article 6 funds because of the regulation. Instead, the flow into these funds depends on other attributes like lagged flow, size, fees, age, and Morningstar overall rating. The results also suggest that investors allocated capital into Article 8 funds relative to their size rather than in absolute terms. Moreover, the results imply investors' uncertainty about the SFDR regulations from the allocated capital into Article 6 funds rather than the more sustainable funds (Article 8 and 9 funds). The event study of flows suggests that investors' response to the application of SFDR was not immediate or concentrated in a single month but rather accumulated over time, especially for Article 8 and 6 funds. This indicates a persistent and gradually unfolding effect of their fund flow. On the other hand, investors did not show any response to the funds classified as Article 9 in or after the application of the SFDR in March 2021.

However, after controlling for time-varying effect using DiD, the results suggest no difference in the flow between funds, after including $Article_i$ to the model. The table reports a relative decline in inflows to Article 9 following the application of the SFDR, compared with Article 8 and Article 6 funds. Nevertheless, the coefficients on $Article_i$ are positive and statistically significant at the 1% level in both specifications. Finally, after controlling for fund attributes using PSM, there is evidence that the inflow into Article 9 funds was higher than both Article 8 and 6 funds and no evidence of difference in flow between Article 8 and 6 funds both before and after the SFDR application. This result indicates that certain fund characteristics played a role in attracting investors post SFDR.

The divergence in the findings highlights the importance of accounting for differences in fund characteristics when evaluating SFDR impact. The DiD panel regression does not explicitly balance the structural differences between Article 9, 8 and 6 funds, such as lagged flows, returns, age, size and four-factor alpha, which may bias the estimate. By contrast, the PSM allows for a reliable comparison by matching funds on observable characteristics, providing stronger evidence that Article 9 funds maintained their inflow compared to Article

8 and 6 funds post the SFDR. Overall, while other methodologies, such as panel and DiD panel regressions, suggest no significant differences in flows into SFDR-labelled funds, and the event study of flows indicates increased flows to Article 6 and 8 funds but not to Article 9 funds, the PSM analysis demonstrates that Article 9 funds remained generally more attractive to investors.

Second, providing the first evidence on fund managers' response to the disclosure requirements of the EU SFDR regulation in November 2019 based on Refinitiv ESG rating of fund holdings. The sample of unique firms includes 10,615 for Article 9 funds, 1376 for Article 8 funds, and 886 for Article 6 funds. The findings suggest that, after controlling for other funds and firm characteristics, only Article 8 fund managers increased their exposure into firms with medium and high Refinitiv ESG score, while Article 9 and 6 managers did not change their positions. These findings suggest that the SFDR had counterproductive outcome as it indicates the inability of SFDR-labelled funds to attract increasing capital into ESG investments. This could reflect the perceptions of fund managers and investors on the regulatory aspects such as the absence of clear definition, transparency, and monitoring. For instance, SFDR has gone through many changes since its announcement and fund managers, possibly, did not clearly understand what qualifies to be labelled as Article 9 or Article 8.

Chapter 3 contributes to the literature on two fronts. First, providing the first evidence for the performance and the flow-performance sensitivity of ESG funds based on monthly frequency data from the US and EU. Second, it contributes to the flow-performance sensitivity literature (Bollen 2007; Renneboog et al. 2011; Gantchev et al. 2024; Wang 2024; Ali et al. 2024) about the behaviour of ESG passive investors and the exploration into their utility of the socially responsible attribute. Hence, this chapter answers three main research questions: Did ESG investing command a premium? And did this premium vary across regions? and did ESG investors' investment behaviour differ from those of conventional investors, across investment styles and regions? The sample consists of 4,171 conventional active funds, 236 ESG active funds, 193 conventional passive funds and 19 ESG passive funds domiciled in the US. 2,525 conventional active funds, 1380 ESG active funds, 170 conventional passive funds, and 132 ESG passive funds domiciled in the EU. The sample period spans from January 1996 to December 2022. First, the chapter implements a two-tailed student t-test to compare the mean returns of ESG and conventional funds, as well as the returns adjusted for common risk factors to examine whether ESG investing commands a premium, and whether this premium varies across regions.

The findings suggest that during the sample period (January 1996 to December 2022) the US ESG active funds' performance is not statistically different from that of their matched conventional peers, in line with prior literature (Statman 2000; Bauer et al. 2005; Geczy et al. 2005; Renneboog et al. 2008a; Renneboog et al. 2008b; ElGhoul et al. 2023; Hornuf and Yüksel 2024), whereas the EU ESG active funds outperform their conventional peers. On the other hand, US ESG passive funds underperformed their conventional peers in both the matched and the unmatched samples. Yet, there is no difference in risk-adjusted returns between EU ESG and conventional passive funds. These findings suggest that the outperformance of ESG active funds in the EU might be attributable to a superiority of ESG active management or may be driven by regulatory and tax reasons.

The second part of the chapter compares the flow-performance sensitivity of conventional and ESG funds, both active and passive, in the US and EU. The findings suggest a difference in the flow-performance sensitivity of ESG and conventional funds, both active and passive, across the US and EU markets, consistent with Renneboog et al. (2011). For example, over the short-term, matched conventional active funds are negatively sensitive to the lowest 20% performers and positively sensitive to the mid performers based on risk-adjusted alpha. In the EU, both matched conventional and ESG active funds show no flow sensitivity to the past 12-month risk-adjusted alpha. Over the long-horizon, US matched conventional active investors penalise funds that underperform the benchmark, US ESG active funds exhibit no flow-performance sensitivity. In the EU, matched conventional funds are positively sensitive to underperformers, whereas ESG active funds are negatively sensitive to underperformers.

In the passive fund space, over the short-term, US matched conventional passive investors show no sensitivity to past risk-adjusted alpha, while ESG passive investors penalise low-ranked funds based on C-4 alpha. In the EU, matched conventional passive investors penalise outperformers (C-4) alpha, whereas ESG passive investors show no sensitivity to past C-4 alpha. Over the long-term, both ESG and matched conventional funds show no sensitivity to the 36-months past performance. One exception is that US ESG passive investors are positively sensitive to mid-performers based on C-4 alpha. Over the long term, matched conventional passive investors show no sensitivity to past performance, while ESG passive investors reward mid performers based on C-4 alpha. However, these results for passive funds should be interpreted with cautious as it is derived from a sample of 19 US ESG index funds.

In addition to the matched sample analysis, the results from the unmatched conventional fund, both active and passive, highlight some important distinctions. The observed variations can largely be attributed to differences in fund age, load fees, and portfolio composition. Furthermore, the evidence suggests that EU ESG investors, whether active or passive, place greater emphasis on the non-financial attributes of ESG investments compared to their US counterparts, while US conventional active investors appear to exhibit a higher degree of investment sophistication than their EU peers.

Chapter 4 contributes to three strands of literature. First, it extends the empirical literature on the impact of ambiguity on asset prices (e.g. Anderson et al. 2009; Antoniou et al. 2015; Anantanasuwong et al. 2024) by examining this relationship in the context of ESG investing. Second, it adds to the fund flow–performance sensitivity literature by providing new evidence on how ESG and conventional investors respond to past performance, highlighting the role of ambiguity aversion across management styles and across regions (US and EU). Finally, it contributes to the growing body of work on ESG rating divergence and its implications for asset pricing (Gibson-Brandon et al. 2021; Avramov et al. 2022; Luo et al. 2023). Hence, this chapter answers the following research question. Did ESG investors respond differently than conventional investors to ambiguity signalled by the worst performance?

The final US sample includes 4,171 conventional active funds, 236 ESG active funds, 193 conventional passive funds and 19 ESG passive funds domiciled. The final EU sample includes 2,525 conventional active funds, 1380 ESG active funds, 170 conventional passive funds, and 132 ESG passive funds. A panel OLS regression model estimates the relationship between fund flows and the minimum performance over multiple horizons. A fund's minimum historical performance is used as a measure of ambiguity given that it reflects the worst-case realisation of funds returns. Ambiguity is also proxied by flow volatility, family size and strategy change.

The empirical findings suggest that ESG active investors show no significant response to ambiguity, while US matched conventional active investors display evidence of ambiguity aversion. In Europe, neither ESG nor matched conventional active investors exhibit sensitivity to the minimum rank measure, consistent with the unmatched sample. The neutrality in ambiguity among US and EU ESG active investors implies that they might derive utility from the non-financial as well as the financial aspect of their investment. Inconsistent with the prediction of ambiguity theory (e.g. Ellsberg 1961; Einhorn and Hogarth 1985), this finding may suggest that US and EU ESG active investors treat ESG information as sufficiently reliable. This could be due to the increasing standardisation, transparency, and availability of ESG data, which reduces uncertainty and allows investors to incorporate ESG factors without penalising their portfolios.

For passive investors, the evidence suggests that US ESG investors have become more sensitive to poor past performance, measured by four-factor alpha, though only at a weak level of significance. By contrast, US matched conventional passive funds show no sensitivity to minimum performance, consistent with results from the unmatched sample. In Europe, ESG passive funds also display no reaction to the worst performance, whereas their matched conventional counterparts are averse to ambiguity when measured by risk-adjusted alpha. This is inconsistent with the unmatched sample, where EU conventional passive investors show no sensitivity to the worst performance. However, this finding should be interpreted with cautious due to the limited sample size of US ESG index funds.

Finally, this heterogeneity in ambiguity aversion among ESG and conventional, active and passive investors, would affect asset prices as a result of only ambiguity-seekers and ambiguity-neutral investors rather than ambiguity-averse investors determine asset prices (Anantanasuwong et al. 2024). The use of other proxies of ambiguity, such as fund flow volatility, family size and strategy change, shows that conventional and ESG investors rely on different fund characteristics when evaluating ambiguity. What is more, it is seen that while some investors focus on raw returns, the others prefer risk-adjusted returns.

The remainder of this thesis is organised as follows. Chapter 2 examines investors and fund managers response to the EU Sustainable Financial Disclosure Regulation (SFDR) announcement in November 2019 and application of level 1 in March 2021; Chapter 3 compares the performance and flow-performance of conventional and ESG funds, both active and passive, in the US and EU; Chapter 4 examines the behaviour of ESG investors when faced with ambiguity and compare this to investors who focus on conventional funds, whether active or passive, in the US and EU; and Chapter 5 concludes.

Chapter 2: The impact of EU SFDR regulation on ESG investing

2.1 Introduction

Recent increasing concerns over environmental issues, especially climate change has brought sustainable investment into the mainstream discussion. Many firms have shown increased awareness towards environmental, social and governance (ESG) issues by allocating more resources towards such activities. In response to these endeavours, asset managers have increased their supply of ESG investment products. Bioy et al. (2025) report that in the second quarter of 2025, the flows into European Union (EU) ESG funds soared, bringing the total managed amount to USD 3.0 trillion which accounts for 85% of the total assets under management (AUM). On the contrary, US ESG funds managed only USD 0.4 trillion, which represents 10% of AUM. Figure 2.1 shows that between 2022 and 2025 ESG funds in the EU have been attracting significantly more flows than the comparable funds in the US, a trend which peaked in the fourth quarter of 2022. As the figure shows, in the first quarter of 2025, EU ESG funds experienced outflow of USD 7.3 billion. However, this trend reversed in the second quarter, with increased inflow of USD 8.6 billion. Despite this recovery, US ESG funds continued to attract less capital than their EU peers across both quarters.

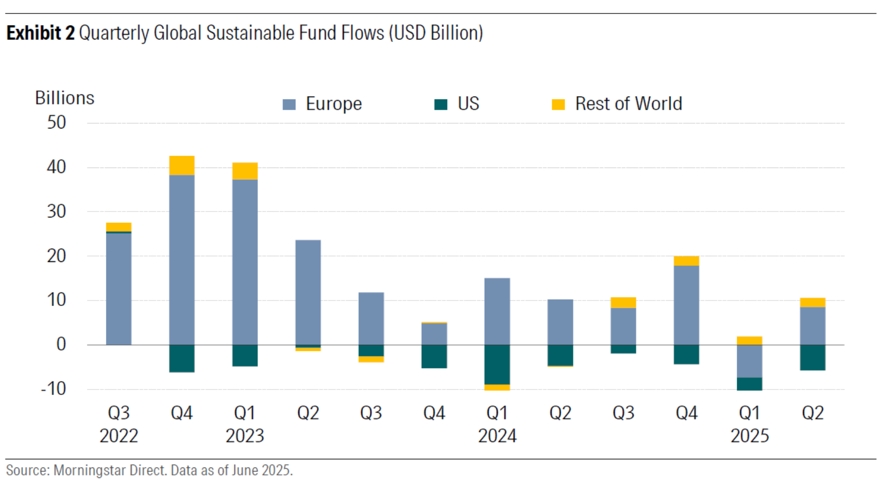

Figure 2.1: Global sustainable fund flow
The figure illustrates the quarterly flow for funds domiciled in US, Europe and the rest of the world (Bioy et al. 2025, p.3)

With the increased supply of ESG funds from multiple asset management firms, concerns are raised regarding the quantification and marketing of ESG portfolios. For example, Chatterji et al. (2016) report two drivers of ESG rating divergence. One is the use of different activities in evaluating a company's ESG score and the second is the adoption of different methodologies. Another study by Berg et al. (2022a) find a divergence between ESG ratings from different ESG raters and suggest that the divergence is driven by the rating methodology applied rather than the type of data being measured. According to Billio et al. (2021), ESG ratings divergence is driven by heterogeneity in ESG definitions and reporting standards. Moreover, Christensen et al. (2022) suggest that disclosure plays a substantial role in driving this divergence in ESG rating.

Furthermore, there is a discrepancy between what the asset managers market as ESG funds and the quantifiable factors that the funds incorporate. This is called "Greenwashing" or "impact washing" (Brandon et al. 2022). The Securities and Exchange Commission (SEC 2022) also identifies the apparent lack of consistency in ESG funds and suggests that this is due to the absence of a common definition and objectives in ESG investing and the methods of applying an ESG strategy. Given the above discussion, it is expected that investors face concerns about the reliability of the ESG marketed funds and the ability to understand the risk-return proposition of ESG investing.

In response to these concerns, the European Commission adopted the EU Taxonomy and the Sustainable Financial Disclosure Regulation (SFDR) with the aim of growing the allocation of capital towards sustainable investing and elimination of risks associated with environmental and social issues (ESMA 2021). The SFDR requires funds offered in the EU to identify as either Article 9 (Dark green), Article 8 (Light green), or Article 6 (other) in their prospectus. Article 9 funds explicitly state sustainable investment in their objectives. These must invest only in sustainable investments and must disclose their compliance with the EU Taxonomy when stating environmental characteristics in their objectives (Bioy et al. 2021). On the other hand, Article 8 funds focus on integrating environmental or social characteristics without sustainability being their core objective. These must disclose proof of meeting relevant characteristics, such as the percentage of their exposure to sustainable investment and their percentage of EU Taxonomy alignment. Article 6 funds do not explicitly set sustainable investment goals and are not marketed in any way as such. These must explain reasons behind their lack of sustainability in their pre-contractual disclosures[1]. In addition to this classification, funds must also disclose (a) the methodology based on which they considered sustainability risk within the investment process and its likely impact on expected returns, (b) the metrics used in evaluating ESG factors, and (c) considerations of negative externalities (Principle Adverse Impacts, PAIs) should be included, along with a reference in the periodic report or statement explaining the justifications and consequences in cases where PAIs are not addressed, as required under SFDR Article 7 (ESMA 2023). These requirements came into force in March 2021 (Bioy et al. 2021).

To support the transition to a greener economy, there should be consistency between financial flows and the path towards sustainable investment (Ceccarelli et al. 2023). To enhance consistency, the availability of sustainability information to investors should be improved, which is the aim of the EU Taxonomy and SFDR. Based on the above, transparency should be elevated, greenwashing should be limited and the demand for ESG investment improve (Ceccarelli et al. 2023). Motivated by the above, this study investigates whether the EU SFDR regulation alter investors' behaviour and whether fund managers change portfolio positions to align with the objectives of the EU SFDR?

The first research question examined in this chapter is: Did investors respond to the application of the SFDR in March 2021? Becker et al. (2022) and Ferriani (2023) examined the effects of the SFDR initiation on fund flows using the difference-in-difference (DiD) panel regression and the entropy balancing method, respectively. They find that Article 9 funds received higher inflows than Article 8 and 6 funds post SFDR. Ferriani (2023) adds that the sustainability ratings drive fund flows rather than the SFDR, especially into Article 8 funds. To gain a comprehensive understanding of the effect of the SFDR on fund flows, this chapter examines investor response to the application of SFDR using different methodological approaches such as fixed effect panel regression, event study of flows, fixed effect panel DiD regression, and Propensity Score Matching (PSM).

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[1] Information disclosed to the investors before a contractual agreement.

The panel regression was estimated for each category of funds (Article 9, Article 8 and Article 6) separately and evaluated fund flows in the 21-month period from April 2021[2] through December 2022. The results show no evidence of response in the flows post-SFDR application for Article 9 funds. However, there is increased inflows into Article 6 funds and into Article 8 funds relative to their size rather than in absolute terms. Subsequently, an event study of flows was conducted to separate effects due to the regulation change from the effects of other characteristics and examine ESG investment allocation decisions by analysing the abnormal flows after the application of SFDR. Consistent with the findings from the panel regression, there is evidence of increased inflows into Article 6 and 8 funds but not Article 9 funds. Investor response to the different categories of the SFDR products was then investigated by comparing three settings: (a) Article 9 funds vs Article 6 funds, (b) Article 8 funds vs Article 6 funds, and (c) Article 9 funds vs Article 8 funds. The findings suggest no difference in flows between SFDR-labelled funds. After including $Article_i$ to the model, Article 9 funds attracted higher inflows compared to Article 8 and 6 funds. However, following the application of the SFDR, there was a relative decline in Article 9 flow compared to Article 8 and Article 6 funds. However, when the comparison was conducted based on the PSM, the inflows into Article 9 funds were higher than inflows into Article 8 and Article 6 in horizons of three to twelve months following the SFDR initiation. Overall, although panel, DiD, and event study of flows analyses show limited or no increased inflows to Article 9 funds, PSM results indicate that these funds remain the most attractive to investors.

The second research question examines the response of fund managers to the announcement of the SFDR in November 2019 as follow: Did fund managers respond to the announcement of the SFDR in November 2019? Becker et al. (2022) estimate difference-in-differences (DiD) regression to analyse Morningstar sustainability rating of SFDR-labelled funds before and after the announcement of the SFDR. They find an increase in the Morningstar sustainability ratings for SFDR-labelled funds after November 2019, which suggests the effectiveness of the EU SFDR regulation in improving the clarity of ESG

[2] Post March 2021.

investments. This chapter uses the Refinitiv ESG rating of the holdings of the SFDR-labelled funds to examine fund manager response to the announcement of the SFDR. The findings suggest that, after controlling for other funds and firm characteristics, only Article 8 fund managers increased their exposure into firms with medium and high Refinitiv ESG score, while Article 9 and 6 managers did not change their positions.

2.2 Theoretical foundation

From the perspective of signalling theory, SFDR functions as a market signal in sustainable finance. SFDR establishes a labelling system by classifying funds into Article 6, 8, and 9 based on their degree of ESG integration. This classification mitigates information asymmetries and enables investors to easily differentiate among funds with varying ESG integration. Consistent with signalling theory, such labelling enhances perceived credibility and reduce uncertainty when full information is otherwise unavailable (Spence 1973). Additionally, SFDR labelling will then address greenwashing and information asymmetry issues in the financial markets (ESMA 2021).

Furthermore, Ethical investing theory posits that certain investors derive utility not only from financial returns but also from other values of their portfolios, often accepting lower expected returns in exchange for alignment with personal or institutional values (Renneboog et al. 2008a). Such investors may be willing to accept potential trade-offs in performance if the investment create values. SFDR facilitates this alignment by standardising ESG disclosure, which in turn allows investor to allocate their capital toward genuinely sustainable funds. From an institutional theory perspective, these classifications also confer legitimacy on funds that comply with the regulation’s standards, strengthening their standing in an increasingly sustainability-conscious market (Suchman 1995). In doing so, SFDR reinforces the institutionalisation of ESG norms across the asset management industry, shaping both investor expectation and manager behaviour.

With the growing number of investors incorporating non-pecuniary motives, the standardisation and comparability through SFDR classifications enable them to assess ESG integration more effectively and to allocate capital towards products consistent with their ethical preferences, increasing the attractiveness of Article 8 and 9 funds. According to

Hartzmark and Sussman (2019), investors with non-pecuniary motives allocate capital to funds with strong sustainability profiles because of two distinct drivers: expectations of superior risk-adjusted returns, or intrinsic preferences for sustainability, whereby investors are willing to incur potential financial costs to align their portfolios with their values.

Moreover, within the principal-agent framework, SRI presents a challenge. Fund managers are expected to deliver competitive financial returns while also advancing ESG objectives in line with the preferences of their investors (Renneboog et al. 2008a). This might increase the potential for agency costs due to the non-financial objectives offsetting the risk-adjusted return maximisation objective (Holmström and Milgrom 1991). By imposing standardised disclosure requirements and classifying funds into Article 9, 8, and 6, SFDR increases the transparency of ESG claims (Eurosif 2022). This reduces fund managers incentive to adopt ESG without fully integrating sustainability into their core investment process, while simultaneously exhibiting herding behaviour toward ESG-labelled strategies in order to align with sustainability trends and attract capital (Amel-Zadeh and Serafeim 2018; Cremsco and Boni 2022). Hence, SFDR functions as a governance mechanism and reduce the information asymmetries in principle-agent relationship concerning how sustainability risks are integrated, how adverse sustainability impacts are assessed, and the extent to which environmental or social characteristics are promoted, or sustainable investments are pursued. To achieve this, it mandates fund managers provide both pre-contractual and ongoing disclosures to investors (SFDR 2019).

2.3 Related literature

2.3.1 Motivations behind the EU SFDR regulation

Based on the increasing interest in ESG in the last two decades, many ESG rating providers provide aggregate ratings of companies' ESG performance based on their evaluation of their management of risks and opportunities related to ESG activities. Hence, these providers play a crucial role as intermediaries between corporations and investors (Christensen et al. 2022). The aim of ESG ratings is to enable institutional investors to evaluate ESG risks and opportunities and integrate them into their portfolios (MSCI 2022). Despite the aims of ratings being common for all providers, the methodologies based on which they estimate ratings are significantly different (Ferriani 2023). Cookson and Niessner (2020) hypothesise that different sets and interpretations of information cause disagreement between providers of ESG rating. More specifically, ESG analysts base their evaluation of a company's ESG performance on unstructured information available at different times and sequences, resulting in heterogeneity in ESG rating (Christensen et al. 2022).

Given the above, the literature examines the causes of ESG rating disagreements. To begin with, Chatterji et al. (2016) report two drivers of rating divergence, specifically, the use of different activities in evaluating a company's ESG and adopting different methodologies which they call "commensurability". Whereas Eccles and Stroehle (2018) advocate for the influence of differing cultural, regulatory, and economic environments on the development of the ESG metrics. By using a larger sample, Berg et al. (2022b) find that ratings divergence is driven mostly by three factors, specifically, "scope", which means different agencies use different attributes in evaluating ESG performance and "measurement", which refers to using different indicators to measure the same attribute. Lastly, "weight", which refers to discrepancies in the assessment of the different attributes. Moreover, Christensen et al. (2022) suggest that disclosure plays a substantial role in driving ESG rating divergence, confirming that the higher the disclosures, the more the ESG rating disagreement among agencies. Unlike financial disclosures, ESG disclosures have no widespread agreement about the meaning of the non-financial variables. Hence, the lack of common understanding of ESG metrics makes it hard for an agent to evaluate the ESG performance of corporations (Christensen et al. 2022).

The above inconsistency in rating ESG performance by different agencies would mislead the financial market participants, particularly fund managers and institutional investors[3]. As Peirce (2019, para.14) noted in her speech, "The different [ESG] ratings available can vary so widely and provide such bizarre results that is difficult to see how they

[3] Financial market participants include insurance firms, investment firms, pension funds, alternative investment fund manager, and other institutions subject to SFDR regulations. This chapter focuses specifically on funds and their obligations under the SFDR.

can effectively guide investment decisions"[4]. Hence, ESG rating methodology should be evident to investors, especially retail investors, who do not have enough knowledge of what they are buying, to avoid the risk of deluding investors through greenwashing (Christensen et al. 2022). The divergence in ESG ratings raises concerns in the market over "**greenwashing**". Lyon and Maxwell (2011, p.9) define greenwashing as "the selective disclosure of positive information about a company's environmental or social performance without full disclosure of negative information on these dimensions, so as to create an overly positive corporate image".

The first common approach to greenwashing is *selective disclosure*. This occurs when a firm does not report all their environmental impacts but pick and choose which to disclose. For example, firms may choose to report only the activities that have positive impact while hiding negative impact activities and, as such, overstate their environmental performance (Marquis et al. 2016). In contrast, other firms may choose not to disclose any positive environmental impact to avoid being accused by activists for any environmental damage or greenwashing (Lyon and Maxwell 2011). The second common approach to greenwashing approach is *exaggeration*. This is when fund managers market their vehicles as responsible, even sign the United Nations Principles for Responsible Investment (PRI) without actually incorporating ESG into their portfolios (Liang et al. 2022). Corporations might be enticed to exaggerate their reporting of ESG impact due to increased pressure from investors and other stakeholders while ESG-related activities might not always a win/win proposition (Kim and Lyon 2015). In addition, some corporations might claim to be environmentally and socially responsible, although this is attributed only to single activity without attention to other environmental and social issues. This is called *the sin of the hidden trade-off* (Lyon and Maxwell 2011).

Greenwashing implies a major risk for the demand for sustainable products (Berg et al. 2022b) and is a significant impeding factor for the transition of financial markets in creating

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[4] https://www.sec.gov/news/speech/speech-peirce-061819

added social impact (Heinkel et al. 2001). To eliminate the asymmetry in ESG information (e.g. ESG rating divergence and greenwashing), the EU's Taxonomy aims to standardise sustainability definition and measurements (Dumrose et al. 2022) to improve the flow of capital into sustainable projects and protect investors from greenwashing[5]. The following sections discuss the EU regulation, its Taxonomy, the SFDR, and evaluate the implications on end investors.

2.3.2 EU Regulation

The EU Taxonomy (EU2020/852) "… is essentially a defined set of activities that are deemed to make substantial contributions to environmental objectives and thereby help to finance the transition to a more sustainable economy" (Pettit and Walton 2020, P.4). It aims to pave the way towards a more sustainable economy and guide market participants to understand sustainability through a science-based framework that defines sustainable economic activities and conform with EU's six environmental objectives: "Climate change mitigation; climate change adaptation; sustainable use and protection of water and marine resources; transition to a circular economy; pollution prevention and control; and protection and restoration of biodiversity and ecosystems". (Article 9, EU Taxonomy). Importantly, the EU Taxonomy measures ESG performance relative to the economic activity it produces, as opposed to rating providers who focus on quantifying a firm' total environmental impact. For example, the Taxonomy evaluates CO2 emission per tonne rather than a firms' total CO2 emissions which the rating providers measure (Bassen et al. 2022). The Taxonomy is a classification tool that determines which economic activity is considered environmentally sustainable. Moreover, it is a screening tool to encourage investments into sustainable activities by setting standardized disclosure requirements[6] (Doyle 2021). Specifically, corporations must (a) disclose how each of their economic activities contributes to at least one of the six EU environmental objectives, (b) follow a set of Technical Screening Criteria (TSC), which guide how well each activity aligns with the Taxonomy (Doyle 2021), and (c) disclose their minimum social safeguards and the do no significant harm (DNSH) (European

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[5] https://finance.ec.europa.eu/sustainable-finance/tools-and-standards/eu-taxonomy-sustainable-activities_en

[6] https://www.spglobal.com/esg/insights/a-short-guide-to-the-eu-s-Taxonomy-regulation

Commission 2022). The minimum safeguard ensures that social and governance standards are upheld and the DNSH ensures that the economic activity labelled as sustainable do not cause harm to any of the above-mentioned environmental objectives.

Beyond the EU Taxonomy, the European Parliament adopted the EU regulation 2019/2088 Sustainable Financial Disclosure Regulation (SFDR) on 27th November 2019. The main purpose of SFDR is to reduce information asymmetries in a principle-agent relationship[7], such as integration of sustainability risks, promotion of social and environmental characteristics and sustainable investment, and management of Principle Adverse Impacts (PAIs) (Lambilon and Chesney 2023). PAIs are defined as negative sustainability factors due to certain sustainability investment decisions and include 64 mandatory and optional indicators. Regarding the optional indicators, financial market participants, particularly fund and asset managers, should choose either social or environmental indicators, where applicable (Morningstar 2021). As of 30th June 2022, some large financial market participants, including fund and asset managers must disclose their due diligence related to investment decisions based on PAIs. Effective from January 2023, financial market participants, including fund and asset managers, must disclose information on 20 PAIs of their choice (18 mandatory, two optional, one voluntary and relevant to their investment decision) following the SFDR-level 2 Regulatory Technical Standards (RTS) (Doyle 2021). This information covers the reference period from January 2022 to 31st December 2022[8], as illustrated in figure 2.2.

[7] https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32019R2088andfrom=EN

[8] https://www.spglobal.com/marketintelligence/en/campaigns/i-need-to-align-with-sfdr

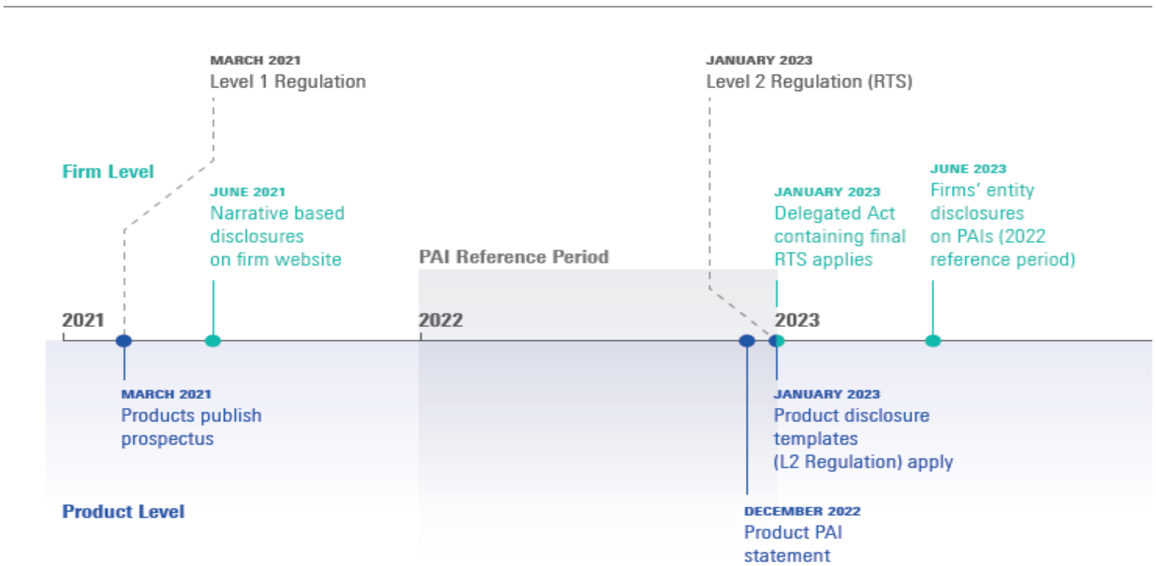

Figure 2.2: SFDR timeline
This figure illustrates the SFDR timeline from 2021 to 2023 (Morningstar 2022b, p.7)

The lack of transparency and methodological unification in ESG mislead investors who need to assess ESG risks and sustainable investment-related objectives. In response to the above, financial market participants, particularly fund managers, operating or selling products in the EU, are required to comply with the EU Taxonomy per SFDR. SFDR classifies compliance in three categories. First, funds complying with SFDR Article 9: *Transparency of sustainable investments in pre-contractual disclosures*, are required to indicate how their investment positions contribute to the EU Taxonomy objectives and how they differ from the traditional financial objectives. Second, funds complying with SFDR Article 8: T*ransparency of the promotion of environmental or social characteristics in pre-contractual disclosures,* are required to explain how their investment positions achieve the stated characteristics and outline the methodology of used to measuring it. Moreover, funds' holdings should follow good governance practices (Morningstar 2022b). Third, funds complying with SFDR Article 6: *Transparency on the integration of sustainability risks*, do not follow sustainability goals yet, they are required to explain the reasons for not considering sustainability risks in the fund managers' website (Cremsco and Boni 2022; Ferriani 2023).

The Taxonomy regulation applies requirements to a broad spectrum of financial products, including investment funds. Under the Sustainable Finance Disclosure Regulation (SFDR), investment funds classified as Article 8 or Article 9 are obliged to provide disclosures relating to the EU Taxonomy in both their pre-contractual documentation and on their official websites. In instances where such Taxonomy-related information is not disclosed, the fund is required to include the following disclaimer that "the investment(s) underlying this financial product does not take into account the EU criteria for environmentally sustainable investments" (Pettit and Walton 2020, P.10). This even applies to funds that have within their holdings corporations that are highly Taxonomy-aligned. Article 9 funds were expected to benchmark against either EU Climate Transition Benchmark (EU CTB) or the EU Paris-aligned Benchmark (EU PAB) in April 2020, the focus of both being decarbonisation. EU CTB allows more diversification and is mostly useful for institutional investors who wish to protect their investments from climate change and transition risks. On the other hand, EU PAB is more stringent with its minimum threshold. It is more suitable for investors who aim to reinforce the transition to a greener economy (Morningstar 2022a).

An interesting discussion emerges when one considers how fund managers responded to the announcement of SFDR. According to Morningstar, fund managers followed different approaches in identifying funds as compliant with either Article 8 or Article 9, even though they follow the same investment strategies[9]. Ferriani (2023) argues that the lack of policy guidance in classifying ESG investment products has led to a confusion between SFDR-label and other sustainable-labelled products used in the market. What is more, the opaque guidance in SFDR has led to more greenwashing concerns among investors (Bioy et al. 2022). For example, fund managers interpreted "*promoting*" under Article 8 as they should have a "*binding element*" in their asset allocation. Most Article 8 funds apply at least one of the exclusion, negative screening, positive screening (Best-in-Class), ESG integration, engagement, and thematic approaches in their asset allocation. Article 9 funds, on the other hand, follow only positive screening and thematic approaches, which also overlap with some

[9] https://www.morningstar.co.uk/uk/news/214207/sfdr-four-months-on.aspx

of Article 8 funds. Such vagueness and confusion can have detrimental effect in financial markets. Information deficiency reduces allocative efficiency (Easterbrook and Fischel 1984), and asymmetric information may lead to misleading or even fraud. Hence, the EU action can potentially support a more sustainable economy if only, its requirements are clear-cut with tighter measurement and reporting requirements (Pettit and Walton 2020). As such, investors would be more confident to invest in ESG.

2.3.3 Implications for investors

This study contributes to the strand of literature that investigates the impact of external ratings on fund flows (Del Guercio and Tkac 2008; Ammann et al. 2019; Hartzmark and Sussman 2019; Huang et al. 2020; El Ghoul and Karoui 2021; Ben-David et al. 2022). Research in this literature takes two approaches, focusing on either performance or sustainability rating. Performance rating focused research includes Del Guercio and Tkac (2008) who analyse equity star rating funds following the initial publication of its Morningstar rating. They find that fund flows are attributable to the change in Morningstar rating and not attributable to any of long-term performance measures (e.g. Jensen-alpha, three-year cumulative return, Sharpe measure). They conclude that funds that experience both a decrease in performance (i.e., returns) and Morningstar rating downgrade exhibit negative flows, whereas if they only experience performance decrease, they do not have significant outflows. In line with Del Guercio and Tkac (2008), Ben-David et al. (2022) show that investors evaluate funds based on both their Morningstar rating and unadjusted return. Indeed, they find that Morningstar rating has the most significant effect on fund flows. Huang et al. (2020) propose a *theory of reputation* which claims that Morningstar star upgrades from four- to five- star group are associated with increased reputation which, in turn, results in increased inflows and better expected performance.

Sustainability rating focused research includes Hartzmark and Sussman (2019) who confirm that investors value sustainability given that low-rated sustainability funds were reported a net outflow of more than $12 billion, while high-rated sustainability funds attracted more than $24 billion inflow. They also show that the simple Morningstar Globe rating attracted more attention than the percentile rank of sustainability within Morningstar even though investors exhibit awareness about sustainable attributes. Similarly, Ammann et al. (2019) examine the impact of the introduction of Morningstar's Sustainability rating on fund flows. They report that retail investors prefer funds with high Morningstar sustainability ratings as evidenced by inflows into high-rated funds and outflow from low-rated funds. Based on this evidence they argue that retail investors exhibit propensity towards Morningstar's sustainability rating as a simple and credible way of evaluating the sustainability of fund. El Ghoul and Karoui (2021) study funds that change their name to include sustainability-related words. Their study shows that funds with high portfolio turnover and exposure to the MSCI KLD 400 social index generate 1.18% monthly increase in inflows after changing their name. The paper shows no evidence of an increase in funds' risk-adjusted return or betas. Based on their observations they suggest that a name change to appear more ESG-oriented is associated with higher inflows and a considerable portfolio rebalancing.

This study is also related to studies on the effectiveness of the EU regulation in directing capital towards more sustainable investments. In this space, only Becker et al. (2022) and Ferriani (2023) study the effect of SFDR on fund flows, sustainability ratings and returns. Becker et al. (2022) examine the effect of introducing SFDR on funds' sustainability and flows. They find strong evidence that ESG ratings increased for EU ESG funds relative to the comparable US funds after the announcement of the SFDR policy. They also find that funds identifying as Article 8 or Article 9 received higher inflows than Article 6 funds. Although this finding is important, they do not explain whether this finding is driven due to sustainability or the regulation initiation.

Ferriani (2023) controls for Morningstar rating and Morningstar sustainability rating to determine what is driving the flow into SFDR-labelled funds. They conclude that sustainability score is a stronger determinant of the higher inflows than SFDR-induced labels, except for Article 9 funds which attracted higher inflow and outperformed Article 8 funds in terms of return. Lambilon and Chesney (2023) examine the frequency with which a company is included in Article 9 funds with regard to its ESG ratings, GHG emissions, net zero target, social and governance PAI indicators, and sector classification. They find that the higher a company's sustainability profile the more frequently is included in Article 9 funds. They also find that this relationship is less significant for Article 9 funds that degraded into Article 8, often due to strict scrutiny on sustainability claims, or difficulties in meeting the Article 9 funds 100% sustainable investment threshold imposed by SFDR-level 2 (RTS). For instance, Scheitza and Busch (2024) analyse the wave of Article 9 downgrades to Article 8 or 6 funds, highlighting the implementation of ESG strategies rather than impact investing and a lower inflow into downgraded funds which indicates lower financing sustainability ambition. Nishi et al. (2024) examine the effect of the downgrade from Article 9 to 8 funds. They find that downgraded funds attracted reduced inflows following their downgrade month. The present study adds to this line of literature by examining investors' behaviour post the application of the SFDR in March 2021 through testing the flow into SFDR-labelled funds post this date.

Another strand of literature related to this paper is the studies on fund managers' behaviour as a function of sustainability factors. For example, to hedge against climate change, Alekseev et al. (2022) follow a quantity-based approach to exploit cross-sectional information on fund managers' trading behaviour. They find that fund managers tend to increase their portfolio holdings in stocks that investors are more likely to purchase after an extreme heat event. Conversely, they tend to decrease their position in stocks that investors likely sell during such an event. Ceccarelli et al. (2023) examine fund managers' reaction to Morningstar Low Carbon Designation (LCD) publication in April 2018. They regress funds' position change on the interaction terms between the dummy variable denoting the period following April 2018 and whether the firm has a high or low LCD score. Their evidence claims that fund managers actively reduce positions in assets with high carbon risk while keeping diversification levels constant. Gantchev et al. (2024) also report that fund managers adjusted their portfolio by increasing their investment in sustainable stocks to attract investors' flows after Morningstar introduced their sustainability (Globe) rating.

Becker et al. (2022) is the only paper that studies the fund manager's behaviour following the initiation of the EU SFDR regulation in November 2019. They focus on comparing the Morningstar sustainability rating of SFDR-labelled funds before and after the launch of the policy by employing difference-in-differences regression. They also compare how EU and US funds score on the ESG scale post-November 2019, controlling for other fund characteristics and fund fixed effects. They find that EU ESG funds experienced increased Morningstar sustainability ratings after November 2019, which suggest the effectiveness of the EU SFDR regulation in improving clarity of ESG investments. Nishi et al. (2024) find that Article 9 funds that downgraded to Article 8 funds actively adjusted their portfolios with lower ESG-score assets post-downgrades. The present study contributes to this line of literature by examining fund managers' responses to the disclosure requirements of the EU SFDR regulation in November 2019. The investigation is conducted by evaluating SFDR-labelled funds' change of their holdings given their ESG score and identification to either Article 9, Article 8 or Article 6.

2.4 Hypothesis development

The following hypotheses examine the behaviour of investors and fund managers in response to the EU SFDR. First, hypothesis one examines investors' response to the application of the SFDR in March 2021. Second, hypothesis two considers fund managers' response to the announcement of the SFDR in November 2019. Examining investors' and fund managers' responses to different dates allow the study to examine fund managers' anticipatory reactions such as the repositioning of the funds in expectation of the regulation and investors' reaction to the publicly available sustainability labels once the SFDR came into force (Becker et al. 2022).

2.4.1 Investors' reaction to EU SFDR application in March 2021

The first hypothesis is motivated by Gennaioli et al. (2015) who propose that investors have limited financial knowledge or are nervous to take risky investment decisions and thus, trust asset managers to earn alpha and financial regulations provide protection. With regards to sustainable finance, it is expected that the investment anxiety should be even greater given the lack of transparency and concerns about greenwashing. This potential impedes funds flowing towards ESG-oriented investments. EU SFDR regulation is expected to provide investors with confidence, especially ethically minded investors. As a result, it is expected that flows into SFDR-labelled funds should have increased following the application of SFDR on March 2021.

Moreover, the reputational element is expected to be a factor for understanding fund flows. Given this, it should be expected that, in equilibrium, top sustainability-rated funds attract higher inflows due to investors expecting them to yield higher returns or that sustainability will drive future return or maximise value (Hartzmark and Sussman 2019; Huang et al. 2020). As such, investors with a multi-attribute utility function (Bollen 2007) use sustainability rating to take decisions aligned with their investing preferences (Huang et al. 2020). This is attributed to investors' naivety, limited financial literacy, restricted resources, fascination with sustainable investment and interest in a simple approach to base their decisions on simple and readily available information (Ben-David et al. 2022). Empirical evidence provides robust evidence that Morningstar sustainability rating impacts fund flows, independently from other influences (Hartzmark and Sussman 2019; Ammann et al. 2019), which highlights that the rating should be a factor when investigating fund flows. Based on this evidence, it is expected that fund inflows into the most stringent of the three categories, Article 9 after the application of the EU SFDR in March 2021. Similarly, it is expected that funds identifying by Article 6 should exhibit the least inflows, as these are non-ESG funds.

H1*: EU SFDR-labelled funds attract higher flows post March 2021 with the stringent category (Article 9) attracting the highest flows compared to the other categories.*

2.4.2 EU SFDR-labelled fund managers reaction to the EU SFDR in November 2019

The second hypothesis is motivated by the empirical evidence on fund managers' behaviour regarding ESG considerations. Gantchev et al. (2024) find that mutual funds' managers changed their investment strategies right after the introduction of Morningstar's sustainability (globe) ratings by increasing exposures in holdings with high ratings in order to attract flows. Similarly, they avoid holdings with low ratings. Nonetheless, this response was only for the short-term. Likewise, Ceccarelli et al. (2023) document a similar reaction after the introduction of Morningstar's Leveraged Commentary and Data (LCD) on April 30, 2018. They find a reduction of LCD-labelled funds' exposure to high carbon risk stocks following LCD's publication.

Additionally, Becker et al. (2022) find that the ESG scores of EU funds had improved compared to the respective US funds following the adoption of the EU SFDR regulation. Hence, they claim that the EU SFDR regulation fulfilled its objective of redirecting capital towards sustainable investments. As per the SFDR regulation, Article 9 funds focus on sustainable investment as their core objectives, explicitly targeting a positive environmental or social impact. Whereas Article 8 funds generally follow one or more responsible investment strategies, promoting for environmental or social characteristics (Lambilon and Chesney 2023). Therefore, it is expected that after the announcement of the EU SFDR Article 9 funds should exhibit higher ESG score assets in their optimal portfolio as compared to Article 8 and Article 6.

H2: *Following the* announcement *of the EU SFDR regulation in November 2019, Article 9 funds increase their holding positions in high ESG assets more intensely than Article 8 and Article 6 funds.*

2.5 Sample sources

2.5.1 Fund level data

The survivorship bias-free dataset on EU sustainable mutual funds is collected from Refinitiv Lipper and Morningstar Direct. According to Brown et al. (1992), non-surviving mutual funds are the funds that are ceased to exist, usually due to poor performance. Thus, controlling for funds' survivorship bias in the data ensures that performance persistence is not overstated due to the exclusion of defunct funds (Wermers 1997). Following Kacperczyk and Seru (2007) and Ferreira et al. (2012), double counting is avoided and for funds with multiple share classes, only their primary share class fund is included as identified in Lipper. Multi-class funds are managed by one manager, hold the same investment portfolio, and have the same returns before load fees and expenses[10]. Funds identified as either Article 6, Article 8, and Article 9 are collected via the Refinitiv fund screener, as of 28 of January 2023. The sample is collected after over 40% of Article 9 funds were downgraded to either Article 8 or 6 funds (Bioy et al. 2023). As reported by Morningstar (2021), active funds dominate passive post-SFDR,

[10] https://morningstardirect.morningstar.com/clientcomm/Share_Class_Types.pdf

accounting for 89% and 90% in Article 8 and 9, respectively. Hence, this research focuses only on active funds. These funds are filtered to include only equity open-ended funds that are actively managed. This provides 650 for Article 9 funds, 4,255 firms for Article 8 funds, and 4,379 firms for Article 6 funds, domiciled in Europe excluding the UK.

A major constraint associated with Refinitiv is that it does not include fund time-series data, unlike Morningstar which provides this. The funds' ISIN identifiers were used to get time-series of monthly returns, total net assets, expense ratio, Morningstar overall (star) rating (MOR), and Morningstar sustainability rating (MSR) from Morningstar API for the period of January 2019 to December 2022. Fund characteristics such as, inception date, equity style box, and domicile were also collected. Funds with missing ISINs and funds unavailable in Morningstar were removed from the sample. Following Hartzmark and Sussman (2019), the sample is limited to only funds with more than one million USD in total net assets as of December 2022. UK funds were excluded as the EU regulation applies only to funds domiciled or available for sale in the EU. The final sample includes 998 Article 6 funds, 1,432 Article 8 funds, and 163 Article 9 funds**.** 76 of Article 9, 488 of Article 8, and 779 of Article 6 funds were defunct since SFDR application.

Table 2.1 reports the summary statistics for Article 9, Article 8 and Article 6 funds, averaging month observations across the sample period. Article 9 funds have the highest average Morningstar Sustainability rating (3.84), followed by Article 8 (3.27) and Article 6 (2.87). Article 9 funds are heavily focused on sustainability than Article 8 and 6 funds, as indicated by a median MSR of 4. Article 8 funds have the highest allocation of total net assets on average, amounting to $262.29 million. This is 0.79 % higher than the average total net assets allocated to Article 9 funds ($260.20 mil.) and 20.39% higher than Article 6 funds ($208.81 mil.). The table shows the mean total net assets of the three funds' categories are larger than their median. This suggests that while most of the funds are relatively small, a few large funds are significantly dominating the market (skewing the average upward). Moreover, Article 9 funds generate slightly lower average negative return (-1.624) than Article 6 (-1.387) and 8 (-1.260) funds. This negative return is attributable to the sample window, which includes the drawdown of early COVID-19 and the significant losses in 2022 driven by inflation, war, and rising interest rates. While the mean returns of the SFDR-labelled funds are negative, Article 9 attracted 58% higher average inflow of 0.029 than Article 8 and 6 funds, as expected. This implies that investors are flowing into these funds regardless of performance.

In terms of fees, on average, Article 9 funds are more costly than the other funds' categories. As of December 2022, Article 6 funds are considered the most mature funds, as indicated by an average fund age of more than 15 years old since their inception date. Article 9 funds, on the other hand, are the least mature, which is reflected by only 13 years since inception. This result indicates that, as compared to other fund types in the sample, Article 9 funds are most costly, less mature, more sustainable, and attract more inflow.

Table 2.1: Summary statistics – Fund-level

This table repots summary statistics for Article 9 (panel A), Article 8 (panel B) and Article 6 funds (panel C) for the period from January 2019 to December 2022. The table shows the mean, standard deviation (SD), and median for the funds' monthly total net assets ($ in million), return, percentage flow, normalised flow, expense ratio, age, MSR, and MOR.

	Mean	SD	Median
Panel A: Article (9) funds			
Total net assets ($ in million)	260.20	617.91	62.69
Return (%)	-1.624	6.303	-0.959
Flow (%)	0.029	0.11	0.02
Normalised Flow	50.085	28.87	50.086
Expense ratio	2.102	1.275	1.840
Volatility	0.058	0.018	0.056
Age (in Years)	12.847	8.011	12
MSR	3.842	1.004	4
MOR	3.173	0.997	3
Panel B: Article (8) funds			
Total net assets ($ in million)	262.29	802.71	75.71
Return (%)	-1.260	6.183	-0.657
Flow (%)	0.012	0.1	0.014
Normalised Flow	50.008	28.868	50.008
Expense ratio	1.760	0.656	1.770
Volatility	0.057	0.019	0.055
Age (in Years)	14.991	9.799	14
MSR	3.269	1.094	3
MOR	3.287	1.019	3
Panel C: Article (6) funds			
Total net assets ($ in million)	208.81	718.58	41.05
Return (%)	-1.387	6.514	-0.844
Flow (%)	0.012	0.1	0.015
Normalised Flow	50.013	28.868	50.013
Expense ratio	1.829	0.852	1.820
Volatility	0.059	0.023	0.055
Age (in Years)	15.605	9.527	14
MSR	2.868	1.076	3
MOR	2.991	1.073	3

2.5.2 Funds' holdings data

Monthly time series of the fund holdings for the survivorship bias-free dataset are collected from Morningstar Analytical lab for the period from January 2019 to December 2022. Following Ceccarelli et al. (2023), non-equity holdings were discarded. For each holding, its monthly close price, returns and ESG score were sourced from Refinitiv Eikon. The initial sample of unique firms for each fund types include 15,138 firms for Article 9 funds, 35,503 for Article 8 funds, and 39,824 for Article 6 funds. After merging the holdings with the fund-level final sample, the final sample of unique firms includes 10,615 for Article 9 funds, 1376 for Article 8 funds, and 886 for Article 6 funds.

Table 2.2 reports summary statistics of monthly firm-level characteristics of the perspective Article 9, Article 8, and Article 6 funds for the full sample (January 2019 until December 2022) and the sub-samples (January 2019 to February 2021; March 2021 to December 2022) to show how fund managers change their investment strategies before and after SFDR application in March 2021. Interestingly, the median position change for all firms averaged across the Articles is 0, implying that managers do not frequently alter their holdings' positions.

The average firm-level ESG score for Article 9 funds is 67.47, which is slightly higher than that of Article 8 (66.80) and Article 6 (66.08). Refinitiv (2023) classifies the firm-level ESG score into four ESG score ratings: High (ESG score between 75 and 100), above-average (ESG score between 50 and 75), medium (ESG score between 25 and 50), and low (ESG score between 0 and 25). Notably, the highest ESG score category firms comprise approximately 40% of Article 9, 38% of Article 8 funds' portfolios and around 37% of Article 6 funds in the full sample. Conversely, the lowest ESG score category firms represent only about 2% of Article 9, 2.7% of Article 8 funds and 3% of Article 6 funds in full sample. The table shows that, after March 2021, the three funds' categories increased their allocation to firms with high ESG scores in their portfolios while cutting back on firms with lower scores. On average, Article 9 funds have higher (lower) allocation to high (low) ESG score firms than other fund categories across the three samples.

Regarding the average total buys and sells, the total buys for the average Article 9 and Article 8 funds were higher than the total sales. The total buy and sale for Article 8 were the highest, followed by Article 6, then Article 9 funds. For Article 9, the total buy and sell before March 2021 were less than post it. For Article 8 and 6 funds, the total buy and sell of shares were higher before March 2021 than after it. This result suggests that fund managers are investing more capital into SFDR-labelled funds than they are withdrawing. Additionally, Article 9 fund managers might be expecting more flow from investor post March 2021 than Article 8 and 6 fund managers. The average churn rate for Article 9 funds is 0.096, while Articles 8 and 6 funds have average churn rate of 0.11 for the full sample, indicating that 5% and 5.5%[11] of Article 9, Article 8, and Article 6 funds' positions, respectively, are turned over during the month. The average churn rate for all funds is approximately the same before and after March 2021.

11 0.096/2, 0.11/2

Table 2.2: Summary statistics – fund holding

This table reports summary statistics of firm-level of the perspective Article 9, Article 8, and Article 6 funds for the full sample (January 2019 until December 2022) and the sub-samples (January 2019 to February 2021; March 2021 to December 2022). The table shows the mean, standard deviation (SD), and median for the monthly firm-level characteristics of the perspective funds such as: position change, return, volatility, ESG score, low ESG score, medium ESG score, high ESG score, churn rate, total buy ($ in million), and total sell ($ in million).

	Full sample (January 2019 – December 2022)			(January 2019 – February 2021)			(March 2021 – December 2022)		
	Mean	SD	Median	Mean	SD	Median	Mean	SD	Median
Panel A: Article 9 funds									
Position change	-0.556	5.821	0	-0.385	5.567	0	-0.749	6.165	0
Return-Firm	1.171	10.42	1.171	1.971	10.871	1.645	0.104	9.906	0.276
Volatility-Firm	9.156	4.246	8.239	9.166	4.269	8.206	8.977	3.997	8.118
ESG score-Firm	67.466	17.247	71.495	65.627	18.05	69.909	69.322	16.222	72.922
Low ESG score	0.020	0.141	0	0.029	0.166	0	0.012	0.107	0
Medium ESG score	0.147	0.354	0	0.168	0.374	0	0.125	0.331	0
Above average ESG score	0.432	0.495	0	0.446	0.497	0	0.417	0.493	0
High ESG score	0.401	0.49	0	0.357	0.479	0	0.446	0.497	0
Churn rate	0.096	0.032	0.092	0.093	0.031	0.089	0.099	0.032	0.093
Total buy (in $million)	3.64	9.82	0.79	3.37	6.24	0.81	3.80	13.02	0.69
Total sell (in $million)	2.25	10.60	0.32	1.81	4.16	0.32	2.66	14.22	0.30
Panel B: Article 8 funds									
Position change	-0.335	14.76	0	-0.395	17.135	0	-0.268	12.428	0
Return-Firm	0.866	9.86	0.768	1.242	10.391	1.077	0.161	9.152	0.127
Volatility-Firm	8.86	3.817	8.093	9.134	4.131	8.33	8.365	3.481	7.713
ESG score-Firm	66.798	17.844	70.203	65.304	18.553	68.57	68.545	16.806	72.008
Low ESG score	0.027	0.161	0	0.035	0.184	0	0.017	0.130	0
Medium ESG score	0.145	0.352	0	0.163	0.369	0	0.124	0.330	0
Above average ESG score	0.448	0.497	0	0.453	0.498	0	0.442	0.497	0
High ESG score	0.380	0.485	0	0.349	0.477	0	0.417	0.493	0
Churn rate	0.114	0.031	0.116	0.114	0.031	0.115	0.114	0.030	0.115
Total buy (in $million)	5.30	20.94	0.73	5.77	23.84	0.79	4.49	15.23	0.63
Total sell (in $million)	4.91	46.21	0.41	6.42	44.20	0.48	3.09	39.86	0.33
Panel C: Article 6 funds									
Position change	-0.033	9.025	0	-0.015	10.497	0	-0.057	6.927	0
Return-Firm	0.749	9.967	0.629	1.096	10.581	0.952	0.109	9.200	0
Volatility-Firm	8.998	3.928	8.232	9.427	4.217	8.651	8.417	3.619	7.723
ESG score-Firm	66.076	18.32	69.601	64.617	18.985	68.06	67.641	17.418	71.204
Low ESG score	0.032	0.177	0	0.04	0.196	0	0.024	0.153	0
Medium ESG score	0.152	0.359	0	0.171	0.377	0	0.132	0.338	0
Above average ESG score	0.443	0.497	0	0.445	0.497	0	0.442	0.497	0
High ESG score	0.372	0.483	0	0.344	0.475	0	0.403	0.490	0

Churn rate	0.116	0.040	0.118	0.117	0.047	0.119	0.114	0.030	0.117
Total buy (in $million)	4.48	33.93	0.45	5.65	43.37	0.48	2.94	9.65	0.38
Total sell (in $million)	3.18	56.03	0.30	4.19	94.73	0.31	2.42	27.73	0.27

2.6 Methodology

2.6.1 Does the EU SFDR SFRD regulation matter to investors? (Investor behaviour)

Panel regression

To study how investors altered their portfolio positions after the application of the EU SFDR regulation, this paper examines fund net flows into SFDR-labelled funds after the initiation of the policy. Given that mutual funds do not have a fixed short-term supply like stocks, fund flows effectively represent investor preferences (Hartzmark and Sussman 2019). To test this hypothesis, the following panel regression is estimated for each category of funds (Article 9, Article 8 and Article 6) separately which explains fund flows in the 21 months (t) from April 2021[12] through December 2022. This effect should not be prior to the application of the regulation, otherwise the high reputation of sustainable funds might be driving the flow.

$$Flow_{i,t} = \alpha_0 + \beta_1 Post_t + \beta_2 X_{i,t} + \delta_i + \epsilon_{i,t} \quad (2.1)$$

$\boldsymbol{Flow_{i,t}}$ is the percentage flows into fund i in month *t*, calculated as: $[\boldsymbol{TNA_{i,t}} - \boldsymbol{TNA_{i,t-1}} * (\boldsymbol{1} + \boldsymbol{R_{i,t}})]/\boldsymbol{TNA_{i,t-1}}$[13], $Post_t$ is a dummy variable that equals to 1 for observations after the application of SFDR on March 2021 and 0 otherwise, and $X_{i,t}$ is a vector of control variables that may drive the fund flows, including fund age, one-month lagged expense ratio, one-month lagged standard deviation of the funds' prior 12 months return (volatility). To control for the effect of performance, the regression was controlled by one-month lagged monthly return. To control for the size effect the one-month lagged log monthly total net assets is also added as control variable. Lastly, the effect of the Morningstar rating is controlled, given the evidence in Del Guercio and Tkac (2008), the Morningstar Sustainability rating (MSR) and Morningstar star (overall) rating (MOR) are added as control variables. Variables definitions are presented in Table 2.3. δ_i represents funds fixed effects to control for the varying flow between different funds, and $\epsilon_{i,t}$ is the error term.

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[12] Post March 2021.

To account for cross-sectional and cross-time dependence, the standard errors are clustered by funds and months. Additionally, fund flow can be noisy but may show systematic variations related to the fund size. Hence, the flow is normalised following Hartzmark and Sussman (2019). To construct the funds' normalised flow, each month, the funds are divided into size decile and then funds are assigned a percentile rank based on their flows within each size decile.

Event study of flows

Unlike the panel regression, event study of flows aims at isolating the EU regulation effect from other influences, such as a fund's performance and other characteristics on fund flows, likely affecting fund flow (Del Guercio and Tkac 2008; Ammann et al. 2019). Hence, this study employs an event study of flows for which each fund within an SFDR label is benchmarked to a model of its own flow following the application of the SFDR as will be described below. Consequently, realising an estimated abnormal flow which is triggered by the application of the new EU SFDR regulation. This segregation of fund flows from the effect of the EU SFDR regulation results in an accurate examination of whether investors value the regulation of sustainable investments without making any assumption about the reliability of the new labelled SFDR funds. The null hypothesis of the event study of flows is that the SFDR regulation has no effect.

To calculate the abnormal flow, the approach of Del Guercio and Tkac (2008) and Ammann et al. (2019) is followed. First, the event month (t=0) is set as March 2021 which was when the SFDR-level 1 came into force. Then, the estimation window is designed to be of length 26 months before the event month (January 2019 – February 2021). This estimation period ensures that the results remain precise and stable (Del Guercio and Tkac 2008). Second, for each individual fund *i* in each SFDR-label category, the time-series benchmark model is estimated. This analogous to the benchmark model used in a traditional event study of flows of estimating abnormal return (Campbell et al. 1997) within the defined estimation window.

$$F_t^i = \gamma^i + \beta_1^i ASF_t^i + \beta_2^i RET_{t-1}^i + \beta_3^i \Delta\alpha_{t-1}^i + \beta_4^i \left(\Delta\alpha_{t-1}^i\right)^2 + \beta_5^i F_{t-1}^i + \epsilon_t^i \qquad (2.2)$$

F_t^i is the estimated flow of fund i flow in month t, ASF_t^i is the average flow of fund i to all funds in the same style (blend, value, growth or others) in month t, RET_{t-1}^i is the one-month lagged return of fund i in month t, $\Delta\alpha_{t-1}^{i}$ is the lagged change in Carhart's (1997) four-factor alpha of fund i[14], F_{t-1}^i is the one-month lagged flow of fund i. $\left(\Delta\alpha_{t-1}^i\right)^2$ represents the lagged change in Carhart's (1997) four-factor alpha squared to adjust for a possible convex relationship between fund flows and recent performance, following Del Guercio and Tkac (2008). These variables are included in the benchmark model given the previous evidence that they are determinants of funds flows.

As in Del Guercio and Tkac (2008) and Ammann et al. (2019), after the estimation of the benchmark model (equation 2.2), the coefficients are used to predict the expected flow in the event windows that are set to be 7 months from the event month (March 2021 to September 2021). Given the length of the event window, it is important to note that, unlike stock returns, fund flows often exhibit persistent responses to new information, with no anomalies in the six months following the event. This persistence reflects that flows may adjust immediately or with a lag, as investors review their funds at different intervals or delay reacting to new information (Del Guercio and Tkac 2008). The abnormal flow of fund i at month t is estimated as follows.

$$\widehat{AF}_t^i = F_t^i - \hat{\gamma}^i - \widehat{\beta_1^i} ASF_t^i - \widehat{\beta_2^i}\, \mathrm{RET}_{t-1}^i - \widehat{\beta_3^i} \Delta\alpha_{t_{-1}}^i - \widehat{\beta_4^i}\left(\Delta\alpha_{t_{-1}}^i\right)^2 - \widehat{\beta_5^i} \mathrm{F}_{t-1}^i - \epsilon_t^i \quad (2.3)$$

This paper applies the event study of flows method of Dodd and Warner (1983) to the abnormal flow estimates. For each fund, the abnormal flow within the event window is standardised by the estimated predicted error, denoted as $\widehat{ASAF_t}$. Note that the standardisation of abnormal flow assigns more weight to funds with lower predicted variance and more accurate abnormal flows. Subsequently, the cumulative standardised abnormal flow for each fund is computed. First, the standardised abnormal flow is calculated as the

[14] This study uses the change in alpha, rather than its absolute value, to correct for multicollinearity (Del Guercio and Tkac 2008).

sum within the event window, divided by the square root of the number of months used in the cumulation. Second the average of $\widehat{ASAF}_t$ and $\widehat{ACSAF}_t$ are calculated across N funds within the event window and for each category (Article 9, Article 8, and Article 6).

In the next stage, to assess the statistical significance of $\widehat{ASAF}_t$ and $\widehat{ACSAF}_t$, the standardised cross-sectional test introduced by Boehmer et al. (1991) is employed. Specifically, $\widehat{ASAF}_t$ and $\widehat{ACSAF}_t$ are divided by their contemporaneous cross-sectional standard error, which is computed across each event window. Following Del Guercio and Tkac (2008) and Ammann et al. (2019), the percentage of positive standardised abnormal flow is also tested using the nonparametric sign test. The null hypothesis for the sign test is that 50 % of the funds within the sample have positive standardised abnormal flow.

Difference-in-difference (DiD) panel regression

To gain a holistic understanding of how EU SFDR impacts fund flows across different Articles, the following fixed effect panel DiD regression is estimated. The aim is to compare SFDR-labelled funds in different settings: Article (6 vs 8), Article (6 vs 9), and Article (8 vs 9).

$$Flow_{i,t} = \alpha_0 + \beta_1 Post_t + \beta_2 Article_i + \beta_3 Article_i * Post_t + \beta_4 X_{i,t} + \delta_i + \epsilon_{i,t} \qquad (2.4)$$

where $Article_i * Post_t$ is the main explanatory difference-in-difference interaction term. $Post_t$ is the main effects variable. $Article_i$ is an indicator variable to represent the article by which a fund identifies. In the first two settings (Article 9 vs Article 6 and Article 8 vs Article 6), the variable equals to 0 if the fund identifies as Article 6 and 1 if it identifies as either Article 9 or Article 8. For the final setting (Article 9 vs Article 8), the variable equals to 0 if the fund identifies as Article 8 and 1 if it identifies as Article 9.

Propensity Score Matching (PS)

The dynamic of fund flows could be explained by other fund characteristics such as the ones mentioned earlier. The earlier approach to correct for these characteristics was to add them to the regression analysis. However, the relationship between fund flow and its characteristics might be non-linear and hence, adding them as linear factors in the regression should be ineffective. For instance, Bollen (2007) documents a non-linear relationship between funds' age and its flow and Sirri and Tufano (1998) find a convex relationship between funds past performance and their flow. Additionally, analysis of fund flow is prone to endogeneity arising from omitted variables. This endogeneity concern affects the dependent variable, causing the error term to correlate with the regressors, leading to biased and inconsistent estimates (Roberts and Whited 2013).

Given that the sample in this paper includes funds with similar characteristics but different SFDR labels and sustainability ratings, the PS matching procedure proposed by Rosenbaum and Rubin (1983) and conducted by Ammann et al. (2019) is employed to mitigate the bias caused by the endogeneity. This enhances comparability and reduces confounding effects (Rosenbaum and Rubin 1983; Stuart 2010). Although matching cannot fully eliminate bias arising from unobservable variables, it offers a more credible approach to causal inference than unmatched comparisons (Heckman et al. 1997). In addition, fixed-effect models are employed to correct for time-invariant unobserved fund-level heterogeneity (Rakowski and Yamani 2021).

First, treatment group and control groups are constructed in each of the three different settings: (a) Article 9 versus a matched control group of Article 6; (b) Article 8 versus a matched control group of Article 6; and (c) Article 9 versus a matched control group of Article 8. Second, the monthly PS for all funds in control and treated groups is estimated by running a logit regression. The independent variables include features such as fund flows, monthly returns, log of total net assets, age and past 60-months Carhart (1997) alpha[15] and the dependent variable is the dummy variable which indicates the treatment group. The fitted values from the logit regression are then used to predict the PS which is the probability of a fund to be in a treatment group. Lastly, each fund in the treatment group is matched with funds from the control group that has the nearest PS score. The *k* nearest neighbour is the 10 closest points to the propensity score for each fund. Matched funds are removed if their PS

[15] To estimate a monthly series of the past 60-month Carhart (1997) alpha, 5 years of fund monthly returns were extracted from December 2013 to December 2018, following the methodology explained in Chapter One.

differ by 25% standard deviation. At this stage, a two-tailed student t-test is estimated to find the difference in SFDR-labelled funds' average net flow (the three different settings mentioned earlier) over six-time intervals relative to March 2021: six months and three months before March 2021 and for the three, six, nine, and twelve months after March 2021.

2.6.2 Fund managers' response to the announcement of the EU SFDR regulation (fund managers' behaviour)

To evaluate the immediate impact of the EU SFDR regulation on funds managers' trading decisions, this chapter examines the average monthly changes in fund holdings based on the Refinitiv ESG score of their portfolio companies following the announcement of the EU SFDR. Due to data access limitation, the Refinitiv ESG score was the only firm-level ESG score used in the analysis. It is expected that Article 9 funds increase their holding positions in high ESG assets more intensely than Article 8 and 6 funds. Following Ceccarelli et al. (2023), for each SFDR-label fund (across Article 9, Article 8, Article 6) a panel of its holdings is constructed, and the following regression is run for each fund *i* position change in holding *j* in month *t*.

$$Position\ change_{j,i,t} = \alpha + \beta_1\ Low\ ESG_j + \beta_2\ Medium\ ESG_j + \beta_3\ Above\ average\ ESG_j + \beta_4\ High\ ESG_j + \beta_5\ Low\ ESG_j * Post_t + \beta_6\ Medium\ ESG_j * Post_t + \beta_7\ Above\ average\ ESG_j * Post_t + \beta_8 High\ ESG_j * Post_t + \gamma' X_{i,t-1} + \delta' Y_{j,t-1} + \mu_i + \epsilon_{j,i,t}. \quad (2.5)$$

$Position\ change_{j,i,t}$ is the change in the number of shares held by fund i in stock j from month *t-1* to month t, normalised by the fund's total net assets (*TNA*) in month *t-1*, as defined by Ceccarelli et al. (2023) and Gantchev et al. (2024).

$$Position\ change_{j,i,t} = \frac{Price_{j,t-1}(Shares_{i,j,t} - Shares_{j,j,t-1})}{TNA_{i,t-1}} \quad (2.6)$$

where; $Price_{j,t-1}$ is the price of stock j in month *t-1*, $Shares_{i,j,t}$ are the number of shares held by stock j in fund i in month t and month *t-1*, respectively, $TNA_{i,t-1}$ is the total net assets of fund *i* in month *t-1*. ESG score data are sourced from Refinitiv. The ESG score is classified according to Refinitiv (2023) methodology into 4 ESG rankings: $High\ ESG_j$ a dummy variable equalling to 1 for firms with ESG score between 75 and 100,

$Above\ average\ ESG_j$ a dummy variable equalling to 1 for firms with ESG score between 50 and 75, $Medium\ ESG_j$ a dummy variable equalling to 1 for firms with ESG score between 25 and 50, and $Low\ ESG_j$ is a dummy variable equalling 1 for firms with ESG score between 0 and 25. The corresponding firm indicators are defines as *low ESG* (firm), *medium ESG* (firm), *above average ESG* (firm), and *high ESG* (firm).

$Post_t$ is an indicator variable that equals to 1 for months following the adoption of EU SFDR regulation in November 2019. Following Ceccarelli et al. (2023), controls are implemented for characteristics which affect holding's position change. $X_{i,t-1}$ contains the following lagged fund-level controls: monthly flow, monthly return and alpha, logarithm of funds' total buys and sells, and funds' churn rate, as shown in Table 2.3. Lagged firm-level controls $Y_{j,t-1}$ includes monthly return, return volatility and weighting in the portfolio. μ_i fund fixed effects and $\epsilon_{j,i,t}$ is the error term. To account for cross-sectional and cross-time dependence, the standard errors are clustered by funds and months.

Table 2. 3: Variables definition

Variable	Definition
Equity style box	According to the equity style box, funds are classified as large-cap (top 70% of the market cap of each style, mid-cap (70%-90%), small cap (90-100%). These funds are ranked within the value-growth orientation of their holdings.
Total net assets	Is equal to summation of the monthly percentage change in funds' net asset value, reinvestment, and distribution of capital gain, divided by the net asset value at the beginning of the month.
Annual report net expense ratio	Derived from annual report, net expense ratio is the management fees and operating expense as a percentage of the funds' assets. It includes 12b-1 fees, administrative fee, other asset-based fees except brokerage costs.
Morningstar overall (star) rating	Morningstar calculate the star rating based on the funds' performance (raw and risk-adjusted return). Funds allocated 5 stars fall within the top (10 %). Funds allocated 4 stars fall within the above average (22.5%). Funds allocated 3 stars fall within the average category (35%). Funds allocated 2 stars fall within the below average (22.5%). Funds allocated 1 star fall within the lowest category (10%). The weighted average of the above star ratings formulates the overall Morningstar Rating.
Morningstar sustainability rating (MSR)	To compute this rating, Morningstar aggregate the funds' holdings sustainable scores, produced by Sustainalytics, based on the asset-weighted of the underlying holdings within the fund. A fund is then ranked on a scale of 1-5 within Morningstar Global Category. A low rating of 1 globe is assigned to funds ranked at the bottom (10%), below average of 2 globes for funds in the 22.5% percentile, average 3 globe for funds in the 35% percentile rank, A 4 globes is a assigned to funds in the above average rank of 22.5%.Finally, the funds assigned the highest globe of 5 are the ones ranked in the top 10% percentile (Barr et al. 2021).
Fund age	The log of the difference between the difference between the
Turnover	Measure the frequency of holdings' buy and sell. Morningstar collect it from disclosure documents which means that it follows the regular turnover methodology. It's an annual measure and expressed as percentage. (Morningstar Direct)
Churn rate	Measures the frequency of changing stocks' positions within the portfolio (Gaspar et al. 2005; Ceccarelli et al. 2023). $$CR_{i,t} = \frac{\sum_{j \in Q} \mid N_{j,i,t}\, P_{j,t} - N_{j,i,t-1}\, P_{j,t-1} - N_{j,i,t-1} - N_{j,i,t-1}\, \Delta P_{j,t} \mid}{\sum_{j \in Q} \frac{N_{j,i,t}\, P_{j,t} + N_{j,i,t-1}\, P_{i,t-1}}{2}}$$
Total buy	Total buys of shares in a mutual fund's portfolio during month t. If Shares change >0 Total buys = $(Price_{i,t} * Number\ of\ shares_{j,i,t})$ Shares change is the monthly change in stock i of a fund j. Pulled out form Morningstar Direct.
Total sell	Total sells of shares in a mutual fund's portfolio during month t. If Shares change < 0 Total sells = $(Price_{i,t} * Number\ of\ shares_{j,i,t})$ Shares change is the monthly change in stock i of a fund j. Pulled out form Morningstar Direct.

2.7 Empirical results: Fund level

2.7.1 Graphical evidence

Figure 2.3 plots the average monthly funds' net flow between January 2021 and December 2022[16] within each of SFDR-labelled funds' categories. This shows inconsistency of fund flows among Article 6, Article 8 and Article 9 over the period. Moreover, increased inflows for Article 6 and 8 funds are seen in March 2021 within the month of SFDR application. However, these funds have attracted less inflow in the following month. As for Article 9 funds, they were attracting a decreased inflow during this period. Interestingly, Article 9 funds have been experiencing net outflow since January 2022 towards the end of the year. Bioy et al. (2023) relates this outflow in Article 9 funds to the reclassifications of Article 9 funds into Article 8 funds following the strict requirements of the SFDR level 2 which states that Article 9 funds must only hold sustainable investments.

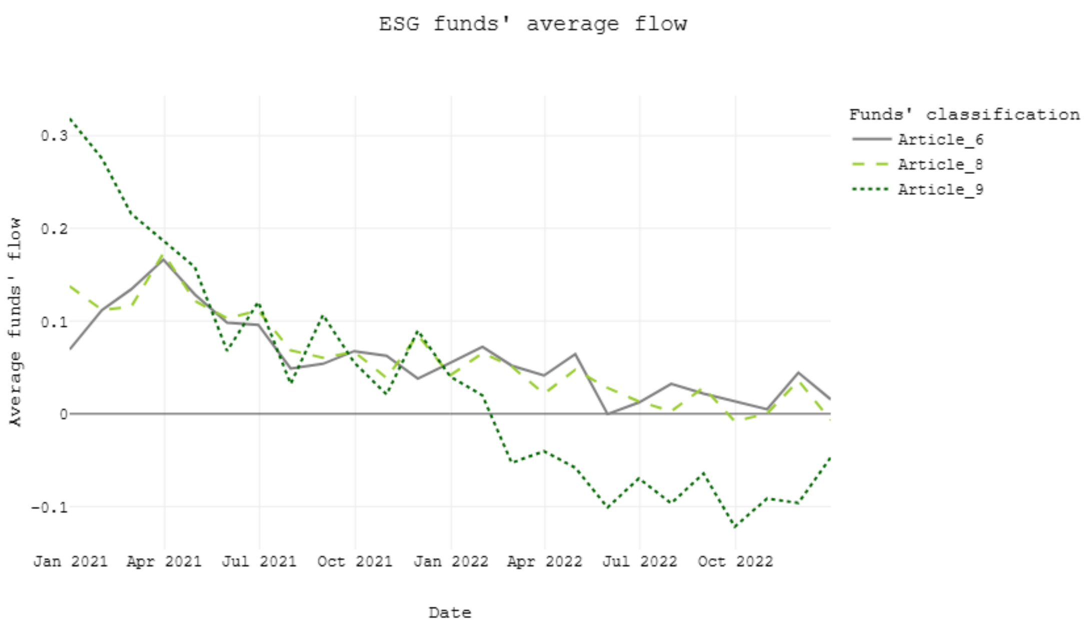

Figure 2.3: ESG fund flows
The chart shows the average monthly net flow for Article 9,8, and 6 funds from January 2021 to December 2022.

[16] The regression model later incorporates data from January 2019. This period is not shown for space consideration.

2.7.2 Panel regression

Panel A of Table 2.4 regresses fund flows on the $Post_t$ dummy variable that equals to 1 for observations after the application of SFDR on March 2021 using Newey and West's (1987) autocorrelation and heteroscedasticity consistent standard error without controlling for other fund characteristics (Panel A of Table 2.4). The results suggest that after controlling for other fund characteristics, Article 6 funds experience increased inflow post the SFDR effectiveness in March 2021. On the other hand, Article 8 funds benefit from marginally higher inflow, while Article 9 funds did not attract any additional capital.

The coefficient on $Post_t$ for Article 9 funds (column 1) is positive and statistically insignificant (0.006). However, the coefficients for the $Post_t$ for Article 8 (column 4) and Article 6 (column 7) are positive and statistically significant coefficients at the 1% level (0.017) and (0.018), respectively. Therefore, the result does not support hypothesis H1 that the EU SFDR-labelled funds attract more inflows after the application of SFDR in March 2021. This result holds for Article 9 (column 2) and Article 8 (column 4) funds after controlling for fund fixed effects which control any variation across funds; and clustering of the standard errors by fund and month which controls for any dependence across funds and time. However, the coefficient on the $Post_t$ variable for Article 6 funds becomes statistically significant at the 1% level (column 6) (0.014).

For Article 9 and 8 funds, the one-month lagged return, flow, and expense ratio have a positive effect on their flow, while the size has a negative effect. In addition, the results show that the higher the Morningstar sustainability rating and overall rating for Article 8 funds, the higher the inflow. For Article 6 funds, there is a positive relationship between fund flow and one-month lagged flow, expense ratio, and MOR. Furthermore, Article 6 fund inflows are lower for older and larger funds. This result suggests that other fund characteristics and variations across funds could be the drivers of the earlier findings for Article 6 funds.

Panel B of Table 2.4 reports the normalised flow variable to mitigate the potential impact of noisy flow during the short sample period. The coefficients from the prior results will decrease if they are driven by the volatile flows from small funds (Hartzmark and Sussman 2019), Conversely, if the noise decreases after normalising the flow, there should be an increase in the coefficients of the normalised flow after the application of the new SFDR regulation. Taking control variables into account, results hold with earlier findings for Article 9 and 6 funds. However, the coefficient on $Post_t$ for Article 8 funds becomes statistically significant, but at weak statistically significant level (10%). This result could mean that small sized Article 8 funds attracted more inflow in relative terms compared to large sized ones.

This result is consistent with the graphical evidence, which confirms no consistent increase in net flow after March 2021. However, this evidence is inconsistent with the hypothesis that expects Article 9 funds to attract higher inflow than Article 8 and 6 funds. This evidence also shows that investors did not necessarily prefer Article 6 funds because of the regulation. Instead, the flow into these funds depends on other attributes like lagged flow, size, fees, age, and Morningstar overall rating. The result also suggests that investors allocated capital into Article 8 funds relative to their size rather than in absolute terms. Moreover, the result implies investors' uncertainty about the SFDR regulations from the allocated capital into Article 6 funds rather than the more sustainable funds (Article 8 and 9 funds).

Table 2. 4: Investors behaviour as a reaction to the EU SFDR regulation

This table shows how SFDR-labelled fund flows varied after the application of the SFDR in March 2021. Panel A shows the results for the OLS DiD regression (Columns 1,3, and 5), and the fixed effect panel DiD regression (Columns 2, 4, and 6) of monthly flow for funds disclosed as Article 9, 8 and 6, respectively. $Post_t$ is a dummy variable that equals 1 for months following March 2021 and 0 otherwise. The control variables include (One-month lagged: return, flow, log total net assets, standard deviation of the funds' prior 12-month return (volatility), and expense ratio, non-lagged: age, Morningstar sustainability rating (MSR) and Morningstar star (overall) rating (MOR). t-statistics (in parentheses) are calculated with Newey-West robust standard errors (Columns 1, 3, and 5). Standard errors are clustered by fund and month (Columns 2, 4, and 6). Panel B repeats the same analysis using Normalised Flow as the dependent variable. *, **, and *** indicate the parameters' significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Flow						
	Article 9		**Article 8**		**Article 6**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Post	0.006	0.008	0.017	0.007	0.018	**0.014*****
	(0.35)	(1.71)	(1.05)	(1.59)	(1.11)	(2.69)
Lag return		**0.082*****		**0.066*****		0.027
		(3.1)		(3.7)		(1.01)
Lag flow		**0.224*****		**0.069*****		**0.050****
		(4.58)		(3.39)		(2.19)
Lag net assets		**-0.031*****		**-0.033*****		**-0.032*****
		(-5.28)		(-8.55)		(-6.72)
Lag return volatility		0.068		-0.046		0.101
		(0.59)		(-0.52)		(0.72)
Lag expense ratio		**0.002***		**0.009*****		**0.009*****
		(1.78)		(3.86)		(6.85)
Age		-0.003		-0.002		**-0.005****
		(-1.07)		(-0.93)		(-2.48)
MSR		-0.000		**0.002****		0.001
		(-0.13)		(2.38)		(0.50)
MOR		0.006**		**0.009*****		**0.007*****
		(2.43)		(9.29)		(5.05)
Intercept	0.023		-0.001		-0.001	
	(1.44)		(-0.05)		(-0.08)	
R^2	0.002	0.099	0.019	0.031	0.021	0.025
Fund fixed effect	No	Yes	No	Yes	No	Yes
Fund-month clustered	No	Yes	No	Yes	No	Yes

Table 2.4: continued						
Panel B: Normalised flow						
	Article 9		**Article 8**		**Article 6**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Post	-0.038	0.080	**0.153*****	**0.078***	**0.146*****	**0.088*****
	(-0.48)	(1.47)	(2.88)	(1.81)	(3.05)	(3.01)
Lag return		**0.106*****		**0.084*****		0.042
		(2.86)		(2.98)		(1.47)
Lag flow		**0.171*****		**0.09*****		**0.076*****
		(6.14)		(7.64)		(6.53)
Lag net assets		**-0.296*****		**-0.219*****		**-0.236*****
		(-4.47)		(-4.26)		(-5.45)
Lag return volatility		-0.034		-0.028		0.008
		(-0.80)		(-0.79)		(0.27)
Lag expense ratio		**0.135*****		**0.185*****		**0.214*****
		(3.77)		(5.17)		(5.22)
Age		**-0.115****		-0.042		-0.041
		(-2.52)		(-1.10)		(-1.55)
MSR		0.072		**0.034****		0.003
		(1.50)		(2.14)		(0.17)
MOR		**0.137*****		**0.157*****		**0.142*****
		(3.15)		(10.17)		(8.44)
Intercept	0.013		-0.084		-0.082	
	(0.210)		(-1.78)		(-1.83)	
R^2	0.005	0.091	0.137	0.035	0.146	0.028
Fund fixed effect	No	Yes	No	Yes	No	Yes
Fund-month clustered	No	Yes	No	Yes	No	Yes

2.7.3 Event study of flows

In this section, Table 2.5 reports result from an event study of flows that isolate the independent effect of the EU SFDR from other influences on SFDR-labelled fund flows. This isolation occurs by benchmarking fund actual flow following the application of the SFDR to a model of its expected flow to determine the abnormal flow attributed to the application of the SFDR in March 2021. This benchmarking of fund flow allows the study to differentiate between flows driven by other funds' characteristics and those influenced by the SFDR. The post-SFDR flow is compared to the predicted benchmark model, which eliminates the impact of other fund characteristics like the average flow across fund investment style, prior return, prior flow, alpha, and squared term of the change in a funds' alpha. The abnormal flow in this context means the actual fund flows compared to its expected flow if there was no SFDR regulation (Del Guercio and Tkac 2008). Panel A of Table 2.5 reports the average standardised abnormal flow ($\widehat{ASAF_t}$) for funds declaring as Article 9, 8, and 6, respectively, for event months 0 to 6. Panel B of Table 2.5 shows the estimates of the corresponding average cumulative standardised abnormal flow.

Panel A of Table 2.5 shows that the average standardised abnormal flow $\widehat{ASAF_t}$ for Article 9 funds in all event windows are not statistically different from zero. Therefore, the null hypothesis of no SFDR regulation effect cannot be rejected. As to Article 8 funds, the $\widehat{ASAF_t}$ is positive and statistically significant (1% level) in the month when the SFDR was introduced (March 2021). In the following month (April 2021), the $\widehat{ASAF_t}$ is negative and statistically significant at the 5% level. Although the average abnormal flow is negative in the following month, more than half of the funds experienced abnormal flow as indicated by the sign test (54.91%). This suggests the asymmetry impact of the SFDR, with most of Article 8 funds attracting modest capital while a few faced significant outflows. Article 6 funds experienced an average abnormal flow in March 2021 (the event month), as indicated by positive and statistically significant $\widehat{ASAF_t}$ at the 1% level. However, the fourth month (July 2021), was marked by abnormal outflow of Article 6 funds, on average (5% significance level). Although Article 6 funds faced average abnormal outflow in July 2021, most funds had positive flow.

Panel B of Table 2.5 shows the average cumulative standardised abnormal flow $\widehat{ACSAF_t}$. The result is robust for Article 9 funds, showing no significant cumulative abnormal flow through the examined event windows. For Article 8 funds, the $\widehat{ACSAF_t}$ is positive and statistically significant in event month 0 to month six except for month 2 (April 2021). For Article 6 funds, the $\widehat{ACSAF_t}$ is positive and statistically significant in all event months from March 2021 to September 2021. These results suggest that investors' response to the application of SFDR was not immediate or concentrated in a single month but rather accumulated over time, especially for Article 8 and 6 funds. This indicates a persistent and gradually unfolding effect of their fund flow. On the other hand, investors did not show any response to the funds classified as Article 9 in or after the application of the SFDR in March 2021.

Table 2. 5: Investor reaction to the EU SFDR regulation - Event study of flows

This table reports the average standardised abnormal flow $\widehat{ASAF_t}$ (Panel A), averaged across EU funds within the same SFDR-label group (Articles 9, 8, or 6) for the 6 months after the application of the SFDR (t= [0;6]). Standardised abnormal flow in month t is calculated as the difference between the fund actual flow and the expected flow, standardised by the estimated predicted error (RMSE) (Dodd and Warner 1983). Expected flow is estimated for each fund i in each SFDR-label category based on a time-series benchmark regression where the fund flow at month t is regressed on average flow at time t to funds in the same style group (blended, value, and growth), one-month lagged return, flow, percentage change in the Carhart (1997) four-factor alpha, percentage change in the Carhart (1997) four-factor alpha squared. Panel B reports the same tests for the average cumulative standardised abnormal flow $\widehat{ACSAF_t}$. The cumulative standardised abnormal flow for each fund is calculated by summing the standardised abnormal flow from event time 0 to t and then dividing it by the square root of the number of event times used in the cumulation. Then, the average of $\widehat{ASAF_t}$ and $\widehat{ACSAF_t}$ across N funds is calculated within each event window and for each fund category (Articles 9, 8, and 6). t-statistics are calculated based on the standardise cross sectional test introduced by Boehmer et al. (1991) and reported in parentheses. The nonparametric sign test is also reported for each fund category to show the percentage of positive standardised abnormal flows within each event window. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Average standardised abnormal flow for the SFDR labelled funds

	Article 9			Article 8			Article 6		
Event month	$\widehat{ASAF_t}$	**t-stat**	**%> 0**	$\widehat{ASAF_t}$	**t-stat**	**%> 0**	$\widehat{ASAF_t}$	**t-stat**	**%> 0**
0	0.110	(1.19)	50.86	**0.117*** **	(4.09)	**58.49*** **	**0.098*** **	(-2.76)	**58.68*** **
1	-0.095	(-1.04)	48.31	**-0.072** **	(-2.53)	**54.91*** **	0.004	(0.12)	**56.12** **
2	-0.010	(-0.11)	43.22	0.016	(0.56)	**54.19** **	-0.019	(-0.54)	**58.09*** **
3	0.052	(0.56)	53.39	0.013	(0.45)	**58.33*** **	0.026	(0.74)	**62.00*** **
4	-0.141	(-1.53)	45.69	-0.019	(-0.67)	48.53	**-0.073** **	(-2.07)	**55.64** **
5	0.070	(0.76)	55.83	0.010	(0.34)	**57.61*** **	0.025	(0.73)	**58.48*** **
6	-0.105	(-1.15)	43.80	0.023	(0.80)	**53.63** **	0.047	(1.35)	**61.52*** **

Panel B: Average cumulative standardised abnormal flow for the SFDR labelled funds

	Article 9			Article 8			Article 6		
Event month	$\widehat{ACSAF_t}$	**t-stat**	**%> 0**	$\widehat{ACSAF_t}$	**t-stat**	**%> 0**	$\widehat{ACSAF_t}$ t	**t-stat**	**%> 0**
0	0.041	(1.21)	50.86	**0.043*** **	(3.99)	**58.49** **	**0.036*** **	(2.67)	**58.68*** **
1	0.005	(0.13)	47.46	0.012	(1.20)	**62.00** **	**0.035** **	(2.37)	**63.56*** **
2	-0.013	(-0.34)	41.53	**0.025** **	(2.42)	**62.89** **	**0.035*** **	(2.85)	**63.74*** **
3	0.023	(0.62)	47.46	**0.031** **	(2.52)	**64.40** **	**0.034** **	(2.41)	**67.38*** **
4	-0.042	(-1.21)	41.38	**0.020* **	(1.71)	**62.07** **	0.016	(1.18)	**65.04*** **
5	-0.014	(-0.34)	47.50	**0.022* **	(1.92)	**63.92** **	0.020	(1.19)	**65.85*** **
6	-0.057	(-1.44)	42.15	**0.033*** **	(2.80)	**63.63** **	**0.045*** **	(3.09)	**69.12*** **

2.7.4 Difference in Difference (DiD) panel regression

To examine comprehensively investor responses to the EU SFDR across different shades of green, we compare the flow into specific SFDR-labelled funds according to Equation (2.4), which analyses the following settings: Article 9 funds (Dark green) vs. Article 6 funds (non-green); Article 8 funds (Light green) vs. Article 6 funds (non-green); and Article 9 fund (Dark green) vs. Article 8 funds (Light green). Panel A of Table 2.6 reports the results using raw flow.

First, the models are estimated without controlling for other fund characteristics (columns 1, 3, and 5). Regarding Article 9 vs. Article 6 funds, the coefficient for, $Article_i$ * Post_t ; where $Article_i$ is a dummy variable that equals to 1 for Article 9 funds and 0 for Article 6 funds, is 0.011 and statistically significant at the 1% level. The coefficient for $Post_t$, which equals to 1 for the months following March 2021 and 0 otherwise, is 0.006 and statistically significant at the 1% level. This result suggests that, post the application of SFDR, the inflow into Article 9 funds was higher than Article 6 funds by 0.011. Comparing Article 8 with Article 6 funds, the coefficient on $Article_i$ * Post_t is 0 and statistically insignificant (column 3). This result suggests no significant difference in flow between Article 8 and 6 funds after March 2021. Finally, in the comparison between Article 9 and Article 8 funds (Column 5), the coefficient on the interaction term is 0.012. As expected, post the application of SFDR, Article 9 funds attracted a higher inflow than Article 8 and Article 6 funds.

However, after controlling for other fund characteristics and fund fixed effects as well as clustering standard errors by fund and month, the results show no difference in fund flow between Article 9 funds and Article 6 and Article 8 funds, nor between Article 8 and Article 6 funds. Inconsistent with the earlier finding which shows that Article 6 funds experienced higher inflow post the SFDR in March 2021, these results suggest that investors showing no incremental preferences for the different shades of green disclosed by the SFDR labels. Moreover, the table shows that other fund characteristics are driving the flow such as the one-month lagged return, flow, size, expense ratio, MSR, and MOR. The higher the funds' return, flow, fees, MSR and MOR, the higher the inflow. Also, the fund flow is higher for smaller size funds. When normalising the funds flow in the three fund comparisons in Panel B of Table 2.6, the results remain unchanged.

Table 2.7, panel A shows the results after including $Article_i$ to the model. The table reports a relative decline in inflows to Article 9 following the application of the SFDR, compared with Article 8 and Article 6 funds. Nevertheless, the coefficients on $Article_i$ are positive and statistically significant at the 1% level in both specifications (Article 9 funds vs. Article 6 funds, and Article 9 fund vs Article 8 funds), indicating that prior to the application of the SFDR, Article 9 funds already enjoyed higher inflows relative to Article 8 and 6 funds. This finding suggests that the regulation was associated with a reduction in this inflow. Panel B of Table 2.7 reports a robust result after normalising the funds flow across the three settings Article 9 funds vs. Article 6 funds; Article 8 funds vs. Article 6 funds; and Article 9 fund vs. Article 8 funds.

Table 2.6: Investors behaviour as a reaction to the specific fund labels disclosed under EU SFDR regulation.
This table shows how SFDR-labelled fund flows vary post the application of the SFDR in March 2021. Panel A shows the results for the panel OLS DiD regression of monthly flow across three different settings that compare a treatment vs. a control group: Article 9 vs. Article 6 (columns 1 and 2), Article 8 vs. Article 6 (columns 3 and 4); and Article 9 vs. Article 8 (columns 5 and 6). The dependent variable is regressed on $Article_i$ * $Post_t$. $Article_i$ is a dummy variable that equals 0 for the control group and 1 for the treatment group in each case. $Post_t$ is a dummy variable that equals 1 for months following March 2021, and 0 otherwise. The control variables include (One-month lagged: return, flow, log total net assets, standard deviation of the funds' prior 12-month return (volatility), and expense ratio, non-lagged: age, Morningstar sustainability rating (MSR) and Morningstar star (overall) rating (MOR). t-statistics (in parentheses) are calculated with Newey-West robust standard errors. Standard errors are clustered by fund and month. Panel B repeats the same analysis using Normalised Flow as the dependent variable. *, **, and *** indicate the parameters' significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Flow

	Article 9 vs. Article 6		**Article 8 vs. Article 6**		**Article 9 vs. Article 8**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Post	**0.006*** **	**0.014*** **	**0.009*** **	**0.011** **	**0.006*** **	**0.007* **
	(6.27)	(2.79)	(11.71)	(2.56)	(8.09)	(1.71)
Post * Article	**0.011*** **	-0.005	-0.000	-0.002	**0.012*** **	-0.003
	(8.81)	(-1.26)	(-0.37)	(-0.86)	(9.28)	(-0.74)
Lag return		0.034		**0.049** **		**0.067*** **
		(1.38)		(2.54)		(3.76)
Lag flow		**0.07*** **		**0.062*** **		**0.081*** **
		(3.12)		(3.55)		(4.18)
Lag net assets		**-0.033*** **		**-0.033*** **		**-0.033*** **
		(-7.59)		(-9.44)		(-8.87)
Lag return volatility		0.096		0.025		-0.035
		(0.75)		(0.26)		(-0.40)
Lag expense ratio		**0.006*** **		**0.009*** **		**0.006** **
		(3.13)		(8.20)		(2.57)
Age		**-0.005** **		-0.003		-0.002
		(-2.37)		(-1.63)		(-0.98)
MSR		0.001		**0.002* **		**0.002** **
		(0.43)		(1.79)		(2.20)
MOR		0.006***		**0.008*** **		**0.008*** **
		(5.52)		(9.45)		(9.94)
Intercept	**0.01*** **		**0.008*** **		**0.01*** **	
	(12.42)		(14.01)		(14.22)	
R^2	0.002	0.029	0.002	0.028	0.002	0.034
Fund fixed effect	No	Yes	No	Yes	No	Yes
Fund-month clustered	No	Yes	No	Yes	No	Yes

Table 2.6: continued						
Panel B: Normalised flow						
	Article 9 vs. Article 6		**Article 8 vs. Article 6**		**Article 9 vs. Article 8**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Post	**0.061*** **	**0.092*** **	**0.141*** **	**0.084** **	**0.084*** **	**0.080* **
	(6.33)	(3.07)	(17.23)	(2.54)	(10.63)	(1.86)
Post * Article	**0.270*** **	-0.024	**-0.031*** **	-0.003	**0.295*** **	-0.018
	(14.34)	(-1.36)	(-3.50)	(-0.17)	(16.48)	(-1.43)
Lag return		**0.051* **		**0.067** **		**0.086*** **
		(1.76)		(2.42)		(3.03)
Lag flow		**0.087*** **		**0.085*** **		**0.095*** **
		(7.43)		(9.23)		(8.34)
Lag net assets		**-0.253*** **		**-0.225*** **		**-0.229*** **
		(-6.48)		(-5.43)		(-4.68)
Lag return volatility		0.000		-0.013		-0.029
		(0.01)		(-0.4)		(-0.84)
Lag expense ratio		**0.176*** **		**0.194*** **		**0.143*** **
		(4.05)		(7.21)		(3.51)
Age		**-0.052* **		-0.043		-0.048
		(-1.89)		(-1.32)		(-1.29)
MSR		0.013		**0.021* **		**0.037** **
		(0.79)		(1.85)		(2.44)
MOR		**0.141*** **		**0.15*** **		**0.155*** **
		(9.22)		(12.28)		(10.69)
Intercept	**-0.048*** **		**-0.059*** **		**-0.054*** **	
	(-7.04)		(-12.86)		(-9.46)	
R^2	0.007	0.031	0.004	0.031	0.007	0.037
Fund fixed effect	No	Yes	No	Yes	No	Yes
Fund-month clustered	No	Yes	No	Yes	No	Yes

Table 2. 7: Investors behaviour as a reaction to the specific fund labels disclosed under EU SFDR regulation -Extended specifications with Article dummy. This table shows how SFDR-labelled fund flows vary post the application of the SFDR in March 2021. Panel A shows the results for the panel OLS DiD regression of monthly flow across three different settings that compare a treatment vs. a control group: Article 9 vs. Article 6 (columns 1 and 2), Article 8 vs. Article 6 (columns 3 and 4); and Article 9 vs. Article 8 (columns 5 and 6). The dependent variable is regressed on $Article_i$ * $Post_t$. $Article_i$ is a dummy variable that equals 0 for the control group and 1 for the treatment group in each case. $Post_t$ is a dummy variable that equals 1 for months following March 2021, and 0 otherwise. The control variables include (One-month lagged: return, flow, log total net assets, standard deviation of the funds' prior 12-month return (volatility), and expense ratio, non-lagged: age, Morningstar sustainability rating (MSR) and Morningstar star (overall) rating (MOR). t-statistics (in parentheses) are calculated with Newey-West robust standard errors. Standard errors are clustered by fund and month. Panel B repeats the same analysis using Normalised Flow as the dependent variable. *, **, and *** indicate the parameters' significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Flow						
	Article 9 vs. Article 6		**Article 8 vs. Article 6**		**Article 9 vs. Article 8**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Post	**0.009*****	0.002	**0.009*****	0.002	**0.008*****	0.000
	(8.97)	(0.80)	(8.97)	(0.64)	(10.29)	(0.07)
Article	**0.023*****	**0.021*****	0.000	0.000	**0.023*****	**0.018*****
	(8.24)	(5.14)	(0.38)	(0.13)	(8.23)	(4.87)
Post * Article	**-0.012*****	**-0.015*****	-0.001	-0.001	**-0.011*****	**-0.012*****
	(-3.82)	(-3.47)	(-0.51)	(-0.77)	(-3.68)	(-3.25)
Lag return		0.014		0.031		**0.052*****
		(0.50)		(1.60)		(3.32)
Lag flow		**0.126*****		**0.111*****		**0.134*****
		(5.09)		(6.08)		(6.34)
Lag net assets		-0.000		-0.000		-0.000
		(-0.03)		(-0.77)		(-1.43)
Lag return volatility		0.090		0.047		0.002
		(1.04)		(0.78)		(0.03)
Lag expense ratio		**0.009*****		**0.011*****		**0.011*****
		(8.18)		(15.31)		(7.54)
Age		**-0.000****		**-0.000*****		**-0.000*****
		(-2.26)		(-3.13)		(-3.41)
MSR		0.000		**0.001****		**0.002*****
		(0.71)		(2.28)		(3.28)
MOR		**0.003*****		**0.004*****		**0.004*****
		(5.57)		(8.24)		(7.42)
Intercept	**0.007*****	**0.004***	**0.007*****	-0.000	**0.008*****	-0.003
	(8.56)	(1.77)	(8.56)	(-0.04)	(11.09)	(-0.83)
R^2	0.005	0.043	0.002	0.033	0.004	0.046
Fund fixed effect	No	No	No	No	No	No
Fund-month clustered	No	Yes	No	Yes	No	Yes

Table 2.7: continued						
Panel B: Normalised flow						
	Article 9 vs. Article 6		**Article 8 vs. Article 6**		**Article 9 vs. Article 8**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Post	**0.115*****	0.024	**0.118*****	0.025	**0.124*****	0.023
	(11.6)	(0.83)	(11.98)	(0.80)	(15.28)	(0.64)
Article	**0.431*****	**0.105*****	**-0.038*****	**-0.026****	**0.466*****	**0.089*****
	(19.76)	(5.09)	(-4.08)	(-1.97)	(22.33)	(5.75)
Post * Article	**-0.161*****	**-0.041****		0.003	**-0.171*****	**-0.033*****
	(-5.59)	(-2.34)		(0.21)	(-6.22)	(-2.6)
Lag return		0.045		**0.064****		**0.085*****
		(1.44)		(2.13)		(2.75)
Lag flow		**0.144*****		**0.143*****		**0.161*****
		(9.66)		(12.64)		(11.03)
Lag net assets		**0.144*****		0.006		-0.005
		(9.66)		(1.05)		(-0.78)
Lag return volatility		-0.029		**-0.038****		**-0.051****
		(-1.52)		(-2.03)		(-2.26)
Lag expense ratio		**0.292*****		**0.275*****		**0.234*****
		(10.73)		(20.5)		(10.06)
Age		**-0.004*****		**-0.004*****		**-0.005*****
		(-2.72)		(-3.68)		(-4.03)
MSR		0.001		**0.024*****		**0.044*****
		(0.08)		(2.83)		(4.31)
MOR		**0.072*****		**0.091*****		**0.093*****
		(5.70)		(8.42)		(7.37)
Intercept	**-0.102*****	-0.232	**-0.036*****	**-0.408*****	**-0.094*****	**-0.286****
	(-14.19)	(-1.52)	(-5.07)	(-3.92)	(-15.74)	(-2.36)
R^2	0.017	0.138	0.004	0.114	0.015	0.118
Fund fixed effect	No	No	No	No	No	No
Fund-month clustered	No	Yes	No	Yes	No	Yes

2.7.5 Propensity score matching

This sub-section presents the findings of the Propensity Score Matching (PSM) analysis. Table 2.8 reports the standardized mean difference (SMD) statistics for each covariate, including fund flow, age, total net assets, return, and alpha, across the treatment and control groups under three different settings: (a) Article 9 versus a matched control group of Article 6; (b) Article 8 versus a matched control group of Article 6; and (c) Article 9 versus a matched control group of Article 8, both before and after the PSM. SMD below 0.10 indicates excellent covariate balance (Zhang et al. 2019), while values between 0.10 and 0.25 indicates acceptable balance (Stuart et al. 2013). The post matching results for the three settings show that all covariates achieve excellent or acceptable balance, suggesting that the matching is of high quality and has substantially reduced the systematic difference between the groups.

Table 2.9 displays the difference in average net flows starting from the six months before the application of SFDR in March 2021 (September 2020 to February 2021) until the twelve months afterwards (March 2021 to February 2022) to observe the funds' average net flow before EU SFDR and its consistency across time. The results are reported for three different settings: a) Article 9 versus a matched control group of Article 6; (b) Article 8 versus a matched control group of Article 6; and (c) Article 9 versus a matched control group of Article 8. The average net flow of the matched control group was subtracted from the average flow of the treatment group.

During the six-month period prior to the EU SFDR application (September 2020 to February 2021), the average net flow into Article 9 funds were statistically significantly higher than Article 6 and Article 8 funds (1% level). However, there was no significant difference in average net flow between Article 8 and Article 6 funds. Similarly, during the three-month period prior to EU SFDR (December 2020 to February 2021), the results remain consistent. During the three-month period from the launch of EU SFDR (March 2021 to May 2021), there was no difference in average net flow between Article 9 and 6 funds, as well as between Article 8 and 6 funds. Yet, there was a higher average net flow into Article 9 funds than Article 8 funds, during the specified period. Lastly, During the six, nine, and twelve months from the launch of EU SFDR (March 2021 to August 2021; March 2021 to November 2021; March 2021 to February 2022), there was a significant difference between Article 9 and 6 funds' average net flow, as well as Article 9 and 8 funds' average net flow. There is no observed difference between Article 8 and 6 funds' average net flow.

The results show consistency in the difference between Article 9 and 8 funds and Article 8 and 6 funds' average net flow over the short and long period and before, during and after the effective date of EU SFDR. These results suggest that the investors consistently differentiated between Article 9 and Article 8 funds, however, they could not differentiate between Article 8 and Article 6 funds. The result also suggests that the announcement of EU SFDR did not affect investors' preferences. Interestingly, the significant difference between Article 9 and 6 funds' average net flow across all month ranges except for the three months from the date of the EU SFDR indicate that the regulation has influenced investors' decisions over time and this insignificant difference in behaviour was temporary.

This result is inconsistent with the prior result from the fixed effect panel DiD regression which show no difference in flow between the funds in the two settings (Article 9 vs 6; Article 9 vs. 8) after the application of SFDR. This finding indicates that addressing the selection bias between Article 9 and 6 funds, as well as Article 9 and 6 funds through PSM is essential to account for the differences between the funds and address the impact of the SFDR on their fund flows. On the other hand, the result for the comparison between Article 8 and Article 6 funds is consistent with earlier finding, suggesting no significant difference in flow between the two funds' categories.

To summarise, the SFDR effect on fund flow varies depending on the methodological approach. While the panel regression and the event study of flows suggest a significant flow into Article 6 and 8 funds, particularly in the short-term, the DiD and the PSM provide mixed evidence. This suggests that the effect of the SFDR varied over time, with an initial reaction, captured in the event study of flows, particularly in Article 8 and 6 funds. However, after controlling for time-varying effect using DiD, the results suggest no difference in the flow between the funds. After including $Article_i$ to the model but without incorporating fixed effect, Article 9 funds attracted higher inflows compared to Article 8 and 6 funds. However, following the application of the SFDR, there was a relative decline in Article 9 flow compared to Article 8 and Article 6 funds. Finally, after controlling for fund attributes using PSM, there is evidence that the flow into Article 9 funds was higher than both Article 8 and 6 funds and no evidence of difference in flow between Article 8 and 6 funds both before and after the SFDR application. This result indicates that certain fund characteristics played a role in attracting investors post SFDR.

Table 2. 8.: Propensity score matching – Sample comparison

This table reports the standardized mean differences (SMD) statistics for each covariate in the treatment and control groups before and after propensity score matching (PSM). Lower values indicate better covariate balance, with SMD values below 0.1 considered excellent and below 0.25 considered acceptable.

Covariate	SMD before	SMD after
	Article 9 vs. Article 6	
Flow	0.092	0.020
Age	0.313	0.004
TNA	0.127	0.010
Return	0.011	0.016
Alpha	0.099	0.021
	Article 8 vs. Article 6	
Flow	0.004	0.006
Age	0.096	0.111
TNA	0.263	0.063
Return	0.030	0.000
Alpha	0.001	0.023
	Article 9 vs. Article 8	
Flow	0.088	0.018
Age	0.200	0.014
TNA	0.145	0.020
Return	0.042	0.018
Alpha	0.105	0.014

Table 2. 9: Investor reaction to the EU SFDR regulation - Propensity score matching

The table reports the difference in net flows between the treatment and control groups from the nearest-neighbour matching across three different settings that compare a treatment vs. a control group: Article 9 vs. Article 6, Article 8 vs. Article 6; and Article 9 vs. Article 8. Funds are matched within their SFDR-labelled group based on flow, return, age, four-factor alpha, and log of total net assets as of December 2022. The difference in SFDR-labelled funds' average flow is calculated by subtracting the average net flow of the matched control group from that of the treatment group over six-time intervals relative to March 2021 (the application of SFDR): six months and three months before March 2021(columns 1 and 2) and for the three, six, nine, and 12 months starting from March 2021 (columns 3 to 6). *t*-statistics are reported in parentheses calculated with two-tailed student t-test. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Flow					
	Months					
	[-6; 0]	**[-3; 0]**	**[0; 3]**	**[0; 6]**	**[0; 9]**	**[0; 12]**
Article 9 vs. Article 6	**0.026*** **	**0.028*** **	0.017	**0.017*** **	**0.014*** **	**0.013*** **
	(4.64)	(3.47)	(1.75)	(3.42)	(4.35)	(4.88)
Article 8 vs. Article 6	0.004	0.003	-0.004	-0.002	0.000	-0.001
	(1.86)	(1.10)	(-1.40)	(-1.22)	(-0.36)	(-0.85)
Article 9 vs. Article 8	**0.030*** **	**0.038*** **	**0.021** **	**0.020*** **	**0.017*** **	**0.016*** **
	(5.97)	(5.88)	(2.38)	(4.09)	(0.02)	(5.96)

2.8 Empirical results: Fund managers' response to the announcement of the SFDR – November 2019 (Holdings)

2.8.1 Graphical evidence

This section answers the second research question examining fund managers' trading decisions post the announcement of the SFDR regulation in November 2019. The investigation is conducted by evaluating SFDR-labelled funds' change of its holdings given their ESG score and identification to either Article 9, Article 8 or Article 6. It is expected that fund managers respond to the regulation. Specifically, it is expected that after the announcement of the EU SFDR Article 9 funds should exhibit higher ESG score assets in their optimal portfolio as compared to Article 8 and Article 6.

First, the average funds' Morningstar sustainability rating for each SFDR-labelled funds is visualised over the sample period to show how the funds' MSR changed around the announcement and the adoption of the SFDR. Figure 2.4 shows the average Morningstar sustainability rating (MSR) for SFDR-labelled funds (Articles 9, 8, and 6) between January 2019 and the end of 2022. The figure depicts Article 6 to be assigned the lowest average Morningstar rating of around 2.9 during this period. At the beginning of 2019, Article 8 funds were rated 3, while Article 9 funds were rated higher at 3.62. Since September 2019, the MSR for Article 8 and 9 funds has increased, while Article 6 funds' MSR has decreased. This shift in the MSR was a direct result of the change in Morningstar methodology[17]. This change has been steady for Article 8 funds, while Article 6 and 9 funds have seen nearly flat line with small variations until the end of the sample. This shows that the SFDR-labelled funds did not change their rating with respond to the regulation. Inconsistent with Becker et al. (2022) who find that EU mutual funds have increased their ESG rating following the adoption of the EU SFDR, the figure shows that the funds' MSR rating have only increased following the change in Morningstar methodology.

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[17] https://www.morningstar.com/content/dam/marketing/shared/pdfs/Research/934613.pdf

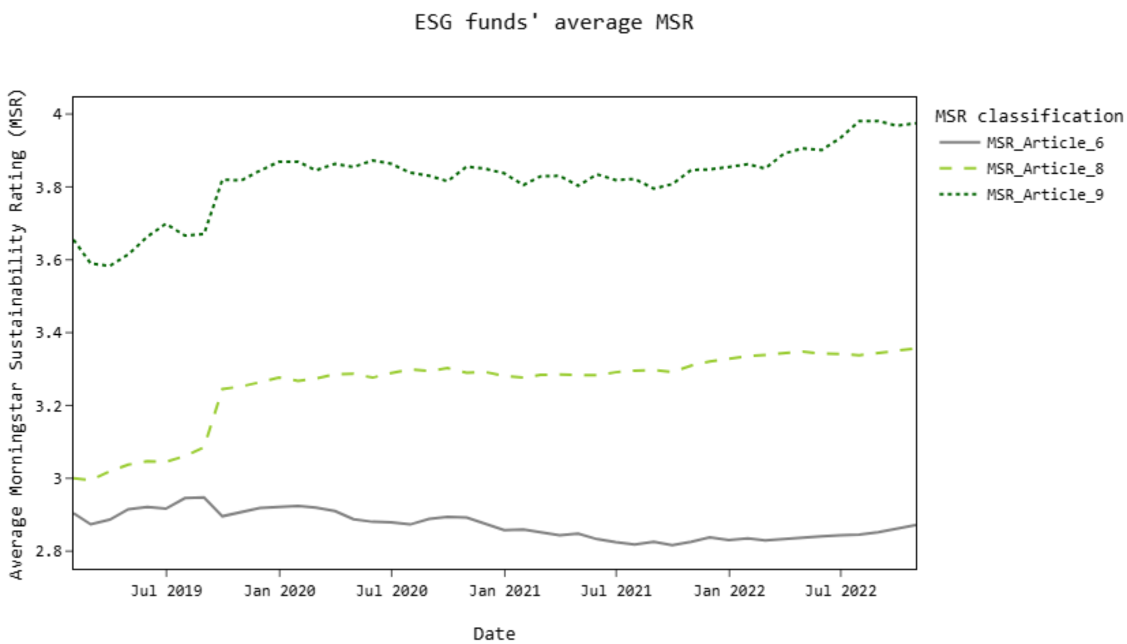

Figure 2.4: ESG funds' MSR
The chart shows the average monthly MSR for Article 9,8, and 6 funds over the sample period.

Next, a visual presentation of each SFDR-labelled fund (Articles 9, 8 and 6) groups' portfolio averaged Refinitiv ESG score is presented to provide insights beyond the fund-level rating and into the ESG rating of the assets that the funds hold (Figure 2.5). The figure shows more fluctuations over the same sample period.

More specifically, at the start of 2019, Article 6 funds had a higher portfolio averaged Refinitiv ESG score than Article 8 and 9 funds, respectively. From June 2019, Article 9 funds' portfolio received higher averaged Refinitiv ESG score than other funds. This is four months before the announcement of the SFDR first draft in November 2019. The figure shows a spike in average portfolio Refinitiv ESG score for all SFDR-labelled funds in January 2020 and January 2021, with Article 9 funds' portfolio having the highest average ESG score, and Article 6 funds' portfolio have the lowest ESG score. These spikes are likely due to funds annual rebalancing or an update at the firms' ESG rating due to annual sustainability disclosure that was then reflected in Refinitiv ESG score rather than the SFDR. This graphical evidence hints at ambiguity and discrepancies in rating EU ESG funds even with the adoption of the EU SFDR, which also indicates its ineffectiveness in increasing transparency and reducing greenwashing in the ESG market.

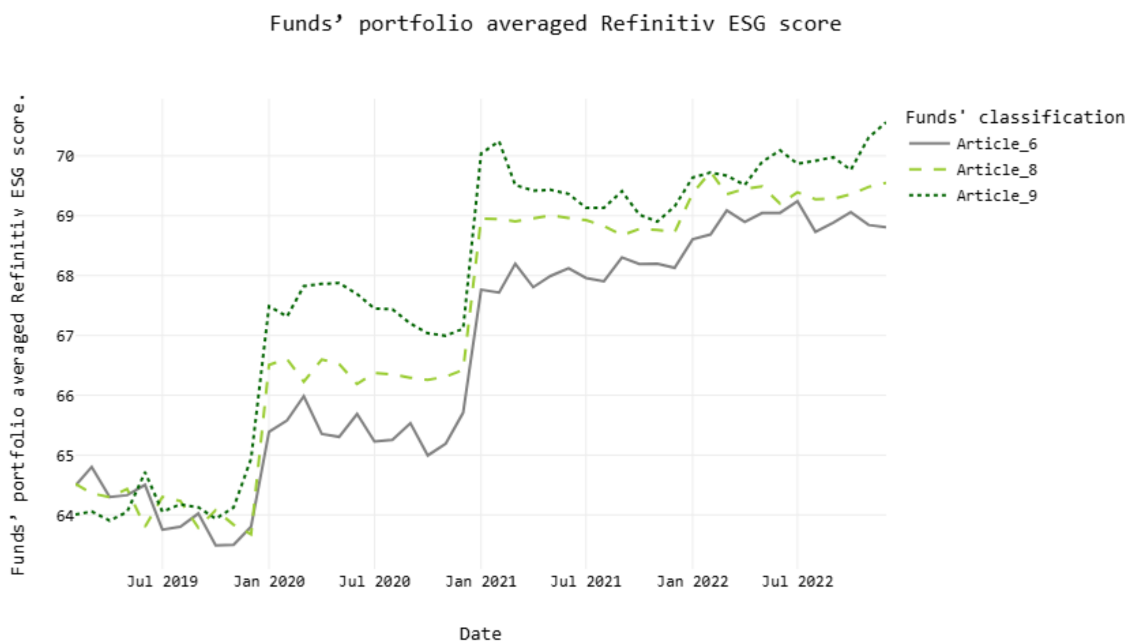

Figure 2.5: Funds' portfolio averaged Refinitiv ESG score.
The chart shows the average monthly Refinitiv ESG score for Article 9,8, and 6 funds' holdings over the sample period.

2.8.2 Main results

This section aims to scrutinize fund managers' compliance with EU SFDR regulations after November 2019 when the SFDR was first published, while investors were still uninformed about it (Panel A of Table 2.7). There is no evidence that Article 8 fund managers increase their positions in assets with high ESG score more than Article 9 and 6 fund managers. In particular, the model in equation 2.5 was first estimated without controlling for other fund and firm characteristics. In this setting, $Post_t$ is a dummy variable that equals to one for the months following the announcement of the SFDR in November 2019, 0 otherwise. The results show that for Article 9 funds (Panel A of Table 2.7), the interaction terms between $Medium\ ESG_j$, $Above\ average\ ESG_j$, $High\ ESG_j$ and $Post_t$ are negative and significant at the 1% level. This means that Article 9 fund managers reduced their positions in firms with medium, above average, and high ESG score after the announcement of the SFDR in November 2019. However, after adjusting for other fund and firm characteristics, these interaction terms become statistically insignificant, suggesting that fund managers did not change their positions in firms with Refinitiv ESG firms ranges from 0 to 100. The result also shows that the effect of the funds' churn rate, which indicate the portfolios' turnover, is negative and statistically significant at the 1% level. This suggest that Article 9 funds with high trading activity are less likely to hold or adjust positions in ESG firms.

For Article 8 funds (columns 3 and 4), the interaction terms between $Low\ ESG_j$, $Medium\ ESG_j$, $Above\ average\ ESG_j$, $High\ ESG_j$ and $Post_t$ are positive and statistically significant at the 1% level. After adjusting for other funds and firms' characteristics, the coefficients for these interaction terms remain the same but with less significancy level. The interaction of $Post_t$ with the $Low\ ESG_j$ and $Above\ average\ ESG_j$ (10% level) and the $Medium\ ESG_j$ and $High\ ESG_j$ (5% level). This result suggests that fund managers increased their positions in ESG firms, with more significant change in firms with medium and high Refinitiv ESG score post the announcement of the SFDR in November 2019. The results also show a negative relationship between Article 8 funds' churn rate and their position change and a positive relationship between lagged total buy and sell and their position change. This result suggests a divergence in Article 8 fund managers' behaviour. Fund managers with high absolute trading activity tend to change their positions, as indicated by positive total buy and sell coefficients. However, they do not make frequent changes to their positions as indicated by negative churn rate.

For Article 6 funds (columns 5 and 6), the interaction terms between $Low\ ESG_j$, $Medium\ ESG_j$, $Above\ average\ ESG_j$, $High\ ESG_j$ and $Post_t$ are negative and significant at the 5% and 1% levels. This means that Article 6 fund managers reduced their positions in firms with low, medium, above average, and high ESG score after the announcement of the SFDR in November 2019. However, the change in above average and high ESG firms were more significant than the change in other firms with lower ESG score. After adjusting for other fund and firm characteristics, these interaction terms become statistically insignificant, suggesting that Article 6 fund managers did not change their positions in firms with Refinitiv

ESG firms ranges from 0 to 100. The result also shows a negative relationship between funds' churn rate, firms' volatility, and funds' position change. In addition, there is a positive relationship between firms' one-month lagged weight and the funds' position change. This could reflect Article 6 fund managers' preference to reallocating capital to assets with significant weight in the portfolio.

For robustness, the model is also examined for the period from January 2019 to February 2021 until before the application of the SFDR in March 2021 (Panel B of Table 2.7), to capture the initial fund managers' adjustments in response to the announcement of the regulation before its application in March 2021. Here, $Post_t$ is a dummy variable that equals to one for the months following the announcement of the SFDR in November 2019, 0 otherwise. After adjusting for other fund and firm characteristics and accounting for the unobserved fund characteristics, the result was robust for Article 9 and 6 funds. On the other hand, the results for Article 8 funds show some variations. There is a significant increase in only firms with medium and high Refinitiv ESG score (5% level).

To examine fund managers' behaviour that was driven by the application rather than the announcement of the SFDR. The model is also examined while $Post_t$ is a dummy variable that equals to one for the months following the application of the SFDR in March 2021, 0 otherwise. Interestingly, Table 2.8 shows that Article 9 funds managers decrease their positions in firms with low, medium, and high Refinitiv ESG score, however this is only true at the 10% significance level. For Article 8 funds, fund managers increased their positions in only firms with medium ESG score, yet at only 10% significance level. The result is robust for Article 6 funds, suggesting no changes in their positions in ESG firms.

To summarise, this result challenges Hypothesis 2 which expects Article 9 fund managers to increase their holdings with high ESG score relatively more than Article 8 and 6 funds following the announcement of the EU SFDR regulation in November 2019. In other words, the result indicates that Article 8 fund managers allocate more capital to firms with superior and medium Refinitiv ESG score post the announcement of the SFDR in November 2019 until February 2021 (One month before its application in March 2021). After the SFDR application in March 2021 until the end of the period, Article 8 fund managers increased their exposure only in assets with medium Refinitiv ESG, yet at only 10% significance level. On the other hand, Article 9 fund managers did not change their positions in ESG firms at any score level. This could indicate that Article 9 fund might have been already holding assets with high ESG score. Interestingly, since the application of the SFDR in March 2021, they decreased their position in firms with low, medium, and high Refinitiv ESG score. Yet, at a weak significance level (10%). This could be reflected by the downgrading of Article 9 funds. Article 6 funds did not change their positions in ESG firms following the announcement of SFDR in November 2019.

Table 2.10: Fund managers reaction to the announcement of EU SFDR regulation – November 2019

This table shows the results of panel OLS DiD regressions of monthly position changes on dummy variables of firms' Refinitiv ESG scores for Article 9 (columns 1 and 2), Article 8 (Columns 3 and 4), and Article 6 (columns 5 and 6) funds from January 2019 to February 2021 (Panel A). The dummy variables are interacted with $Post_t$, which is a dummy variable that equals 1 for months following **November 2019**. $High\ ESG_j$ is a dummy variable equal to 1 for firms with an ESG score between 75 and 100, $Above\ average\ ESG_j$ is a dummy variable equal to 1 for firms with an ESG score between 50 and 75, $Medium\ ESG_j$ is a dummy variable equal to 1 for firms with an ESG score between 25 and 50, and $Low\ ESG_j$ is a dummy variable equal to 1 for firms with an ESG score between 0 and 25. The model controls for lagged fund-level controls including monthly flow, return and alpha, the logarithm of a fund's total buys and sells, and a fund's churn rate. It also controls for lagged firm-level characteristics of fund holdings, including the monthly return, return volatility, and weighting in the portfolio. t-statistics (in parentheses) are calculated with Newey-West robust standard errors. Standard errors are clustered by fund and month. Panel B repeats the same analysis for a subsample that spans from January 2019 – February 2021. *, **, and *** indicate the parameters' significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Full sample (January 2019 – December 2022)						
	Position change					
	Article 9		Article 8		Article 6	
	(1)	(2)	(3)	(4)	(5)	(6)
Low ESG$_j$	0.001	0.003	**-0.137*****	-0.133	**0.106*****	0.128
	(0.05)	(0.10)	(-2.90)	(-1.35)	(2.73)	(1.31)
Medium ESG$_j$	**0.141*****	0.138	**-0.318*****	-0.311	**0.207*****	0.235
	(3.02)	(1.26)	(-4.00)	(-1.57)	(3.01)	(1.16)
Above average ESG$_j$	**0.213*****	0.233	**-0.284*****	-0.262	**0.372*****	0.368
	(3.06)	(1.03)	(-2.90)	(-1.20)	(3.32)	(1.24)
High ESG$_j$	**0.206*****	0.272	**-0.46*****	-0.435	**0.467*****	0.425
	(2.71)	(1.12)	(-3.86)	(-1.62)	(3.18)	(1.11)
Low ESG$_j$* Post$_t$	0.006	-0.012	**0.189*****	**0.183***	**-0.101****	-0.125
	(0.20)	(-0.17)	(3.60)	(1.70)	(-2.53)	(-1.35)
Medium ESG$_j$ * Post$_t$	**-0.288*****	-0.269	**0.42*****	**0.426****	**-0.163****	-0.228
	(-4.30)	(-1.3)	(4.70)	(2.15)	(-2.23)	(-1.15)
Above average ESG$_j$ * Post$_t$	**-0.543*****	-0.439	**0.427*****	**0.439***	**-0.305*****	-0.378
	(-5.51)	(-1.3)	(3.77)	(1.67)	(-2.65)	(-1.24)
High ESG$_j$ * Post$_t$	**-0.501*****	-0.477	**0.572*****	**0.584****	**-0.407*****	-0.455
	(-5.13)	(-1.36)	(4.23)	(2.04)	(-2.71)	(-1.26)
Lag churn rate		**-0.303*****		**-0.314*****		**-0.068***
		(-2.89)		(-3.45)		(-1.66)
Lag return		0.016		-0.016		-0.002
		(0.59)		(-1.14)		(-0.2)
Lag flow		-0.041		-0.003		0.009
		(-0.68)		(-0.23)		(0.39)
Lag log total buy		0.065		**0.057***		0.034
		(1.53)		(1.65)		(1.50)
Lag log total sell		0.065		**0.076****		0.014
		(0.75)		(2.38)		(0.93)
Lag return-firm		0.011		-0.019		-0.011

		(0.65)		(-0.92)		(-0.71)
Lag volatility		-0.028		-0.019		**-0.017***
		(-0.81)		(-1.25)		(-1.93)
Lag weight		-0.052		-0.079		**0.169****
		(-0.72)		(-0.41)		(2.03)
Intercept	**-0.627*****		**-0.337*****		**-0.022***	
	(-38.43)		(-24.55)		(-1.91)	
R^2	0.0004	0.001	0.00004	0.0002	0.0001	0.0003
Fund fixed effect	No	Yes	No	Yes	No	Yes
Fund-month clustered	No	Yes	No	Yes	No	Yes

Table 2.10: continued						
Panel B: sub sample (January 2019 – February 2021)						
Position change						
	Article 9		Article 8		Article 6	
	(1)	(2)	(3)	(4)	(5)	(6)
Low ESG_i	-0.025	-0.040	**-0.165*** **	-0.154	**0.112** **	0.141
	(-0.81)	(-0.75)	(-2.94)	(-1.33)	(2.49)	(1.45)
Medium ESG_j	**0.110** **	0.036	**-0.362*** **	-0.359	**0.194*** **	0.229
	(2.28)	(0.36)	(-4.19)	(-1.62)	(2.70)	(1.29)
Above average ESG_i	**0.215*** **	0.109	**-0.325*** **	-0.320	**0.354*** **	0.355
	(3.06)	(0.60)	(-3.21)	(-1.36)	(3.03)	(1.34)
High ESG_i	**0.236*** **	0.120	**-0.506*** **	**-0.499* **	**0.427*** **	0.386
	(3.16)	(0.66)	(-4.07)	(-1.86)	(2.98)	(1.24)
Low ESG_j * $Post_t$	**0.189*** **	0.195	**0.213*** **	0.184	**-0.085* **	-0.118
	(3.59)	(1.62)	(3.02)	(1.51)	(-1.80)	(-1.38)
Medium ESG_i * $Post_t$	0.158	0.214	**0.442*** **	**0.424** **	**-0.142* **	-0.217
	(1.43)	(0.93)	(4.13)	(2.02)	(-1.82)	(-1.36)
Above average ESG_i * $Post_t$	0.150	0.257	**0.453*** **	0.430	**-0.263** **	-0.349
	(0.96)	(0.80)	(3.36)	(1.49)	(-2.14)	(-1.39)
High ESG_j * $Post_t$	0.109	0.239	**0.571*** **	**0.544** **	**-0.324** **	-0.409
	(0.84)	(0.78)	(3.54)	(2.07)	(-2.14)	(-1.62)
Lag churn rate		**-0.182** **		**-0.299*** **		-0.100
		(-2.36)		(-3.29)		(-1.37)
Lag return		**0.005*** **		-0.016		**-0.014*** **
		(2.59)		(-1.02)		(-2.79)
Lag flow		0.062		-0.010		-0.011
		(1.09)		(-0.59)		(-0.87)
Lag log total buy		0.071		**0.039* **		-0.031
		(1.26)		(1.73)		(-1.38)
Lag log total sell		0.003		0.064		0.037
		(0.13)		(1.61)		(1.27)
Lag return-firm		0.003		-0.007		-0.022
		(0.11)		(-0.20)		(-1.43)
Lag volatility		0.006		-0.003		-0.034
		(0.25)		(-0.18)		(-1.15)
Lag weight		0.057		-0.220		**0.246** **
		(0.68)		(-0.57)		(2.20)
Intercept	**-0.35*** **		**-0.398*** **		-0.019	
	(-14.08)		(-18.48)		(-1.07)	
R^2	0.0004	0.001	0.0001	0.0003	0.0001	0.0004
Fund fixed effect	No	Yes	No	Yes	No	Yes
Fund-month clustered	No	Yes	No	Yes	No	Yes

Table 2.11: Fund managers reaction to the application of EU SFDR regulation – March 2021

This table shows the results of panel OLS DiD regressions of monthly position changes on dummy variables of firms' Refinitiv ESG scores for Article 9 (columns 1 and 2), Article 8 (Columns 3 and 4), and Article 6 (columns 5 and 6) funds from January 2019 to February 2021 (Panel A). The dummy variables are interacted with $Post_t$, which is a dummy variable that equals 1 for months following **March 2021**. $High\ ESG_j$ is a dummy variable equal to 1 for firms with an ESG score between 75 and 100, $Above\ average\ ESG_j$ is a dummy variable equal to 1 for firms with an ESG score between 50 and 75, $Medium\ ESG_j$ is a dummy variable equal to 1 for firms with an ESG score between 25 and 50, and $Low\ ESG_j$ is a dummy variable equal to 1 for firms with an ESG score between 0 and 25. The model controls for lagged fund-level controls including monthly flow, return and alpha, the logarithm of a fund's total buys and sells, and a fund's churn rate. It also controls for lagged firm-level characteristics of fund holdings, including the monthly return, return volatility, and weighting in the portfolio. t-statistics (in parentheses) are calculated with Newey-West robust standard errors. Standard errors are clustered by fund and month. Panel B repeats the same analysis for a subsample that spans from January 2019 – February 2021. *, **, and *** indicate the parameters' significance at the 10%, 5%, and 1% levels, respectively.

Full sample (January 2019 – December 2022)						
	Position change					
	Article 9		Article 8		Article 6	
	(1)	(2)	(3)	(4)	(5)	(6)
Low ESG_j	**0.044****	0.036	-0.028	-0.031	**0.05*****	0.057
	(2.24)	(1.54)	(-0.96)	(-0.52)	(3.10)	(1.14)
Medium ESG_j	**0.115****	0.101	**-0.076***	-0.076	**0.104*****	0.094
	(2.53)	(1.35)	(-1.65)	(-0.53)	(3.45)	(0.96)
Above average ESG_j	**0.146****	0.177	-0.032	-0.023	**0.186*****	0.142
	(2.20)	(1.11)	(-0.51)	(-0.14)	(3.98)	(1.05)
High ESG_j	**0.16*****	0.183	**-0.128***	-0.115	**0.223*****	0.143
	(2.88)	(1.13)	(-1.69)	(-0.52)	(3.74)	(0.71)
Low ESG_j * $Post_t$	**-0.101*****	**-0.111***	**0.085****	0.094	**-0.062*****	-0.069
	(-3.32)	(-1.69)	(2.24)	(1.53)	(-2.83)	(-1.13)
Medium ESG_j * $Post_t$	**-0.506*****	**-0.433***	**0.208*****	**0.238***	-0.062	-0.094
	(-6.12)	(-1.73)	(2.88)	(1.68)	(-1.21)	(-0.73)
Above average ESG_j * $Post_t$	**-0.909*****	-0.718	**0.193****	0.248	**-0.136****	-0.175
	(-7.52)	(-1.62)	(2.01)	(1.32)	(-2.16)	(-0.88)
High ESG_j * $Post_t$	**-0.872*****	**-0.712***	**0.279*****	0.331	**-0.195*****	-0.194
	(-8.13)	(-1.70)	(2.58)	(1.29)	(-2.65)	(-0.77)
Lag churn rate		**-0.301*****		**-0.315*****		**-0.067***
		(-2.88)		(-3.44)		(-1.65)
Lag return		0.017		-0.016		-0.001
		(0.60)		(-1.16)		(-0.12)
Lag flow		-0.039		-0.003		0.010
		(-0.65)		(-0.25)		(0.40)
Lag log total buy		0.063		**0.057***		0.033
		(1.52)		(1.65)		(1.46)
Lag log total sell		0.067		**0.076****		0.014
		(0.77)		(2.37)		(0.93)
Lag return-firm		0.014		-0.020		-0.010

		(0.84)		(-0.98)		(-0.69)
Lag volatility		-0.028		-0.019		**-0.017***
		(-0.82)		(-1.25)		(-1.89)
Lag weight		-0.051		-0.079		**0.169****
		(-0.71)		(-0.40)		(2.03)
Intercept	**-0.626*****		**-0.336*****		**-0.023****	
	(-38.23)		(-25.07)		(-2.01)	
R^2	0.001	0.001	0.00003	0.0002	0.00004	0.001
Fund fixed effect	No	Yes	No	Yes	No	Yes
Fund-month clustered	No	Yes	No	Yes	No	Yes

2.9 Conclusion

The announcement of the EU SFDR was driven by longstanding concerns about the transparency and consistency in ESG funds. Investors face divergence in ESG ratings across providers, making it difficult to assess the sustainability of ESG funds (Berg et al. 2022a). This lack of standardisation created opportunities for greenwashing, as funds could market themselves as sustainable without clear or consistent criteria. Hence, investors face concerns about the reliability of ESG marketed funds and difficulties in understanding the risk-return proposition of ESG investing. By establishing harmonised disclosure requirements and common classification system, SFDR aims to increase transparency, reduce information asymmetries, and increase the allocation of capital towards sustainable investing and eliminating environmental and social issues (ESMA 2021).

The SFDR requires funds offered in the EU to be classified as either Article 9 which explicitly state sustainable investment in their objectives, Article 8 funds which promote sustainability without being core objectives, and Article 6 funds that do not explicitly set sustainable investment as their goal and are not marketed as sustainable. In addition to this classification, funds are required to disclose the methodology they used to assess sustainability risks in their investment process, including the potential impact on expected returns, ESG metrics, and principal adverse impacts (PAIs), or to provide a justification if such factors were not considered.

Building on this context, this chapter examines the implications of EU SFDR regulations for portfolio investing and management and provides empirical evidence on the effects of EU SFDR on the behaviour of investors and fund managers. Using a sample of EU SFDR-labelled funds, this chapter analyses investor and fund manager response to the EU SFDR which was introduced in November 2019 and applied in March 2021. Such a study is crucial to understand the impact of SFDR on investment decision-making and the allocation of capital into ESG-related products. Furthermore, the study of fund manager response to the announcement of the SFDR aids to understand how the SFDR is shaping investment strategies, enhancing transparency and ultimately facilitating the growth of sustainable finance and the transition into a green economy.

Hypothesis 1 examines investor response to the application of the SFDR. The evidence in this chapter indicates that there are significant inflows into Article 6 funds, weak but significant inflows into Article 8 funds relative to their size, and insignificant inflows into Article 9 funds. Consistent with this finding, the event study of flows suggests a significant inflow into Article 6 and Article 8 funds but not Article 9 funds. Moreover, the DiD panel regression shows no evidence of a difference between the mean flows into Article 8 and Article 6 funds. This does not support the expectation that Article 9 funds receive higher inflows than Article 8 and Article 6 funds post the initiation of SFDR. It also contrasts with Becker et al. (2022) and Ferriani (2023) findings which document higher inflows into Article 9 and Article 8 funds than Article 6 funds. after including $Article_i$ to the model. The table reports a relative decline in inflows to Article 9 following the application of the SFDR, compared with Article 8 and Article 6 funds. Nevertheless, the coefficients on $Article_i$ are positive and statistically significant at the 1% level in both specifications (Article 9 funds vs. Article 6 funds, and Article 9 fund vs Article 8 funds), indicating that prior to the application of the SFDR, Article 9 funds already enjoyed higher inflows relative to Article 8 and 6 funds. This finding suggests that the regulation was associated with a reduction in this inflow. However, after controlling for fund attributes using PSM, the results show higher mean flows into Article 9 funds than their matched peers of Article 8 and Article 6. This could reflect that other fund characteristics like lagged flows, returns, age, size and four-factor alpha influence fund flows.

The divergence highlights the importance of accounting for differences in fund characteristics when evaluating SFDR impact. The DiD panel regression does not explicitly balance the structural differences between Article 9, 8 and 6 funds, such as lagged flows, returns, age, size and four-factor alpha, which may bias the estimate. By contrast, the PSM allows for a reliable comparison by matching funds on observable characteristics, providing stronger evidence that Article 9 funds maintained their inflow compared to Article 8 and 6 funds post the SFDR. Overall, while other methodologies, such as panel and DiD panel regression, suggest no significant differences in flows into SFDR-labelled funds, and the event study of flows indicates increased inflows to Article 6 and 8 funds but not to Article 9 funds, the PSM analysis demonstrates that Article 9 funds remained generally more attractive to investors.

Hypothesis 2 examines the response of fund managers to the announcement of the SFDR. The results show that only Article 8 funds increased their exposure into firms with medium to high Refinitiv ESG scores since SFDR took effect. Conversely, Article 9 and Article 6 funds did not change their exposure. This result is inconsistent with Becker et al. (2022) who find that the Morningstar sustainability rating for Article 9 funds increased following the announcement of the SFDR in November 2019. This result is also inconsistent with Lambilon and Chesney (2023) who confirm that Article 9 funds hold companies with high sustainability scores. This inconsistency is most likely due to differences in the ESG rating used in the analysis. For example, Lambilon and Chesney (2023) use MSCI ESG ratings, while this study uses Refinitiv ESG ratings.

Furthermore, the results indicate that Article 9 funds attracted greater inflows relative to other funds when analysed using PSM, though this effect was not consistent across alternative methodologies. This result aligns with Hartzmark and Sussman (2019), who suggest that investors with non-pecuniary motives allocate capital to funds with strong sustainability objectives, either because they anticipate superior risk-adjusted return or because they are willing to align their portfolios with their values even at the expense of financial performance. It is also in line with ethical investing theory, which emphasizes the integration of moral and social considerations into investment decisions and that investors may be willing to accept potential trade-offs in performance if ESG investment creates values. Moreover, this suggests that the Article 9 label functions as a credible signal of sustainability, helping investors overcome information asymmetry. A behavioural finance perspective supports this by highlighting investors use regulatory labels as simplifying heuristics, making them prone to emotions and systematic biases in their allocation decisions (Barberis et al. 2002; Baker et al. 2014). However, the findings about the fund managers' response to the SFDR reflect greenwashing and agency dynamics, whereby labels may shape perceptions without substantive portfolio adjustments.

This could reflect the perceptions of fund manager and investors on the regulatory aspects such as the absence of clear definition, transparency, and monitoring. For instance, SFDR has gone through many changes since its announcement and fund managers, possibly, did not clearly understand what qualifies a fund to be labelled Article 9 or Article 8. This confusion led to the downgrading of some of these funds at a later time [18]. Hence, the EU ESG market did not perceive the regulation as effective, and investors got disutility from the regulation in its early stages. The SFDR might have widened the gap between expectations of ESG investment in Europe and the real practice (Autorité des marchés financiers 2023). Yet, the regulation is still evolving, and further research would investigate the effects of SFDR Level 2 and the PAI for the transition towards a green economy through regulated investment management and ESG portfolio investing.

[18] https://www.morningstar.co.uk/uk/news/231438/esg-fund-downgrade-accelerates.aspx.

Chapter 3: ESG fund performance and flow-performance sensitivity: Evidence from the US and the EU

3.1 Introduction

In recent years, Environmental, Social, and Governance (ESG) investing has become a central focus in global finance, aligning with the objectives of responsible investors seeking to create long-term sustainable value. The adoption of ESG criteria within investment strategies has expanded rapidly, driving substantial growth in assets managed under ESG principles worldwide. While the United States continues to hold the largest overall mutual fund market, Europe remains the dominant region for ESG-oriented assets under management (AUM) (Starks 2023). Together, Europe and the United States represent the world's two largest ESG markets. As reported by Bioy et al. (2025), European ESG AUM are estimated at around USD 3.0 trillion, compared with approximately USD 0.4 trillion in the United States."

As ESG investing continues to gain momentum, it becomes increasingly important to examine both the growth of these funds and investor behaviour. Early evidence, largely based on samples up to the mid-2010s, focused on ESG/SRI fund performance and flow–performance sensitivity, particularly in comparison with conventional funds. Studies comparing ESG and conventional fund performance provide mixed evidence. On a raw return basis, some studies report differences in performance (e.g. Goldreyer et al. 1999; Bauer et al. 2005; Bollen 2007), while others find no significant difference on a risk-adjusted basis (Statman 2000; Bauer et al. 2005; Geczy et al. 2005; Gregory and Whittaker 2007; Renneboog et al. 2008a; Renneboog et al. 2008b; El Ghoul et al. 2023; Hornuf and Yüksel 2024). Some studies focused on specific countries such as the UK and Germany (e.g. Luther et al. 1992; Bauer et al. 2005). Renneboog et al. (2008b) is one of the few to examine an international sample. Later literature investigates the impact of ESG ratings on fund performance, yielding mixed results: some studies find that highly rated ESG funds outperform lower-rated funds (Steen et al. 2019; Pástor and Vorsatz 2020; Abate et al. 2021; Omura et al. 2021; Fang and Parida 2022), while others report the opposite (El Ghoul and Karoui 2021; Pavlova and de Boyrie 2022). This chapter revisits the literature on ESG versus conventional fund performance and extends it by including passively managed equity mutual funds domiciled in the US and EU, in addition to the predominantly actively managed funds previously studied. This allows for a broader assessment of performance patterns across different fund types and markets.

On the flow-performance sensitivity side, studies suggest that ESG active funds exhibit less flow-performance sensitivity than their peers of conventional active funds in the US and around the world (Bollen 2007; Benson and Humphrey 2008; Renneboog et al. 2011; Białkowski and Starks 2016; Ridel and Smeets 2017; El Ghoul and Karoui 2021; Humphrey et al. 2021). Understanding how investors behave is important because stable investment flows help fund managers minimise fluctuations and optimise investment benefits for shareholders, asset managers, and the fund (Bollen 2007). From the academic perspective, the rise of ESG investing allows researchers to explore the theme of responsible investing (Bollen 2007). For example, Bollen (2007) shows that responsible investors are loyal because their investment decision is driven by non-financial as well as financial factors, and Hartzmark and Sussman (2019) report that investors value sustainability, especially if ESG funds are generating positive return. More recent studies examine the flow–performance sensitivity of ESG funds based on their ESG ratings, yielding mixed evidence. For example, Gantchev et al. (2024) and Wang (2024) find that highly rated ESG funds are less sensitive to past performance compared to lower-rated funds. Conversely, Ali et al. (2024) report that Morningstar five Globe funds exhibit greater sensitivity to past performance than their lower-rated peers.

These studies conclude that past performance is a determinant of fund flows. To account for the dynamic nature of financial markets, this study revisits the earlier literature to analyse the flow–performance relationship at a monthly frequency, thereby capturing short-term investor responses to past performance. Whereas earlier studies predominantly examined actively managed mutual funds to assess ESG flow-performance sensitivity, this chapter extends the analysis to include both active and passive ESG funds. Moreover, by conducting a comprehensive investigation of ESG fund performance and investor behaviour across the US and the EU, this study contributes to a deeper understanding of the determinants and implications of this rapidly expanding segment of financial markets. Accordingly, this chapter seeks to address the following research questions:

1. **Did ESG investing command a premium? and did this premium vary across regions?**
2. **Did ESG investors' investment behaviour differ from those of conventional investors, across investment styles and regions?**

To answer the research questions related to performance, this chapter implements a two-tailed student t-test to compare the mean returns of ESG and conventional funds, as well as the returns adjusted for common risk factors. Furthermore, the investigation explores two dimensions; specifically, active vs passive funds and US vs. EU funds. The findings suggest that during the sample period (January 1996 to December 2022) the US ESG active funds' performance is not statistically different from that of their matched conventional peers, whereas the EU ESG active funds outperform their matched conventional peers consistent with prior literature (Statman 2000; Bauer et al. 2005; Geczy et al. 2005; Renneboog et al. 2008a; Renneboog et al. 2008b). The performance difference is traced to the different portfolio compositions across the two regions. Specifically, US ESG active funds are skewed towards growth stocks, less risky assets, and follow momentum reversal more strongly, as compared to the US conventional funds. On the contrary, EU ESG active funds are skewed towards smaller capitalisation, growth stocks, with weaker operating profitability and follow momentum more strongly than their conventional peers. Additionally, the variations of the findings between the unmatched and matched samples confirm that age, load fees, and portfolio composition affect fund performance.

On the other hand, US ESG passive funds underperformed their conventional peers in both the matched and the unmatched samples. Yet, there is no difference in risk-adjusted returns between ESG and conventional passive funds. These findings suggest that the outperformance of ESG active funds in the EU might be attributable to a superiority of ESG active management or may be driven by regulatory and tax reasons.

To answer the second research question, this chapter implements a piecewise regression methodology, following Huang et al. (2007), to capture the flow-performance sensitivity at different performance levels. The findings suggest a difference in the flow-performance sensitivity of ESG and conventional funds, both active and passive, across the US and EU markets, consistent with Renneboog et al. (2011). For example, over the short- term, matched conventional active funds are negatively sensitive to the lowest 20% performers and positively sensitive to the mid performers based on risk-adjusted alpha. In the EU, both matched conventional and ESG active funds show no flow sensitivity to the past 12-month risk-adjusted alpha. Over the long- horizon, US matched conventional active investors penalise funds that underperform the benchmark, US ESG active funds exhibit no flow-performance sensitivity. In the EU, matched conventional funds are positively sensitive to underperformers, whereas ESG active funds are negatively sensitive to underperformers.

In the passive fund space, over the short-term, US matched conventional passive investors show no sensitivity to past risk-adjusted alpha, while ESG passive investors penalise low-ranked funds based on C-4 alpha. In the EU, matched conventional passive investors penalise outperformers (C-4) alpha, whereas ESG passive investors show no sensitivity to past C-4 alpha. Over the long-term, both ESG and matched conventional funds show no sensitivity to the 36- months past performance. One exception is that US ESG passive investors are positively sensitive to mid-performers based on C-4 alpha. Over the long term, matched conventional passive investors reward low-ranked funds and penalise the mid-ranked funds based on raw return, while ESG passive investors reward mid performers based on C-4 alpha. However, these results should be interpreted with caution as they may lead to a biased estimate, limited generalisability, and challenge the validity of the findings (Faber and Fonseca 2014).

In addition to the matched sample analysis, the results from the unmatched conventional funds, both active and passive, highlight some important distinctions. The observed variations can largely be attributed to differences in fund age, load fees, and portfolio composition. Furthermore, the evidence suggests that EU ESG investors, whether active or passive, place greater emphasis on the non-financial attributes of ESG investments compared to their US counterparts, while US conventional active investors appear to exhibit a higher degree of investment sophistication than their EU peers.

3.2 Literature review

3.2.1 Fund performance

The research question of whether ESG funds underperform relative to conventional funds has been heavily debated. Hamilton et al. (1993) propose three alternative hypotheses for the ESG performance research question. The first is the "doing good but not well" hypothesis which claims that ESG funds yield a lower risk-adjusted returns as compared to conventional funds. This argues that since ESG funds are constrained to hold securities form a restricted universe, the resulting expected returns should be lower due to the limited range of potential investment. Based on the Modern Portfolio Theory (MPT), ESG portfolios cannot be expected to achieve mean-variance efficiency because of excluding high-return stocks like so called "sin stocks" such as tobacco (Renneboog et al. 2008a; Hong and Kacperczyk 2009). Hence, this limited diversification is expected to result in a less optimal risk and return for ESG funds.

Another key theoretical explanation for the underperformance of ESG funds lies in the effect of investors' preferences on asset prices. According to Bauer et al. (2005), socially responsible investors drive up the value of socially responsible companies because of their demand for ESG-compliant companies, which in turn decreases their expected return and the cost of capital. Building on this argument, Pástor et al. (2021) propose a three-fund separation model which assumes that investors have differing ESG preferences. Investors with stronger ESG preferences allocate more heavily to green assets and less to brown assets, whereas those with weaker preferences allocate more to brown and less to green. Investors with average preferences hold the market portfolio. This variation in ESG preferences results in pricing pressure, which increases the valuation of green firms, hence reducing their expected return. Thus, regardless of ESG investment's positive social impact generated through low cost of capital, it results in lower financial performance. As noted by Armstrong (2021) in the Financial Times Unhedged Newsletter, investors with non-pecuniary utility accept lower expected return in exchange for holding ESG assets.

In contrast to the first hypothesis, the second one claims that ESG funds outperform their conventional peers, "do well by doing good". Cummings (2000) argues that companies with strong ethical commitments may develop competitive advantages that translate into sustainable long-term profits. This advantage may result in superior long-term profitability and stock market performance relative to their conventional counterparts. Ghoul et al. (2011) suggest that firms with high Corporate Social Responsibility (CSR) scores benefit from reduced cost of equity. Similarly, Shanaev and Ghimire (2022) provide evidence that companies with high ESG ranking outperformed those with low ESG ranking.

Further, Allen et al. (2009) suggest that stock markets in countries with a stakeholder governance model tend to outperform those dominated solely by shareholder value. This reinforces the notion that CSR can significantly contribute to corporate value. In this context, SRI screening might serve as an effective process for identifying value-relevant information to investors, which potentially generate more attractive risk-return profiles than those offered by conventional funds (Rennboog 2008a). Moreover, shareholder engagement in ESG funds, particularly through advocating for policies that improve employee relations and corporate governance, has been shown to positively influence firm performance and stock returns (Tosun and Moon 2025). Hence, integrating ESG can contribute to reduced cost of capital and improved risk-adjusted return.

In addition to the outperformance, Hamilton et al. (1993) suggest that companies with strong social and environmental commitments are less vulnerable to adverse market reactions, thereby benefiting investors. The rationale is that firms with strong CSR can shield costs associated with environmental disasters and corporate crises (Cremers and Nair 2005; Gompers et al. 2003). For example, Pástor and Vorstaz (2020) find that, during the market downturn caused by COVID-19, funds with high sustainability rating performed well. Starks (2023) states that ESG funds may outperform if the ESG investing approach is based on a value (risk and return) perspective. In this case, ESG investing results in a more effective risk management and opens pathways to return potential. As also suggested by Hamilton et al. (1993), this could happen when ESG securities are mispriced.

Finally, the “no-effect” hypothesis describes how ESG and conventional funds yield the same risk-adjusted performance (Hamilton et al. 1993). In scenarios where CSR does enhance investment return, ESG considerations are assumed to be indifferent to market pricing (Auer and Schuhmacher 2016). This aligns with the conventional financial concept which posits that non-financial risk-related factors should not systematically generate excess returns. Hence, investing based on ESG criteria does not lead to a decreased cost of capital, reducing its effectiveness for achieving superior portfolio performance (Hamilton et al. 1993). This neutrality arises from the assumption that market participants do not associate the financial costs of ESG practices with future profitability. In this case, the demand for shares in ESG firms remains unaffected, regardless of whether investors' motivations are purely financial or ethical (Tsang et al. 2023).

Another theoretical explanation of the "no-effect" hypothesis posits that while CSR benefits investors, these advantages are offset by the costs required to implement them. Thus, any positive impact from ESG investment performance is effectively neutralized, yielding no abnormal risk-adjusted return (Statman and Glushkov 2016). Furthermore, as ESG factors are generally not priced by the market, that is, companies are neither systematically rewarded nor penalized for their ESG performance, ESG-focused funds are unlikely to generate any return premium (Hamilton et al. 1993).The earliest strand of empirical literature focused on directly comparing the performance of conventional and ESG/SRI funds, providing robust evidence for the "no effect" hypothesis in the US. For instance, Hamilton et al. (1993) report no statistical difference between the CAPM-derived Jensen's alpha for 32 US ESG funds as compared to 320 randomly selected conventional funds. Similarly, Goldreyer et al. (1999) and Mallin and Saadouni (1995) document no underperformance for socially screened equity, bond, and balanced funds using Jensen's alpha, Sharpe (1996) ratio and Treynor (1965) ratio. Statman (2000) finds no statistical difference between the Domini social index (DSI) and the S&P 500 based on risk-adjusted returns. Geczy et al. (2005) document that the risk-adjusted alpha of conventional funds is lower than that of ESG funds, yet the difference is statistically insignificant.

Statman and Glushkov (2016) devise two ESG factors as an extension to the traditional four-factor model. First, the "Top-Minus-Bottom factor" (TMB) is composed as the difference between the returns of stocks ranked in the top and the bottom thirds based on ESG criteria (e.g. community relations, employee relations, environmental protection, and diversity and product). Second, the "Accepted-Minus-Shunned factor" (AMS) differentiates between the returns to companies that are classified as socially responsible based on the SR investors' activism and those that are shunned (e.g. tobacco, alcohol, gambling, military, nuclear industries, and firearms). They examined the performance of ESG mutual funds against conventional fund performance based on the established four-factor model and their new six-factor model and their results remain consistent with previous studies in finding no significant difference between the performances of the two types of funds. Similarly, Białkowski and Starks (2016) document no difference in risk-adjusted return of SRI and conventional funds, suggesting that SRI funds do not sacrifice return for values.

Using a sample of 144 mutual funds; 80 European and 64 US funds, Milonas et al. (2022) find no statistically significant difference in performance between ESG and non-ESG funds over the period 2017 to 2021. Klinkowska and Zhao (2023) find that ESG and conventional funds managed by the same companies with comparable objectives show no significant performance differences. Drawing on a sample of 2,255 US domestic equity funds between 2010 and 2021, El Ghoul et al. (2023) observe that ESG funds underperform their conventional peers. The underperformance, though relatively small, was evident across raw returns, risk-adjusted measures, and Sharpe ratios. A comprehensive meta-analysis of SRI conducted by Hornuf (2024), documents no consistent superiority of ESG funds and the market portfolio after controlling transaction costs and diversification limitations.

Overall, the above findings converge to the conclusion that there is no difference between ESG and conventional fund performance, as predicted by the "no effect" hypothesis. According to the literature, there are three explanations to the "no effect" hypothesis. First, Statman and Glushkov (2016) argue that, in financial markets, the ESG theme is not assigned a price and thus, investors are eager to buy ESG stocks regardless of their price. Second, the ESG strategies adopted by companies are not effective enough to yield benefits higher than their cost. Therefore, the weighting towards high ESG score companies will not result in a significant difference in portfolio risk-adjusted return. Third, the screening types might not be significant enough to affect the ESG mutual fund performance. For example, according to a study conducted by Goldreyer et al. (1999), the screening types (tobacco, diversity, alcohol, community, and employment relations) have no significant effect on mutual fund performance except for environmental and military mutual funds which showed superior performance over other screening types.

Subsequent literature extended the scope by examining the effect of fund ESG rating on their financial performance. This line of empirical research has provided mixed findings. For example, Steen et al. (2019) examine 146 Norwegian mutual funds, ranked by Morningstar sustainability rating and MSCI ESG rating and divided the funds into ESG quintiles. They conclude no effect of ESG rating on risk-adjusted alpha. Fang and Parida (2022) find that high ESG rating funds outperform low-rated funds, especially during COVID-19 pandemic and post-crash pandemic. This finding is robust to earlier literature that examined ESG rated funds during economic downturn and COVID-19 pandemic (Becchetti et al. 2015; Pástor and Vorsatz 2020; Abate et al. 2021; Omura et al. 2021). Conversely, other research report that funds with low ESG profiles outperform high rated funds (El Ghoul and Karoui 2021; Pavlova and de Boyrie 2022). However, this body of literature largely moved away from the fund-level comparative analysis of conventional versus ESG fund performance.

This study revisits and extends the earliest line of research that directly compared conventional and ESG fund performance by investigating the performance differentials between ESG and conventional mutual funds. This allows the study to expand the analysis based on monthly frequency data from the US and EU and to examine passively managed funds. Accordingly, it proposes the following hypothesis.

H1: *There is no difference in risk-adjusted returns between ESG and conventional funds.*

3.2.2 Conventional fund flow-performance sensitivity

Financial theory assumes that investor decision making is based solely on the risk-return trade-off (Markowitz 1952). Therefore, past performance has been a vital source of information for investors, signalling managerial ability (Berk and Green 2004). The prior empirical evidence on the relationship between fund flow and past performance is mixed where early studies find the relationship to be linear (e.g. Spitz 1970; Smith 1978; Hendricks et al.1993; Lakonishok et al. 1992), while later studies show an asymmetric flow-performance relationship. Specifically, investors favour funds with strong performance more than they redeem from those with poor performance (Chevalier and Ellison 1997; Sirri and Tufano 1998; Busse 2001; Del Guercio and Tkac 2002; Huang et al. 2007; Ferreira et al. 2012).

Spitz (1970) documents a stronger positive flow-performance relationship among no-load funds than load funds. In line with Spitz (1970), Smith (1978) reports a positive relationship between lagged performance and mutual fund growth based on the Forbes performance rating. However, the relationship was negative on a risk-adjusted basis. Hendricks et al.(1993) document a positive linear relationship between the fund annual dollar net flow and their ranked raw return. Finally, Lakonishok et al. (1992) report a positive linear relationship between industry adjusted return and new accounts gained for 250 institutional money managers.

In contrast to the above, other studies find that investors react asymmetrically to past performance. For example, Ippolito (1992) finds stronger net flows to funds that outperformed the market as compared to those that underperformed. Similarly, Gruber (1996) reports a positive and non-linear relationship between average dollar flows, normalised flow, and four-index alpha. The author believes that such investor behaviour is influenced by their level of financial sophistication and tax advantages received. Sophisticated investors can predict future performance from past performance, therefore their sensitivity to top performing funds is high. On the other hand, non-sophisticated investors do not base their decisions on performance, they lack information, seek brokers advice, and focus on advertisements. They are also tax disadvantaged, meaning that they would hold the poor performing funds to avoid the capital gain taxes.

Along the same line, Sirri and Tufano (1998) examine the relationship over different investment horizons. They report disproportionate flows into top and bottom ranked funds over the short and long investment horizons. They also find that investors respond strongly to short-term performance as compared to a longer five-year horizon. They also suggest that research costs play a crucial role in determining the flow-performance relation. Similarly, Del Guercio and Tkac (2002) find asymmetric flow-performance relationship based on raw return and Jensen's alpha for mutual funds but not for pension funds.

The flow-performance relationship contradicts the Efficient Market Hypothesis (EMH), which assumes investors are rational and aim to optimise their mean-variance trade-off. Bollen (2007) justifies this financial anomaly due to investor psychological bias to weight recent performance more intensely or have short-term learning behaviour about managerial ability. In fact, several studies (e.g. Ippolito 1992; Lynch and Musto 2003; Berk and Green 2004) support the rational learning explanation, whereby investors adjust their beliefs about managers' superior skills based on fund past performance.

Huang et al. (2007) argue that the convexity of the flow-performance relationship is formed due to participation costs. Specifically, investors flock into funds with recent high returns and thus, higher participation costs. Hence, abnormally large future returns are expected in stocks with strong past performance due to the flocking behaviour. The authors discuss three different ways of how participation costs drive the convexity of the fund flow-performance relationship. First, is due to investors with different levels of financial sophistication. The superior the fund past performance is the more likely investors will incur high costs to invest in them. Second, the higher the participation costs mean limited funds to research due to time and effort. Thus, investors pick the winners to reduce their participation costs. Finally, investors will not trade in mutual funds unless the fund have performed exceptionally (to buy) or performed poorly (to sell) due to the high transaction costs.

3.2.3 ESG Fund flow-performance sensitivity

The investigation of flow-performance sensitivity has been extended to ESG funds. Bollen (2007) was the first to compare the flow-performance sensitivity relationship between ESG and conventional funds, based on the CAPM and Carhart (1997) models. He finds that, over the period from 1980 to 2002, ESG funds show higher sensitivity following one-year positive returns as compared to conventional funds, as well as lower sensitivity following one-year negative returns. This difference persists over time and as the funds mature. He suggests that ESG investors are more tolerant to negative performance and derive added utility from investing in socially responsible funds, especially when these funds deliver positive return. Hence, they value both the financial and non-financial aspect of their investment.

In line with Bollen (2007), Benson and Humphrey (2008) document a convex flow-performance relationship for ESG funds based on current monthly flows and current and lagged raw returns. Moreover, they report that the flow sensitivity of ESG funds is lower than that of conventional. Given the above, they suggest that the ESG theme is a driver of the flow-performance relationship whereby investors will not liquidate poor performing funds because of the limited options available in the restricted stock universe. Renneboog et al. (2011) compare a sample of 295 ESG funds and matched 590 conventional funds and confirm that ESG investors are less sensitive to past negative returns in comparison to conventional investors. As such, they claim that ESG investors are factoring non-financial factors into their investment decisions. They also examine the flow-performance relation as a function of the screening intensity and find that negative screening is associated with weaker flow sensitivity to negative performance, while socially screened funds show reduced flow sensitivity to positive performance. In contrast, the environmentally screened funds demonstrate strong flow sensitivity to past performance overall.

Similarly, El Ghoul and Karoui (2021) find that ESG investors put less weight on past performance than conventional investors do, which points to investors finding value in non-financial attributes in their investment choices. Furthermore, Ridel and Smeets (2017) and Humphrey et al. (2021) suggest that responsible investment behaviour is driven by social preferences rather than financial motivations. Inconsistently, Białkowski and Starks (2016) document higher flow sensitivity to the funds falling into the top quintile than the ones ranked in the bottom quintile. As compared to conventional funds, ESG funds are more sensitive to high past performance than conventional funds and insignificant difference in sensitivity to the low past performance.

Turning from ESG labels to ESG ratings, the literature indicates that funds' ESG ratings can affect their flow. Based on a natural experiment conducted by Hartzmark and Sussman (2019), they report substantial inflow into five-globe funds, while one-globe funds experienced significant outflow, concluding that investors value sustainability using US actively managed mutual funds across different Morningstar categories. Similarly, Pástor and Vorstaz (2020) study US actively managed equity mutual funds during COVID-19 crisis by examining the funds Morningstar globe rating and their flow. They find that funds with higher sustainability (globe) ratings attracted larger net flow during COVID-19. Conversely, a study conducted by Wee et al. (2020), document a weaker net inflow into Korean funds with high ESG scores, whereas funds with lower ESG scores experienced greater inflow, based on a constructed and classified ESG score.

More recent papers extend the analysis to compare the flow-performance sensitivity of ESG funds based on their ESG ratings. For instance, Gantchev et al. (2024) analyse US domiciled Morningstar sustainability rated-mutual funds and find that high rated funds attract more inflow than their low-rated peers. However, investors in highly rated funds are less sensitive to past performance as compared to those in low rated funds, meaning that they are less likely to outflow of highly rated funds based solely on past performance. Similarly, A study by Wang (2024) documents a weaker flow sensitivity to short-term performance for high ESG funds than their peers of lower ESG ratings, potentially investors focus on long-tern sustainability goals than short-term volatility in performance. Conversely, Ali et al. (2024) examine equity funds domiciled in Australia and New Zealand from August 2018 to December 2022. They document a stronger flow-performance sensitivity for Morningstar five globe funds.

Given the above empirical evidence, it can be concluded that the flow-performance sensitivity is different for ESG funds than conventional funds and that investors value non-financial, as well as financial aspects in their investments. Typically, investors make decisions based on their risk preference, risk-return dynamic of the fund, and their investment horizons. In contrary, there is a non-financial aspect that investors take into consideration when it comes to ESG funds. This non-financial aspect could hinder their decision to buy or sell funds due to the higher search cost (Sirri and Tufano 1998; Huang et al. 2007) or the restricted number of ESG funds that satisfy their social responsibility demands (Benson and Humphrey 2008). These barriers will not make it as simple for investors to pull out of underperforming funds.

This Chapter revisits the earlier literature that compared ESG and conventional fund flow-performance sensitivity which allows for an expanded analysis that incorporates the use of monthly frequency data from the US and EU. Additionally, examining the behaviour of ESG passive investors and the exploration into their utility of the socially responsible attribute.The resulting hypothesis is that:

H2: *ESG fund flow-performance sensitivity is different than that of conventional funds.*

3.2.4 Regional differences

Despite the fact that the research on performance and flow-performance sensitivity is very diverse for US ESG funds, investigations for non-US funds are rather limited. Nonetheless, studying the flows into ESG funds across geographies can potentially offer a deeper understanding of the increasing popularity of ESG funds and the disparities of the driving factors behind investor behaviour (Starks 2023). For example, evidence from the UK confirms that performance differences between ESG and conventional funds are not statistically significant (e.g. Luther et al. 1992; Mallin and Saadouni 1995; Gregory and Whittaker 2007). Bauer et al. (2005) document a statistically insignificant difference in performance between ESG their conventional funds for the US, UK, and German markets. Similar, relationships have also been evidenced in the Australian and Canadian markets (Bauer et al. 2006; Bauer et al. 2007).

Renneboog et al. (2008b) conduct a comparative study of various non-US markets and find evidence contrasting the US evidence of Bauer et al. (2005). They show that ESG funds in Asia-Pacific and Europe underperformed their matched conventional peers, whereas no statistical difference was found for UK funds. Muñoz et al. (2014) document no difference in performance between US and European ESG funds and their matched conventional counterparts. Auer and Schuhmacher (2016) construct portfolios based on Sustainalytics ESG scores using stocks from the Asia-Pacific region, the US, and Europe. They report no superior performance from either high or low rated portfolios as compared to passive stock market benchmark across the three regions.

With regard to the fund flow-performance sensitivity, Ferreira et al. (2012) find a difference in the sensitivity between developed and undeveloped countries. In developed countries, investors are more sophisticated and hence, they show lower convexity in flow-performance sensitivity as compared to investors in less developed countries. About ESG investment, on a global level (the US, Europe excluding the UK, the UK, Asia-pacific, and Africa), Renneboog et al. (2011) confirm that ESG investors are less sensitive to negative past returns relative to their conventional peers.

Overall, the above studies show a difference in fund performance and flow-performance sensitivity across different regions due to unique market dynamics and investor behaviour (Bauer et al. 2005; Renneboog et al. 2008b). Additionally, the different culture, social and ethical considerations, investment opportunities, and legal restrictions across different countries can result in varying outcomes for socially responsible activities (Auer and Schuhmacher 2016). Lastly, regulatory environments are distinct across countries which affect the performance of ESG funds across multiple regions (Renneboog et al. 2008b). Given the above evidence, two hypotheses are proposed:

H3: *ESG and conventional fund performance is different across regions.*

H4: *ESG and conventional fund flow-performance sensitivity is different across regions.*

3.3 Data and methodology

3.3.1 Data and summary statistics

The survivorship bias-free mutual fund sample was obtained from Refinitiv Lipper. According to Brown et al. (1992), non-surviving mutual funds are the funds that are ceased to exist, usually due to poor performance. Thus, controlling for funds' survivorship bias in the data ensures that performance persistence is not overstated due to the exclusion of defunct funds (Wermers 1997). The sample was limited to ESG and conventional equity mutual funds while allowing only the primary share class to avoid double counting. This is due to multi-class funds being managed by one manager, hold the same investment portfolio, and generate same returns before load fees and expenses (Kacperczyk and Seru 2007; Ferreira et al. 2012). Subsequently, the funds were filtered using the Lipper screener to identify ESG active, ESG passive, conventional active, and conventional passive equity funds, domiciled in the US and the EU. This yielded 4,850 conventional active funds, 367 ESG active funds, 217 conventional passive funds and 22 ESG passive funds domiciled in the US. In the EU, 2,710 conventional active funds, 1,424 ESG active funds, 173 conventional passive funds, and 135 ESG passive funds were identified. A major limitation of Refinitiv is that it does not provide fund time-series data. The ISIN identifiers of the sample were used to collect the time-series data from Morningstar. This includes monthly net returns, total net assets, annual expense ratio, and inception date for the period of January 2019 to December 2022[19]. Lastly, Fama and French (1993) factors for the US and EU markets were extracted from Kenneth French's website[20].

Following Pástor and Vorsatz (2020), the sample is limited to only funds with more than fifteen million USD in total net assets as of December 2022 to eliminate small-sized funds with volatile growth. Additionally, included funds must trade publicly for at least six years as of December 2022 to exclude young funds. The final US sample includes 4,171 conventional active funds, 236 ESG active funds, 193 conventional passive funds and 19 ESG passive funds domiciled. The final EU sample includes 2,525 conventional active funds, 1380 ESG active funds, 170 conventional passive funds, and 132 ESG passive funds. The limited dataset consisting of just 19 US ESG index funds may lead to a biased estimate, limited generalisability, and challenge the validity of the findings (Faber and Fonseca 2014). The US defunct funds include 1,485 conventional active, 134 ESG active, 23 conventional passive and 1 ESG passive. The EU defunct funds include 5,085 conventional active, 885 ESG active, 94 conventional passive, and 36 ESG passive.

Table 3.1 reports the summary statistics for ESG and conventional funds across the investment style (active and passive), as well as the region (US in Panel A and EU in Panel B), computed by averaging monthly observations across the sample period. In terms of mean return, US conventional funds, both active and passive, show higher returns than their ESG peers. The opposite is observed for EU-domiciled funds whereby ESG funds show higher

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[19] The sample period starts in January 1996 because the momentum factor data for EU becomes available starting in November 1990. A minimum of 5 years of data was needed to estimate alpha, making January 1996 the earliest start date for this analysis.
[20] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

returns than their non-ESG peers. Regarding fund flows, conventional active funds in the EU have the highest mean flows (1.22%), followed by ESG active funds flows (0.98%). In the US, ESG active funds have higher mean flows (0.47%) than conventional active funds (0.33%). Interestingly, US conventional passive funds show mean outflows of -0.26%, while US ESG passive funds have mean inflows of 0.13%. The EU ESG passive funds have lower inflows than their US peers (0.09%).

With regard to total-net-assets (TNA), US ESG funds hold a total of \$0.83 trillion, 65% of which are allocated to ESG active funds. EU ESG funds collectively manage \$0.75 trillion in net assets, 55% of which are managed by active funds. This implies that responsible investor preferences in the US are skewed towards active strategies. On the contrary, ESG investments in the EU are partly split between the two investment styles. Regarding conventional funds, the aggregate net assets of US-domiciled funds is 91% higher than the EU (\$5.92 trillion vs. \$0.56 trillion). The statistics highlight that US conventional funds are managing 88% of total US investments, while ESG funds are holding only 12%. In contrast, in the EU the allocation of total net assets is balanced between conventional and ESG funds.

EU funds, both ESG and conventional, are more costly than their US peers as shown by the expense ratios. According to Antoniewicz et al. (2021), EU funds exhibit higher expense ratios than US mutual funds due to EU funds being typically smaller in size than US funds. Another contributor to the higher EU funds' expense ratio is the fact that EU funds must comply with cross-border regulation unlike US funds that comply only with the SEC (Hoorn and Duvall 2023). Furthermore, in the EU, ESG active funds are the more mature than non-ESG, whereas in the US conventional funds are more mature. Lastly, the analysis shows no significant variations in return volatility among the different fund categories across both regions, implying consistency in the fund risk structure.

Table 3.1: Summary statistics

This table reports summary statistics for conventional active, ESG active, conventional passive, and ESG passive domiciled in the US (Panel A) and EU (panel B) from January 1996 to December 2022. The summary statistics include the mean and the median of the funds 'monthly return, flow, total net assets (TNA) in USD trillion, expense ratio, age, and return volatility.

	Return		*Flow*		*TNA ($in trillion)*		*Expense ratio*		*Age*		*Return volatility*	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Panel A:US												
Conventional active	0.70	0.92	0.33	0.02	1.51	0.27	0.99	1.00	14.90	12	4.15	3.73
ESG active	0.68	0.94	0.47	0.13	0.54	0.14	1.12	1.10	14.40	12	4.21	3.85
Conventional passive	0.73	1.23	-0.26	-0.75	4.41	0.55	0.42	0.31	12.26	11	4.47	4.18
ESG passive	0.64	1.20	0.13	-0.43	0.29	0.09	0.72	0.50	8.82	7	4.49	4.25
Panel B: EU												
Conventional active	0.40	0.58	1.22	1.01	0.26	0.07	1.60	1.53	12.96	11	4.38	3.87
ESG active	0.50	0.68	0.98	0.75	0.41	0.12	1.45	1.48	14.35	13	4.67	4.15
Conventional passive	0.59	0.90	0.09	-0.24	0.30	0.11	0.66	0.50	10.91	10	4.93	4.52
ESG passive	0.60	0.90	0.09	-0.24	0.34	0.13	0.67	0.50	11.04	10	4.93	4.53

3.3.2 Fund performance and risk exposures

To study whether investors pay a premium to invest in ESG funds, this chapter evaluates the performance of ESG funds relative to their conventional peers. The performance hypothesis is tested based on excess returns according to the CAPM, as described by the regression model in 3.1. The use of CAPM ensures any performance differences between ESG and conventional funds are driven by ESG attributes rather than differences in portfolio compositions (e.g. Bauer et al. 2005; Bollen 2007). Moreover, the relationship is also evaluated using multi-factor models to ensure robustness with other common risk factors. This includes the four-factor model of Fama and French (1993) and Carhart (1997) and the six-factor model which add the operating profitability and the investment factors to the four-factor model above. The regression models in equations 3.2 and 3.3 describe the two models.

$$r_{i,t} - r_t^f = \alpha + \beta_{MKT}(r_t^m - r_{i,t}) + +\varepsilon_t \tag{3.1}$$

$$r_{i,t} - r_t^f = \alpha + \beta_{MKT}(r_t^m - r_{i,t}) + \beta_{SMB}\, r_t^{smb} + \beta_{HML}\, r_t^{hml} + \beta_{MOM}\, r_t^{mom} + \varepsilon_t \tag{3.2}$$

$$r_{i,t} - r_t^f = \alpha + \beta_{MKT}(r_t^m - r_{i,t}) + \beta_{SMB}\, r_t^{smb} + \beta_{HML}\, r_t^{hml} + \beta_{MOM}\, r_t^{mom} + \beta_{RMW}\, r_t^{rmw} + \beta_{CMA}\, r_t^{cma} + \varepsilon_t \tag{3.3}$$

$r_{i,t}$ is the return of fund *i* in month *t*, r_t^f is the return on the local risk-free rate at time *t*, α denotes the Jensen (1968) alpha, β_{MKT} , β_{SMB} , β_{HML}, β_{MOM}, β_{RMW}, β_{CMA} are the sensitivity to the market, size, value, momentum, profitability, and investment factors, respectively. r_t^{smb}, r_t^{hml}, are the factor mimicking portfolios for the size and book-to market. r_t^{mom} is the replicated portfolio for the12-month return momentum factor, r_t^{rmw}, r_t^{cma} are the profitability and investment factor replication portfolios. ε_t is the error term at time *t*. Subsequently, a two-tailed sample *t*-test is performed to test the means of the estimated alphas and risk factor loadings. As such, the comparison of the performance and risk exposures between ESG and conventional funds is conducted for samples of active and passive funds, in the US and EU.

3.3.3 Fund flow-performance sensitivity

The second part of this chapter investigates whether ESG investors behave differently than conventional investors by examining the fund flow-performance sensitivity. Investor behaviour is reflected in fund flows; whereby increased flows suggest the increasing appetite for investment (Hartzmark and Sussman 2019). Given that mutual fund investors are likely to put emphasis on historical raw returns (Del Guercio and Tkac 2002). This induces causality concerns for the flow-performance relationship (Del Guercio and Tkac 2002) and thus, lagged performance over multiple horizons are used as control variable. Specifically, this chapter controls for the past performance over the last 12, 24, and 36 months. Following prior literature, performance is measured by raw returns and the Carhart (1997) (C-4) alpha estimated for the preceding 60 months[21] (Białkowski and Starks 2016). Under the assumption that ESG investors are allocating their capital based on risk-return optimisation strategy, traditional asset pricing models should sufficiently capture the rationale behind investment decisions (Bollen 2007).

To calculate monthly Carhart (1997) four-factor alpha, the following methodology is applied following Li et al. (2017). First, the fund factor loadings of the Carhart (1997) C-4 model is estimated by regressing the preceding 60 months' excess returns on the four factors in equation 3.4. Second, for each month, the fund factor adjusted alpha is calculated as shown in equation 3.5.

$$r_{i,t} - r_t^f = \alpha + \beta_{MKT}\left(r_t^m - r_{i,t}\right) + \beta_{SMB}\, r_t^{smb} + \beta_{HML}\, r_t^{hml} + \beta_{MOM}\, r_t^{mom} + \varepsilon_t \tag{3.4}$$

$$\alpha_{i,t} = ER_{i,t} - \left[\left(F_{MKT_{i,t}} * \hat{\beta}_{MKT_{i,t}}\right) + \left(F_{SMB_{i,t}} * \hat{\beta}_{SMB_{i,t}}\right) + \left(F_{HML_{i,t}} * \hat{\beta}_{HML_{i,t}}\right) + \left(F_{MOM_{i,t}} * \hat{\beta}_{MOM_{i,t}}\right)\right] \tag{3.5}$$

[21] The Fama and French (2015) five-factor model (FF5) is also examined, and the result was robust to the other models with some variations, as shown in appendix 2.

$\alpha_{i,t}$ is the monthly Carhart (1997) four-factor alpha, $F_{MKT_{i,t}}, F_{HML_{i,t}}, and\ F_{MOM_{i,t}}$ are the factor realisation of fund i in month t, and $\hat{\beta}_{MKT_{i,t}}, \hat{\beta}_{SMB_{i,t}}$, $\hat{\beta}_{HML_{i,t}}$, and $\hat{\beta}_{MOM_{i,t}}$ are the estimated factor loadings of fund i in month t.

Since the primary interest is examining the flow-performance sensitivity of ESG funds relative to their conventional peers, a piecewise linear regression model is implemented following Huang et al. (2007). This allows to capture the flow-performance sensitivity at different levels of performance. Specifically, the performance of funds is ranked within the same investment objective (Growth, Value, or Blend) from worst (zero) to best (one) according to their 12-, 24-, and 36-month raw returns and 12-, 24-, and 36-month Carhart (1997) four-factor alpha. The performance rank is then classified into three-performance portfolios. The Low portfolio is comprised of funds with the bottom 20% in performance, the Mid portfolio is composed by funds with performance within the 20^{th} to 80^{th} percentiles, and the High portfolio include funds with the top 20% performance. To avoid autocorrelation in the cross-sectional flow-performance estimation, the Newey and West (1987) autocorrelation and heteroskedasticity consistent standard errors is used.

$$Flow_{i,t} = \alpha + \beta_1\ Low_{i,t-n} + \beta_2\ Mid_{i,t-n} + \beta_3\ High_{i,t-n} + \beta_4\ X_{i,t-n} + \delta_i + \epsilon_{i,t} \qquad (3.6)$$

$\boldsymbol{Flow_{i,t}}$ is the percentage flows into fund i in month t, calculated as: $[\boldsymbol{TNA_{i,t}} - \boldsymbol{TNA_{i,t-1}} * (\boldsymbol{1} + \boldsymbol{R_{i,t}})]/\boldsymbol{TNA_{i,t-1}}$ (Sirri and Tufano 1998; Del Guercio and Tkac 2002; Bollen 2007; Renneboog et al. 2011). $TNA_{i,t}$ and $TNA_{i,t-1}$ are the fund total net assets in month t and month t-1, respectively, and $R_{i,t}$ is the net return of fund i on month t. $\boldsymbol{Low_{i,t-n}}$ is fund i lowest performance quintile rank at time t-n, $\boldsymbol{Mid_{i,t-n}}$ is fund i middle performance quintile rank at time t-n, $\boldsymbol{High_{i,t-n}}$ is fund i highest performance quintile rank at time t-n. n refers to the different time horizon 12- , 24-, or 36- months. $\boldsymbol{X_{i,t-n}}$ is vector of control variables that may drive the fund flow: one-month lagged: raw return, flow, log total net assets, return volatility, expense ratio, and current age. δ_i represents funds fixed effects to control for the varying flow between different funds, and $\epsilon_{i,t}$ is the error term. To account for cross-sectional and cross-time dependence, the standard errors are clustered by funds and months. Given that only 19 US ESG index funds met the selection criteria, the robustness and external validity of the result might be affected.

Matching

Analysis of the fund flow-performance relationship is prone to endogeneity, most notably the issue of reverse causality whereby flows can influence performance and vice versa, as highlighted by Rakowski and Yamani (2021). However, the existing literature comparing ESG and conventional funds has primarily focused on mitigating endogeneity arising from omitted variable bias. Studies typically control for observable fund characteristics, such as fund size, age, and risk exposures, to ensure that differences in fund performance or flows are not simply due to systematic differences between fund types (Bollen 2007; Renneboog et al. 2011). While this approach reduces bias from observable heterogeneity, it generally does not address the reverse causality concern highlighted in the broader flow-performance literature, whereby fund flows influence their performance and vice versa. To address the omitted variables concern, this study employs the matching approach of Bollen (2007), pairing ESG funds with conventional peers on key observable characteristics.

This approach reduces the risk of omitted variables which affects the dependent variable, causing the error term to correlate with the regressors, leading to biased and inconsistent estimates (Roberts and Whited 2013; Rakowski and Yamani 2021). Although matching cannot fully eliminate bias arising from unobservable variables, it offers a more credible approach to causal inference than unmatched comparisons (Heckman et al. 1997). In addition, fixed-effect models are employed to correct for time-invariant unobserved fund-level heterogeneity (Rakowski and Yamani 2021). The combination of matching and fixed-effect provides a more robust framework for comparing ESG and conventional fund flow-performance sensitivity, although reverse causality between fund flow-performance relationship remains a potential concern.

First, to control for lifecycle and macroeconomic effects, the funds were matched by fund age. To match a conventional with an ESG fund the former must be at most 3 years younger or older than the ESG. Second, to control for the impact of fund load fees and the fund flows, only ESG active and ESG passive funds with no-load fees were eligible candidates for comparison with no-load fees conventional peers. Third, for each ESG fund, both active and passive, a matching score is calculated using the following least-squares algorithms that measure the similarity in risk exposures between pairs of funds.

$$Score(a)_{i,j} = \left(AUM_i - AUM_j\right)^2/\sigma^2_{AUM} + \left((\beta_{MKT_i} - \beta_{MKT_j}\right)^2 \; / \; \sigma^2_{MKT} + \left(\beta_{SMB_i} - \beta_{SMB_j}\right)^2/\sigma^2_{SMB} + \left(\beta_{HML_i} - \beta_{HML_j}\right)^2/\sigma^2_{HML} + \left(\beta_{MOM_i} - \beta_{MOM_i}\right)^2/\sigma^2_{MOM} \tag{3.8}$$

In these equations, i represents each ESG active or passive fund and j refers to either conventional active or passive funds. AUM is the maximum fund size for the fund during its life. σ^2_{AUM} is the cross-sectional variance of AUM. $\beta_{MKT}, \beta_{SMB}, \beta_{HML}, \beta_{MOM}$ are the risk exposures of each fund return to the five factors nested in the five-factor model. σ^2_{MKT} , σ^2_{SMB} , σ^2_{HML} , σ^2_{MOM} are the cross-sectional variances of the estimates of the exposures to the four risk factors across all funds in each category and region. This narrator in each term captures the deviation in risk exposure of fund j from fund i. This is scaled by the cross-sectional variance to ensure that the weights on the matching criterion are normalised. For each ESG fund, either active or passive, three conventional active and three conventional passive funds with the lowest matching scores are added to the matched sample control group.

3.4 Results

3.4.1 Fund performance and risk exposure

This section examines the results of the two-tailed student *t*-test to understand whether investors pay a premium when investing in ESG funds, and whether this varies across regions. Table 3.2 analyses this research question by examining hypothesis 1 (H1), which assumes that ESG and conventional funds yield the same risk-adjusted return and hypothesis 3 (H3), which claims that the fund performance is distinct across regions. Panel A estimates CAPM for conventional and ESG funds, both active and passive, in the US and EU.

The results show that on a risk-adjusted basis ESG funds underperform conventional funds in the US, while the opposite is true for funds domiciled in the EU. This evidence fails to uphold H1 and confirm H3. The evidence suggests that US ESG active funds underperform their conventional peers which is statistically significant at the 1% level. It should also be noted that both ESG and conventional funds underperform the benchmark. This evidence supports the argument that the restricted stock universe associated with ESG investments generates sub-par performance (Statman 2000). This finding is inconsistent with prior literature that document no difference in performance between US conventional and ESG active funds (Statman 2000; Geczy et al. 2005; Bauer et al. 2005; Renneboog et al. 2008b). In contrast to the US findings, the evidence for the EU sample shows that ESG active funds outperform their conventional active peers. This challenges the conclusion drawn by Renneboog et al. (2008b) who show that EU ESG funds underperform their conventional peers. These results are robust across the C-4 (Panel B) and FF6 (Panel C) models.

The above findings suggest that US ESG active funds may be underinvesting in financially attractive industries, or they employ an intense screening process which negatively restricts their options and thus, missing out on high returns from non-ESG stocks (Renneboog et al. 2008b). On the other hand, ESG active strategies in the EU is investing in industries that perform well like technology, healthcare, or renewable. The outperformance of EU ESG funds could be due to companies with good ESG practices delivering shareholder value (Derwall et al. 2004; Cremers and Nair 2005) or due to the increased focus on ESG and sustainability through regulation which increases the demand for ESG investments (Martinez-Meyers et al. 2004).

In contrast with the results of Bauer et al. (2005) and Bollen (2007) regarding the risk exposures, table 3.2 Panel A shows that US ESG active funds are more market sensitive than conventional active funds. ESG fund returns are, on average, 0.89% less volatile than the market, whereas conventional funds are 0.82% less volatile than the market, as per the CAPM estimation. These results are consistent across the C-4 and FF6 with a slight variation in the numbers. Similarly, the findings remain consistent for EU funds. This evidence indicates that both US and EU ESG active funds are tracking the market index closely, which means that ESG active funds in both regions are not distinct from conventional funds in terms of their portfolio compositions.

Panel B shows that, based on the C-4 model, both US ESG and conventional active funds show a preference for small caps, with ESG active funds having a marginally smaller exposure than conventional active funds, although this difference is statistical insignificant. The equivalent results for EU active funds are not similar, as EU ESG active funds are significantly more skewed towards small caps as compared to their conventional peers. This evidence is consistent with Luther et al. (1992) but diverges from Bauer et al. (2005) who find that ESG funds across the US, UK and Germany tend to be more exposed to large caps than their conventional counterparts. Nonetheless, this relationship becomes insignificant in the FF6 model due to the effects of the profitability and investment risk factors.

With regard to the value risk factor, consistent with Guerard (1997) and Bauer et al. (2005), US ESG active funds are significantly less concentrated in value stocks as compared to conventional active funds based on both C-4 and FF6. Bauer et al. (2005) argue that ESG funds are more skewed towards growth stocks due to the exclusions of value sectors, given that these are included in industries with high environmental risks, such as energy and chemical. On the other hand, EU ESG active funds are less skewed towards growth stocks than their conventional peers, a relationship which is significant at the 1% level. Nonetheless, this difference, again, becomes insignificant when estimating the FF6 model.

Regarding the momentum factor, in contrast to Bollen (2007), both US conventional and ESG active funds exhibit negative momentum, which is statistically equal between the two. A negative momentum coupled with negative alpha could be the result of a highly volatile market, or a long period of poor management skills (Daniel and Moskowitz 2016). The focus on value investing might also explain the negative momentum. Unlike the US, EU active funds, both ESG and conventional, show a pattern of upward momentum. The results also show a higher momentum for EU conventional active funds than ESG active funds, which is statistically significant at the 1% level. The positive momentum in the EU active funds with negative alphas could mean that this momentum is driven by short-term market conditions rather than active management skills and it is likely that EU funds are seeing short-term improvement in their performance which is not yet reflected in their risk-adjusted alpha. This evidence from both markets remains consistent for the FF6 estimation.

With regard to the operating profitability factor, the US conventional and ESG active funds show a positive exposure, which indicates that they both invest in assets with robust operating profitability. In fact, the difference between the two is statistically insignificant. On the other hand, in the EU both conventional and ESG active funds engage more in assets with weak operating profitability, while ESG active funds exhibit this portfolio composition more strongly. Furthermore, regarding the investment factor, both conventional and ESG active funds follow more aggressive investment strategies, across both regions. ESG active funds are evidence to be engaging less than conventional funds in such risky investments.

Considering passive funds, the results for the difference in risk-adjusted returns of US ESG and conventional passive funds continue to align with the outcomes from active funds. US ESG passive funds underperform their conventional counterparts by 0.03% (significant at the 1% level). On the contrary, EU passive funds show no statistically significant difference between conventional and ESG fund alpha. This evidence is robust across the C-4 and FF6 models. Lastly, passive funds show no significant difference in all risk factors across the three risk models, in both markets.

In summary, US ESG active funds underperform conventional, have more exposure to market risk, tend to focus more on growth stocks and invest less in risky aggressive investments than conventional active funds. EU ESG active funds outperform conventional, are more exposed to market risk, more skewed towards small capitalisation and growth stocks, have higher momentum, invest more in stocks with weak operating profitability and less in risky assets than their conventional peers. In both regions, these discrepancies in risk exposures suggest that ESG active portfolios are offering very different portfolio choices for ESG investors with no difference in performance. US ESG passive funds underperform their conventional peers. There is no evidence of a difference in performance between EU ESG and conventional passive funds. There is no significant difference in all risk factors across the three risk models, in both markets.

Table 3.2: Fund performance and risk exposure – Conventional vs. ESG

This table reports the estimation from three risk models (CAPM, C-4, and FF6) from January 1996 to December 2022. Reported are the OLS estimates for conventional and ESG funds, both active and passive and within two different regions (US and EU). Difference is calculated by subtracting the mean of ESG from conventional fund estimated alphas and risk factors. Panel A shows the results for the Capital Asset Pricing Model (CAPM). Panel B shows the results for the four-factor model which incorporates the size (*SMB*), value (*HML*), and momentum (*MOM*) factors to the CAPM model. Panel C shows the results for the six-factor model which augment the operating profitability (*RMW)* and the investment (*CMA)* factors to the four-factor model. For each fund, regression is estimated with Newey-West robust standard errors. *T-statistics (in parentheses)* calculated with two-tailed student t-test. ∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% level, respectively.

	Active						Passive					
	US			EU			US			EU		
	Conv.	ESG	Difference	Conv.	ESG	Difference	Conv.	ESG	Difference	Conv.	ESG	Difference
Panel A: CAPM												
α_1	-0.010	-0.012	**0.002*****	-0.016	-0.014	**-0.002*****	-0.005	-0.008	**0.003*****	-0.005	-0.005	0.000
			(3.84)			(-7.83)			(2.64)			(-0.05)
β_M	0.818	0.886	**-0.068*****	0.768	0.822	**-0.054*****	0.957	0.966	-0.009	0.909	0.910	-0.001
			(-3.05)			(-6.15)			(-0.21)			(-0.06)
Panel B: Four-Factor Model												
α_4	-0.010	-0.012	**0.002*****	-0.017	-0.015	**-0.002*****	-0.005	-0.008	**0.003*****	-0.005	-0.005	-0.000
			(3.82)			(-7.92)			(2.74)			(-0.11)
β_M	0.794	0.866	**-0.072*****	0.780	0.837	**-0.057*****	0.934	0.949	-0.015	0.917	0.916	0.001
			(-3.45)			(-6.76)			(-0.38)			(0.05)
β_{SMB}	0.085	0.068	0.017	0.233	0.255	**-0.022****	0.036	-0.035	0.071	0.118	0.138	-0.020
			(0.90)			(-2.25)			(0.99)			(-0.61)
β_{HML}	0.061	0.008	**0.053*****	-0.038	-0.094	**0.057*****	0.067	0.029	0.039	-0.143	-0.146	0.004
			(3.10)			(7.76)			(0.81)			(0.14)
β_{MOM}	-0.027	-0.023	-0.005	0.051	0.033	**0.017*****	-0.045	-0.061	0.016	-0.016	-0.020	0.004
			(-0.69)			(4.89)			(0.74)			(0.38)
Panel C: Six-Factor Model												
α_6	-0.010	-0.012	**0.002*****	-0.017	-0.015	**-0.002*****	-0.005	-0.008	**0.003*****	-0.005	-0.005	-0.000
			(3.78)			(-7.46)			(2.80)			(-0.13)
β_M	0.792	0.861	**-0.069*****	0.781	0.828	**-0.048*****	0.934	0.945	-0.011	0.903	0.901	0.001
			(-3.35)			(-6.06)			(-0.29)			(0.06)
β_{SMB}	0.105	0.091	0.014	0.217	0.229	-0.012	0.062	0.001	0.061	0.088	0.107	-0.019
			(0.74)			(-1.30)			(0.86)			(-0.60)
β_{HML}	0.041	0.002	**0.039*****	-0.102	-0.106	0.004	0.039	0.012	0.027	-0.116	-0.122	0.006
			(2.82)			(0.41)			(0.75)			(0.22)
β_{MOM}	-0.025	-0.018	-0.007	0.053	0.045	**0.008****	-0.045	-0.057	0.012	0.000	-0.003	0.003
			(-1.09)			(2.44)			(0.55)			(0.31)
β_{RMW}	0.021	0.039	-0.017	-0.150	-0.116	**-0.035*****	0.031	0.051	-0.020	-0.093	-0.101	0.009
			(-1.34)			(-3.17)			(-0.60)			(0.28)
β_{CMA}	-0.009	-0.039	**0.030*****	-0.043	-0.125	**0.083*****	0.028	0.029	-0.001	-0.158	-0.159	0.002
			(2.65)			(7.55)			(-0.02)			(0.05)

3.4.2 Fund flow-performance

Fund flow-performance relationship

Fund flows are associated with past performance, fund size and future performance (Berk and Green 2004), which has implications for its persistence (Ferreira et al. 2012). To examine this relationship, fund performance is ranked from worst (zero) to best (one) according to their 12-, and 36-month raw returns[22], and the Carhart (1997) four-factor alpha. Then, the performance is classified into three-ranked portfolios. The Low portfolio includes the funds in the bottom 20% performance, the Mid portfolio includes funds in within the 20th and 80th percentiles and the High portfolio include the top 20% performing funds. A 'High-minus-Low' (HML) portfolio is formed by subtracting the mean monthly flows of the Low from High portfolio, according to raw returns and four-factor alpha. The two-tailed *t*-statistic is calculated on the time series flow of the Low, High, and HML portfolios.

Tables 3.3 and 3.4 report the fund flow by past performance over a short-term (12 months) and a long-term (36 months) horizons, where performance is measured by raw returns and four-factor alpha. Table 3.3 reports the results for the short-term horizon for the US in Panel A and the EU in Panel B. The findings highlight that, for both conventional and ESG active funds, net outflows are reported from poor performing funds and net inflows into well performing funds, a relationship which is statistically significant at the 1% level for both mean returns and alphas. The findings also show that the net flows into well performing funds are statistically higher than the net flows into poor performing funds. The results for the EU funds are similar, as shown in Panel B, except for the EU ESG active fund flow being statistically insignificant. In fact, this relationship is robust in the long term (36M), as presented in Table 3.4, for US funds. EU funds, on the other hand, show a robust result to the short-term period except that the outflow from poor performing conventional and ESG active funds is statistically insignificant, as measured by raw return.

[22] within the same investment objective (Growth, Value, or Blend)

Regarding passive funds, US conventional funds have higher inflows into well performing funds than poor performing ones (significant at the at 1% level), based on raw returns. On risk-adjusted basis, there is no significant difference in fund flows between the Low and High quintile portfolios. In contrast, ESG passive funds show no significant difference between the two portfolios, based on raw returns, but this difference is statistically significant as measured by C-4 alpha. This suggests that the inflow into well performing funds is higher than that of poor performing funds. In the EU, both conventional and ESG passive funds exhibit statistically significant inflows into poor and well performing funds. In fact, no statistical difference exists between the two, as measured by raw return and risk-adjusted basis. On a longer horizon (36M), the difference in flows for US conventional passive funds becomes insignificant, while the results for passive funds remain consistent, as measured by raw return. On risk-adjusted basis, there is a higher inflow into high performing conventional passive funds than poor performing ones at 5% statistically significant level. The difference between ESG passive portfolios becomes insignificant. As to EU funds, the results are robust to the shorter period.

Tables 3.5 and 3.6 report the mean flows of the Low and High portfolios of conventional and ESG funds, across the US (Panel A) and the EU (Panel B), over 12-month and 36-month periods. Table 3.5 shows no difference between US and EU average flows following either a weak or strong 12-month performance. This finding is consistent across both performance measures; raw return and C-4 alpha except for a higher inflow into well performing conventional active funds than that of ESG funds, on a risk-adjusted basis. However, this difference is only statistically significant at the 10% level. The findings over the long-term (Table 3.6) are consistent with the short-term observations across the US and the EU. One exception is a higher inflow into US ESG active well performing funds compared to those of conventional funds at 5% statistically significant level.

In short, US active funds, either conventional or ESG, in the Low portfolio exhibit substantial outflows, while the well performing funds attract significant inflows over the short and long-term. This evidence is consistent with the established literature in fund flow-performance relationship (e.g. Ippolito 1989; Chevalier and Ellison 1997; Sirri and Tufano 1998; Huang et al. 2007; Ferreira et al. 2012). In contrast, the flow-performance relationship for EU active funds is linear, meaning that the poor performing funds experience outflows which are proportional to the inflows into high performing funds. This evidence suggests that there is no difference between conventional and ESG active fund flow performance relationship and the relationship is different across regions.

Regarding passive funds in the short-term horizon, US conventional High portfolio receives higher inflows as compared to the Low portfolio. On the other hand, there are similar inflows into poor and well performing US ESG passive funds. In the longer horizon, there is no difference between conventional and ESG passive fund portfolios as they capture a proportionate share of inflow. In the EU, both conventional and ESG passive funds receive significant inflows regardless of past performance. This evidence shows that ESG passive investors behave differently than conventional passive investors by investing in funds that faced poor performance. However, this difference is only true in the short-term horizon. Over the long term, conventional and ESG passive investors behave in the same way, with no significant variations in passive investors behaviour across the regions.

Table 3.3: Fund flow-performance relationship – 12 months

This table reports fund flow statistics for conventional and ESG funds, both active and passive and within two different regions (US and EU). First, each month, the funds were ranked and divided into five quintile portfolios based on their last month raw return or their past 60-month four-factor model alphas. The low quintile holds the funds with the lowest 20% and the high contains the highest 20% performed funds. Then, the funds raw return or four-factor alphas are averaged over 12- month. The High minus Low portfolio is formed by subtracting the average monthly flow of the low from the high portfolio, according to return or four-factor alpha. Two-tailed t-stat is calculated on the time series flow of the high-minus low portfolio. ∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% level, respectively.

	Mean flow											
	Raw return						Four-factor alpha					
	Low quintile		High quintile		High minus Low		Low quintile		High quintile		High minus Low	
	Mean	t-stat	Mean	t-stat	Mean	t-stat	Mean	t-stat	Mean	t-stat	Mean	t-stat
Panel A: US												
Conventional active	**-0.005*****	(-3.34)	**0.025*****	(13.18)	**0.03*****	(12.22)	**-0.011*****	(-25.84)	**0.011*****	(19.12)	**0.022*****	(30.70)
ESG active	**-0.006*****	(-2.73)	**0.026*****	(13.36)	**0.032*****	(10.60)	**-0.010*****	(-9.79)	**0.008*****	(5.98)	**0.018*****	(10.56)
Conventional passive	-0.009	(-1.20)	**0.009****	(2.01)	**0.018****	(2.12)	-0.000	(-0.15)	0.002	(0.50)	0.002	(0.51)
ESG passive	**0.006*****	(2.68)	**0.017****	(2.29)	0.011	(1.50)	0.003	(1.08)	**0.015*****	(3.50)	**0.012*****	(2.60)
Panel B: EU												
Conventional active	**-0.006***	(-1.78)	**0.012*****	(5.04)	**0.018*****	(4.47)	**-0.003****	(-2.56)	**0.006*****	(5.88)	**0.008*****	(5.90)
ESG active	-0.004	(-1.62)	**0.012*****	(4.70)	**0.016*****	(4.46)	**-0.002****	(-2.08)	**0.007*****	(7.68)	**0.009*****	(6.84)
Conventional passive	**0.008*****	(3.30)	**0.008*****	(3.42)	0.000	(-0.10)	-0.001	(-0.47)	0.002	(0.73)	0.003	(0.86)
ESG passive	**0.006****	(2.24)	**0.007*****	(2.89)	0.001	(0.40)	0.000	(0.03)	0.003	(0.95)	0.002	(0.74)

Table 3.4: Fund flow-performance relationship – 36 months

This table reports fund flow statistics for conventional and ESG funds, both active and passive and within two different regions (US and EU). First, each month, the funds were ranked and divided into five quintile portfolios based on their last month raw return or their past 60-month four-factor model alphas. The low quintile holds the funds with the lowest 20% and the high contains the highest 20% performed funds. Then, the funds raw return or four-factor alphas are averaged over 36-month. The High minus Low portfolio is formed by subtracting the average monthly flow of the low from the high portfolio, according to return or four-factor alpha. Two-tailed t-stat is calculated on the time series flow of the high-minus low portfolio. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Mean flow											
	Raw return						Four-factor alpha					
	Low quintile		High quintile		High minus Low		Low quintile		High quintile		High minus Low	
	Mean	t-stat	Mean	t-stat	Mean	t-stat	Mean	t-stat	Mean	t-stat	Mean	t-stat
Panel A: US												
Conventional active	**-0.006*****	(-4.43)	**0.017*****	(12.47)	**0.023*****	(11.94)	**-0.012*****	(-29.38)	**0.007*****	(15.27)	**0.019*****	(30.58)
ESG active	**-0.007*****	(-2.83)	**0.022*****	(10.81)	**0.029*****	(8.9)	**-0.011*****	(-11.00)	**0.008*****	(7.01)	**0.018*****	(12.64)
Conventional passive	0.000	(-0.05)	**0.012*****	(3.46)	0.013	(1.29)	-0.003	(-1.25)	0.003*	(1.78)	**0.006****	(2.09)
ESG passive	0.000	(-0.18)	0.008	(1.38)	0.008	(1.44)	0.002	(0.74)	0.004	(0.98)	0.002	(0.48)
Panel B: EU												
Conventional active	-0.002	(-0.93)	**0.008*****	(3.81)	**0.010*****	(3.47)	**-0.003****	(-2.37)	**0.003*****	(2.91)	**0.006*****	(3.59)
ESG active	0.002	(1.18)	**0.007*****	(6.02)	**0.006*****	(2.91)	**-0.002****	(-2.15)	**0.004*****	(4.89)	**0.006*****	(4.63)
Conventional passive	**0.004****	(2.18)	**0.007****	(2.38)	0.003	(0.74)	0.002	(0.78)	0.004	(1.32)	0.002	(0.48)
ESG passive	**0.005****	(2.27)	0.004	(1.46)	-0.001	(-0.35)	0.003	(1.22)	0.003	(0.85)	-0.001	(-0.19)

Table 3.5: Difference in fund flows – 12 months

This table compares the mean flows of the lowest 20% and the highest 20% performed fund portfolios of conventional and ESG funds across the US and EU. First, each month, the funds are ranked and divided into five quintile portfolios based on their last month raw return or their past 60-month four-factor model alpha. Each month, the fund raw return or four-factor alpha are averaged over 12-month. Two portfolios were formed for each region. One is a portfolio of the lowest 20% performed conventional and ESG funds and the other is a portfolio of the highest 20% performed conventional and ESG funds, according to their average monthly return or past 36-month four-factor alpha. Difference is a portfolio constructed by subtracting the average monthly flow of low (high) ESG fund from low (high) conventional fund, within both regions. Two-tailed t-stat is calculated on the time series flow low or high portfolio. ∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% level, respectively.

	Active				**Passive**			
	Mean flow							
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
	Difference	t-stat	Difference	t-stat	Difference	t-stat	Difference	t-stat
Panel A: US								
Low: Conv - ESG	0.001	(0.45)	-0.001	(-1.23)	-0.015	(-1.37)	-0.003	(-0.79)
High: Conv - ESG	-0.001	(-0.42)	**0.003***	(1.89)	-0.008	(-0.90)	-0.013	(-1.88)
Panel B: EU								
Low: Conv - ESG	-0.002	(-0.41)	-0.001	(-0.49)	0.003	(0.77)	-0.001	(-0.36)
High: Conv - ESG	0.000	(0.14)	-0.001	(-0.93)	0.001	(0.30)	-0.001	(-0.13)

Table 3.6: Difference in fund flows – 36 months

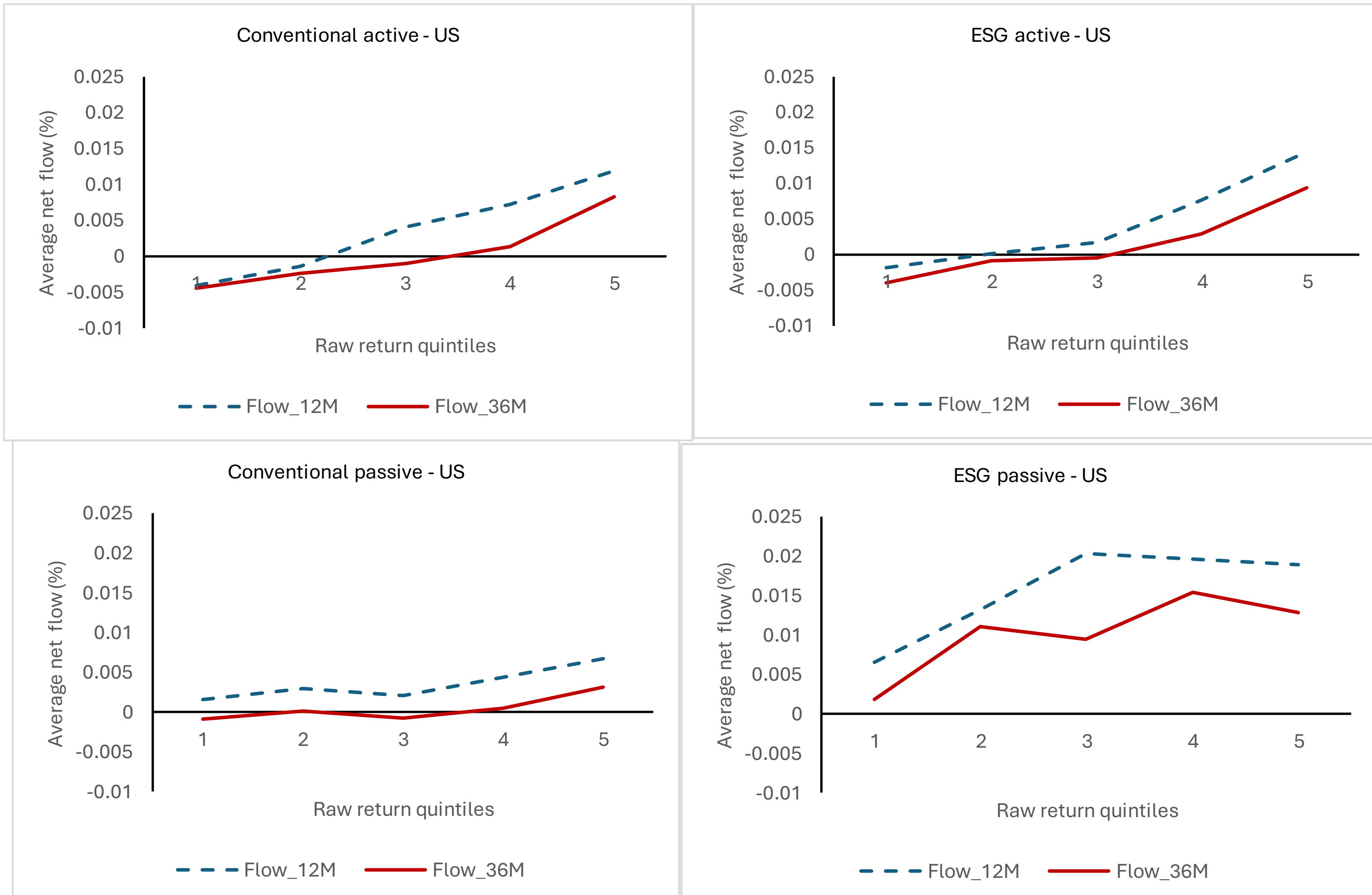
This table compares the mean flows of the lowest 20% and the highest 20% performed fund portfolios of conventional and ESG funds across the US and EU. First, each month, the funds are ranked and divided into five quintile portfolios based on their last month raw return or their past 60-month four-factor model alpha. Each month, the fund raw return or four-factor alpha are averaged over 36-month. Two portfolios were formed for each region. One is a portfolio of the lowest 20% performed conventional and ESG funds and the other is a portfolio of the highest 20% performed conventional and ESG funds, according to their average monthly return or past 36-month four-factor alpha. Difference is a portfolio constructed by subtracting the average monthly flow of low (high) ESG fund from low (high) conventional fund, within both regions. Two-tailed t-stat is calculated on the time series flow low or high portfolio. ∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% level, respectively.

	Active				**Passive**			
	Mean flow							
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
	Difference	t-stat	Difference	t-stat	Difference	t-stat	Difference	t-stat
Panel A: US								
Low: Conv - ESG	0.001	(0.44)	-0.001	(-0.86)	0.000	(-0.00)	-0.004	(-1.31)
High: Conv - ESG	**-0.005****	(-1.96)	-0.0001	(-0.06)	0.005	(0.73)	-0.001	(-0.25)
Panel B: EU								
Low: Conv - ESG	-0.004	(-1.46)	-0.001	(-0.46)	-0.001	(-0.29)	-0.001	(-0.34)
High: Conv - ESG	0.001	(0.33)	-0.001	(-1.12)	0.003	(0.75)	0.001	(0.34)

Fund flow-performance sensitivity

Figure 3.1 illustrates the average fund flow by performance quintile for conventional and ESG funds across investment method and region. Fund flows are presented in percentage basis for comparability. Consistent with the earlier findings and prior literature (Ippolito 1989; Sirri and Tufano 1998; Huang et al. 2007; Ferreira et al. 2012), the US active fund flow-performance relationship is seen to be sensitive for the bottom portfolio, weak in the middle, and the most sensitive for the top, for both conventional and ESG funds. This pattern suggests that US investors, whether active or passive, are influenced by past performance and thus, this is viewed as predictor of future returns. However, the flow-performance relationship for EU active funds is linear and flat.

For passive funds, the figure shows a concave flow-performance relationship for US conventional funds, which indicates that the sensitivity of the flow-performance declines for top-performing funds. This might suggest that investors do not make their investment decisions based on past performance but consider other factors such as market uncertainty, fund fees, market and selling activities. The plot, on the other hand, shows a linear relationship for conventional and ESG passive funds. For funds domiciled in Europe, the flow-performance relationship is still flat like active funds, which means a weak flow-performance relationship in all quintiles ranks. This might indicate that performance is not a good predictor of EU fund flows (Berk and Green 2004). It also suggests that investors might be rational, not allocating their investment based on extreme performance. Investors are rewarding funds for consistent performance rather than outliers. In both markets, conventional and ESG investors are behaving the same way.


Conventional active - US
Average net flow (%)
0.025
0.02
0.015
0.01
0.005
0
-0.005
-0.01
1
2
3
4
5
Raw return quintiles
Flow_12M
Flow_36M
ESG active - US
Average net flow (%)
0.025
0.02
0.015
0.01
0.005
0
-0.005
-0.01
1
2
3
4
5
Raw return quintiles
Flow_12M
Flow_36M
Conventional passive - US
Average net flow (%)
0.025
0.02
0.015
0.01
0.005
0
-0.005
-0.01
1
2
3
4
5
Raw return quintiles
Flow_12M
Flow_36M
ESG passive - US
Average net flow (%)
0.025
0.02
0.015
0.01
0.005
0
-0.005
-0.01
1
2
3
4
5
Raw return quintiles
Flow_12M
Flow_36M

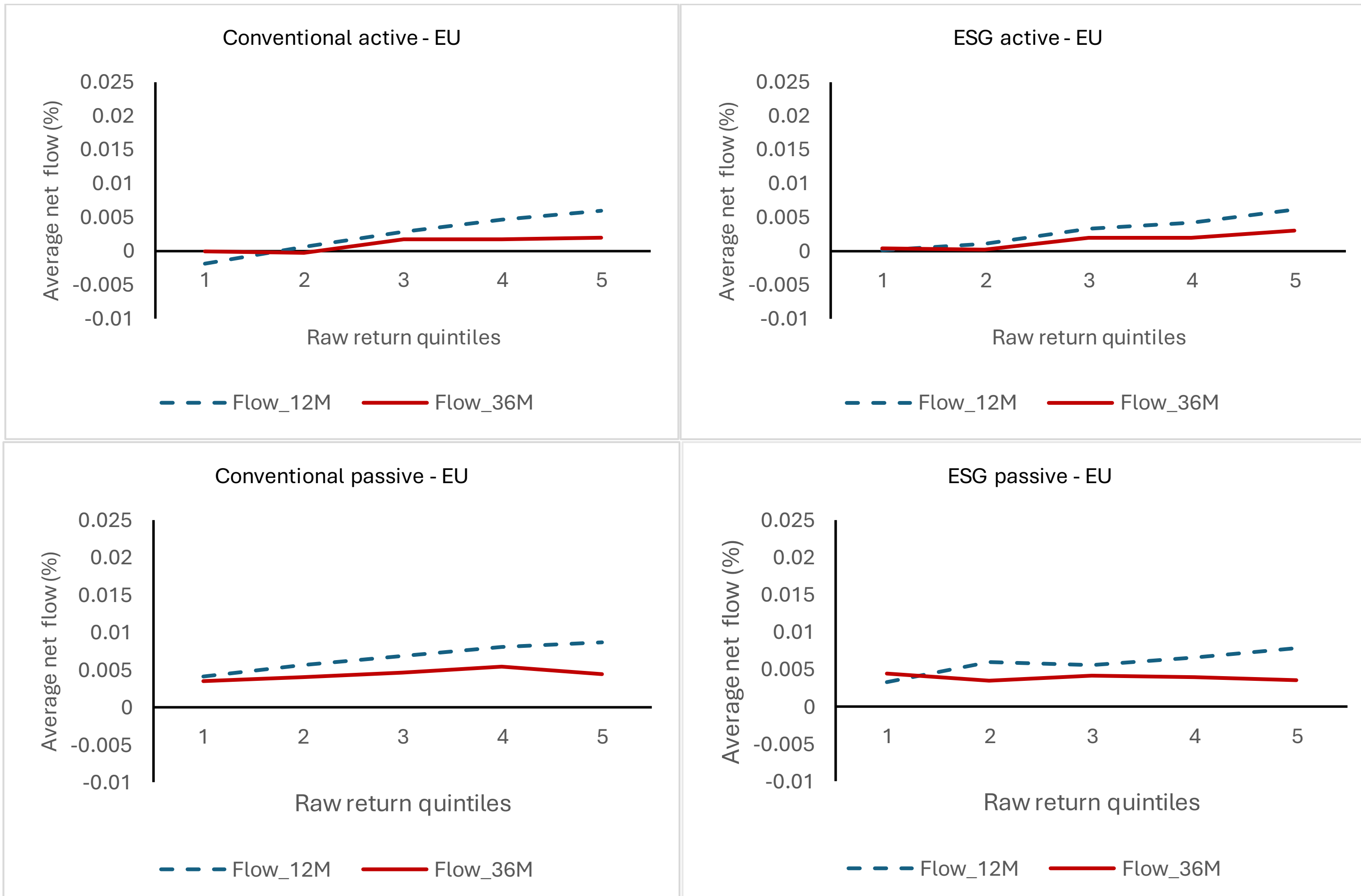


Figure 3.1: Flow-performance convexity
The charts show the fund average monthly net flow by raw return quintile rank for ESG and conventional, both active and passi ve funds in the US and EU. For each fund group each month, funds raw return was ranked in quintile. Then the average fund net flow was plotted by raw return quintile.

To formally examine hypotheses H2 and H4 stating that the ESG fund flow-performance sensitivity is different from that of conventional funds and ESG and conventional fund flow-performance sensitivity is distinct across regions, this section regresses the sensitivity of average fund flow (capture investor behaviour) over 12-, and 36-months horizons on the performance-quintile ranked portfolios using Newey and West's (1987) autocorrelation and heteroscedasticity consistent standard error. Performance is measured by either raw return or the Carhart (1997) four-factor alpha over 12- and 36-month horizons. The results suggest a difference between US ESG and conventional investors' behaviour, while EU ESG and conventional investors exhibit a comparable behaviour pattern.

Tables 3.7, 3.8, 3.9, and 3.10 present the results of the flow-performance sensitivity, whether raw return or the Carhart (1997) four-factor alpha, over 12- and 36-month period in the US and EU. In panel A of Table 3.7, US conventional and ESG active funds are examined, whilst Panel B analyses US conventional and ESG passive funds. Focusing on the conventional active funds, consistent with the flow-performance relationship presented in Figure 3.1, there is asymmetric relationship between fund flow and 12-month past performance, as measured by raw return. The coefficient for the low performance range is negative and significant at the 10% level (-0.02%), and the coefficients for the medium and high-performance ranges are positive and significant at the 1% level (0.06%, 0.20%). Unlike earlier result, the sensitivity to the medium performance rank is the highest. Adjusting the model for other fund characteristics, the coefficients for the three performance ranks become smaller in magnitude and statistically insignificant. The other fund characteristics' effect is aligned with prior literature (Benson and Humphrey 2008; Huang et al. 2007). For example, the result shows positive relationship between fund flow and one-month lagged return and flow. This suggests that investors favour maintaining their positions in their existing investment, consistent with Benson and Humphrey (2008) who find persistence in fund flow. Furthermore, in line with Huang et al. (2007), the result shows that the level of fund flow is lower for older and more volatile funds.

On risk-adjusted basis, there is a negative and statistically significant coefficient for the lowest quintile, a positive and statistically significant coefficient for the middle quintile and a negative but insignificant coefficient for the highest quintile. Considering other fund characteristics, the relationship between flow and the three-ranked portfolios becomes less in magnitude. However, only the mid quintile is significant at the 10% level. In this case, the one-month lagged returns and expense ratio might explain the insensitivity between flows and 12-month past risk-adjusted returns. This is indicated by a positive and statistically significant relationship between fund flows, lagged returns and expense ratio.

A similar result is reported for the long-term horizon (36-month), based on the raw returns, with a slight variation in the significance level. However, in terms of risk-adjusted performance, the fund flow-performance relationship becomes convex. There are significant outflows from the lowest quintile funds (-0.62%) at the 1% level and significant inflows into the mid and high quintiles (0.37% and 0.21%, respectively) at the 1 % level. After adjusting for control variables, the mid-rank portfolio becomes insignificant whilst the other ranked portfolios remain significant at the 5% confidence level. This indicates that conventional investors consider other factors than past performance over the short-term. However, on a longer period, investors are more sensitive to risk-adjusted performance, rewarding outperformers and penalising underperformers. This shows the rationality of US conventional active investors is enhanced over a longer period.

Regarding the flow-performance sensitivity for ESG active funds, the findings point to variations between US conventional and ESG active funds based on raw returns. The coefficient of the lowest quintile portfolio is negative and insignificant, the coefficient of the mid-rank is positive and insignificant, and the coefficient for the highest quintile is positive and significant at the 1% level. In fact, this finding remains consistent after control factors. As to other fund characteristics, the results show that fund flows are positively related to the one-month lagged returns and one-month lagged flows, both of which are statistically significant at the 1% level.

Accounting for other risk factors, there is evidence of positive flow sensitivity to the outperformers at 1% statistically significant level, whereas the other portfolios remain insignificant. When considering risk-adjusted returns, there is no evidence of flow-performance sensitivity for all performance portfolios. This insensitivity of the flow to the past 12-month performance could be explained by the expense ratio or age. This might suggest that after adjusting for other risks, investors consider the fund age or expense ratio rather than the risk-adjusted returns when allocating capital into ESG active funds. On a longer period of 36-month, this finding remains consistent, nonetheless, at a lower magnitude.

While the models which employ raw returns show no flow-performance sensitivity for US conventional active funds, the results are different based on risk-adjusted returns. For instance, the evidence suggests that investors are attracted to the mid-performers in the short-term, whilst their long-term investment is focused on rewarding outperformers and penalising underperformers. In contrast, the raw return model for US ESG active funds show high sensitivity to the well performing funds in the short-term, taking other fund characteristics into considerations. In the long-run, the flow-performance sensitivity diminishes. On the other hand, when considering the C-4 alpha the US ESG active investors appear insensitive to either 12- or 36- past performance. This supports H2 which claims that the flow-performance sensitivity is different between ESG and conventional funds. It should be noted that, this is not aligned with Benson and Humphrey (2008) who find a positive and convex flow-performance sensitivity.

Panel A in tables 3.9 and 3.10 report the results of the EU conventional and ESG active funds over a 12-month and 36-month horizons, respectively. Based on the raw return model, over 12-month period the coefficient for the lowest quintile is negative and statistically insignificant, whilst the coefficients for the mid and high-quintile portfolios are positive and statistically significant at the 1% level. When adjusting for other fund characteristics, only the mid-ranked portfolio is sensitive to past performance, however this is true only at a 10% significance level. Unlike conventional active funds, only the expense ratio has a negative relationship with the fund flow, suggesting that EU conventional active investors inflow into funds that offer lower expense ratio regardless of their past performance.

In the longer period (36-month), Panel A of Table 3.10 shows variations as the flow-performance relationship becomes concave, especially after adjusting for control variables. For example, the coefficient for the lowest quintile becomes positive and statistically significant at the 5% level, whilst the coefficients for the mid- and high ranked portfolios become negative and statistically significant at the 5% level. While the performance at the three-quintile ranks has the strong influence on EU conventional active fund flow, the effect of fund lag return, volatility and expense ratio are statistically significant. This suggest that the less volatile fund with higher return and less expense ratio attract more flows, independent of their past 36-month raw return.

Based on a risk-adjusted model, over the 12-month period (Table 3.9, panel A), the coefficient for the lowest quintile is negative and statistically significant at the 5% level. The coefficients for the other ranked portfolios are not statistically different from zero. This evidence holds after controlling for other fund characteristics. Over the long-period (36-month), the result remains consistent. However, investors also consider characteristics as return volatility in their investment decision. More volatile funds attract more flows.

Panel A of Table 3.9 reports that the EU ESG active funds exhibit positive and statistically significant coefficients for the mid- and high quintiles portfolios, based on raw returns. After adjusting for control variables, only the mid-ranked portfolio is significant, yet at only a 10% significance level. The results show that one-month lagged fund flows and expense ratio are strong determinants of current flows. The higher the past inflows and lower the fees, the higher inflows which are attracted. Interestingly, Table 3.10, panel A, shows contradicting evidence. The lowest quintile has a positive and statistically significant coefficient at the 10% level, the mid-quintile becomes negative and statistically significant at the 5% level, and the highest quintile becomes negative but statistically insignificant. When adjusting for control variables, the mid and high quintile portfolios have negative and statistically significant coefficients at the 5% and 10% levels, respectively. The lagged one-month fund flows, volatility, and expense ratio are similarly important determinant of current flows.

Based on the risk-adjusted model, panel A of Table 3.9, shows a negative and statistically significant coefficient for the lowest quintile (1% level). However, after adjusting for other characteristics, the relationship between flow and 12-month past risk-adjusted alpha is statistically insignificant for the three ranked portfolios. Over the long period, there is a statistically significant and negative sensitivity to the underperformers. There is also evidence that the more volatile the fund the more flow it attracts.

Overall, in the short-term and after controlling for other characteristics, there is no significant flow-performance sensitivity for both EU conventional and ESG active funds, based on both performance measures. However, over the longer period, a concave flow-performance relationship is shown for the same funds. This indicate that raw returns is an important factor for both conventional and ESG active investors when making their decisions, however they show lower sensitivity to well rather than poor performers. After control factors, conventional and ESG active investors maintain their positions into the mid and high ranked portfolios, while showing negative sensitivity to the underperformers.

In the EU, there is no pronounced difference in the flow-performance between conventional and ESG active funds over both the short and long terms. This supports H2. Moreover, the results for both US and EU active funds supports H4 that the difference in flow-performance sensitivity of conventional and ESG funds is distinct across countries. This is also consistent with the earlier findings. In the short term, US conventional and ESG passive funds show different flow-performance sensitivity based on whether the examination is conducted with the raw return or C-4 alpha (Panel B of Tables 3.7). Investors are attracted to high performers (raw return) and penalise outperformers (C-4 alpha), yet only at the 10% significance level. On the other hand, US ESG passive investors show no significant sensitivity to past performance. Raw return, rather than C-4 alpha, accounts for the difference in flow-performance sensitivity between US conventional and ESG passive funds. Over the long-term (Panel B of Tables 3.8), the inflow into US high performing funds is higher than their ESG peers, based on raw return. Based on C-4 alpha, US ESG passive investors do not show sensitivity to past performance as US conventional passive investors do. US conventional passive investors penalise underperformers and reward outperformers.

Considering EU passive funds (Panel B of Tables 3.9 and 3.10), there is no significant flow-performance sensitivity for both EU conventional and ESG passive funds similar to the findings from the EU active funds. Over the long-term, EU conventional and ESG passive funds have no flow-performance sensitivity based on raw returns. However, after adjusting for control factors, both conventional and ESG passive investors are attracted to the mid performers only. Like active funds, this evidence shows no difference in flow-performance sensitivity between EU conventional and ESG passive funds over short and long periods.

Table 3.7: Flow-performance sensitivity – 12 months, US

This table examines the flow-performance sensitivity of conventional and ESG active funds, in the US (Panel A), for a sample period ranges from January 1996 to December 2022. Performance is measured by raw return or past 60-month four-factor alpha. Fund performance is ranked from zero to one according to their 12-month raw return within the same investment objective (Growth, Value, or Blend), or Carhart (1997) four-factor alpha. Then, the performance rank is classified into ranked into three-performance ranked portfolios. Low quintile portfolio representing the bottom 20% performed funds (Low). Mid quantile portfolio composes of the three middle 20% performed funds. The high quintile portfolio includes the top 20% performed funds. The control variables include one-month lagged: raw return, flow, log total net assets, return volatility, expense ratio, and current age. Panel B repeats the same analysis for conventional and ESG passive funds in the US. Reported are the time-series average coefficients and *t-statistics* (in parentheses) are calculated with Newey-West robust standard errors. ∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Active – US	**Conventional**				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low	**-0.018***	-0.007	**-0.226*****	-0.106	-0.012	-0.005	0.087	0.011
	(-1.87)	(-0.95)	(-2.89)	(-1.55)	(-1.10)	(-0.46)	(1.00)	(0.10)
Mid	**0.061*****	0.017	**0.314*****	**0.105***	0.025	0.001	-0.081	0.015
	(3.99)	(1.47)	(4.62)	(1.69)	(1.40)	(0.06)	(-0.95)	(0.14)
High	**0.020*****	0.004	-0.053	-0.075	**0.022*****	**0.013*****	**0.209*****	0.116
	(4.10)	(1.35)	(-1.04)	(-1.53)	(4.40)	(2.69)	(3.20)	(1.12)
Lag return		**0.021****		**0.022*****		**0.041*****		0.018
		(2.50)		(2.84)		(3.20)		(1.44)
Lag flow		**0.312*****		**0.233*****		**0.210*****		0.063
		(4.80)		(3.45)		(3.12)		(0.73)
Lag net assets		-0.004		-0.002		-0.002		-0.004
		(-1.27)		(-0.88)		(-0.60)		(-0.93)
Lag return volatility		**-0.058****		-0.015		-0.023		-0.022
		(-2.12)		(-0.60)		(-0.65)		(-0.50)
Lag expense ratio		0.192		0.443***		0.043		**0.348*****
		(1.47)		(3.23)		(0.29)		(3.42)
Age		**-0.001****		0.000		-0.001		**0.001***
		(-1.97)		(-0.06)		(-1.17)		(1.88)
Intercept	0.000	0.070	**-0.003****	-0.004	0.002	0.049	**-0.003***	0.011
	(0.23)	(1.03)	(-2.00)	(-0.11)	(1.56)	(0.86)	(-1.84)	(0.16)
R^2	0.079	0.568	0.141	0.461	0.055	0.232	0.051	0.115

Table 3.7: continued								
Panel B: Passive – US								
	Conventional				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low	0.003	0.017	-0.040	-0.154	**0.041****	**0.042***	**-0.881*****	**-0.293***
	(0.23)	(1.08)	(-0.31)	(-1.44)	(2.02)	(1.77)	(-4.00)	(-1.92)
Mid	-0.013	-0.005	**0.461*****	0.071	0.016	0.021	**0.879****	0.038
	(-0.73)	(-0.31)	(3.24)	(0.44)	(0.40)	(0.56)	(2.80)	(0.18)
High	**0.024****	**0.016****	**-0.350****	**-0.226***	**0.035***	-0.002	**-0.665****	-0.082
	(2.36)	(1.96)	(-2.19)	(-1.77)	(1.70)	(-0.12)	(-2.39)	(-0.33)
Lag return		-0.017		-0.025		0.001		0.028
		(-0.92)		(-1.32)		(0.03)		(0.86)
Lag flow		**0.166*****		0.113		0.218		**0.150***
		(2.86)		(1.26)		(1.49)		(1.93)
Lag net assets		**-0.011*****		**0.006****		-0.008		-0.005
		(-2.83)		(2.10)		(-0.95)		(-1.38)
Lag return volatility		-0.032		0.114		0.026		-0.062
		(-0.61)		(1.61)		(0.20)		(-0.46)
Lag expense ratio		**-1.116*****		**1.393*****		-0.012		-0.034
		(-4.46)		(2.77)		(-0.14)		(-0.51)
Age		**-0.001*****		**-0.001*****		0.002		0.001
		(-2.82)		(-3.48)		(0.81)		(1.14)
Intercept	**0.006*****	**0.272*****	0.004	**-0.165****	**0.017*****	0.131	0.002	0.076
	(2.79)	(3.49)	(1.28)	(-2.15)	(3.83)	(1.06)	(1.01)	(1.35)
R^2	0.048	0.290	0.046	0.166	0.035	0.072	0.091	0.060

Table 3.8: Flow-performance sensitivity – 36 months, US

This table examines the flow-performance sensitivity of conventional and ESG active funds, in the US (Panel A), for a sample period ranges from January 1996 to December 2022. Performance is measured by raw return or past 60-month four-factor alpha. Fund performance is ranked from zero to one according to their 36-month raw return within the same investment objective (Growth, Value, or Blend), or Carhart (1997) four-factor alpha. Then, the performance rank is classified into ranked into three-performance ranked portfolios. Low quintile portfolio representing the bottom 20% performed funds (Low). Mid quantile portfolio composes of the three middle 20% performed funds. The high quintile portfolio includes the top 20% performed funds. The control variables include one-month lagged: raw return, flow, log total net assets, return volatility, expense ratio, and current age. Panel B repeats the same analysis for conventional and ESG passive funds in the US. Reported are the time-series average coefficients and *t-statistics* (in parentheses) are calculated with Newey-West robust standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Active – US	**Conventional**				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low	**-0.090****	-0.030	**-0.615*****	**-0.252****	-0.038	-0.028	0.040	-0.114
	(-2.10)	(-1.04)	(-5.47)	(-2.07)	(-0.77)	(-0.66)	(0.22)	(-0.65)
Mid	0.009	-0.004	**0.365*****	0.031	0.001	-0.001	-0.127	0.242
	(0.36)	(-0.20)	(4.12)	(0.27)	(0.03)	(-0.03)	(-0.86)	(1.27)
High	**0.027*****	-0.004	**0.211*****	**0.167****	**0.017***	-0.006	**0.328*****	0.059
	(4.14)	(-0.62)	(3.05)	(1.98)	(1.91)	(-0.65)	(3.15)	(0.32)
Lag return		**0.023*****		**0.022*****		**0.043*****		**0.022***
		(2.80)		(2.94)		(3.49)		(1.79)
Lag flow		**0.303*****		**0.216*****		**0.230*****		0.056
		(4.78)		(2.97)		(3.30)		(0.45)
Lag net assets		0.000		-0.002		0.003		-0.003
		(0.02)		(-0.85)		(0.63)		(-0.58)
Lag return volatility		**-0.067****		-0.014		-0.017		-0.004
		(-2.36)		(-0.58)		(-0.52)		(-0.12)
Lag expense ratio		**0.294****		**0.387*****		0.073		**0.406*****
		(2.30)		(3.56)		(0.48)		(3.16)
Age		**-0.001***		0.000		-0.001		**0.003****
		(-1.82)		(0.51)		(-1.05)		(2.32)
Intercept	-0.001	-0.012	**-0.012*****	-0.003	0.001	-0.044	**-0.006****	-0.047
	(-0.29)	(-0.17)	(-7.05)	(-0.07)	(0.43)	(-0.58)	(-2.48)	(-0.67)
R^2	0.073	0.569	0.355	0.473	0.018	0.219	0.061	0.155

Table 3.8: continued

Panel B: Passive – US

	Conventional				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low	-0.054	0.005	**-0.68*****	**-0.590*****	0.020	0.037	-0.738	-0.023
	(-1.31)	(0.12)	(-3.26)	(-2.71)	(0.30)	(0.50)	(-1.54)	(-0.07)
Mid	0.038	0.003	**1.226*****	**0.835*****	**0.164****	0.137	**1.071***	**0.826***
	(1.34)	(0.09)	(5.35)	(2.90)	(2.10)	(1.56)	(1.69)	(1.67)
High	**0.035*****	**0.029****	0.153	0.148	**0.049****	0.041	-0.134	-0.230
	(2.79)	(2.32)	(1.15)	(0.82)	(2.38)	(0.84)	(-0.15)	(-0.21)
Lag return		-0.006		0.017		0.009		0.054
		(-0.35)		(1.01)		(0.27)		(1.47)
Lag flow		**0.168*****		0.022		0.164		0.132
		(2.92)		(0.34)		(1.08)		(1.03)
Lag net assets		**-0.016*****		**-0.004***		-0.016		-0.004
		(-3.05)		(-1.70)		(-1.53)		(-0.85)
Lag return volatility		-0.091*		-0.062		0.047		**-0.349*****
		(-1.77)		(-1.05)		(0.35)		(-2.85)
Lag expense ratio		**-1.251*****		-0.199		**-0.248***		-0.150
		(-4.67)		(-0.49)		(-1.88)		(-1.60)
Age		0.000		0.000		0.004		0.003
		(-0.97)		(-0.90)		(1.17)		(1.32)
Intercept	-0.002	**0.375*****	**-0.005****	0.096	-0.001	**0.273***	**0.005*****	0.063
	(-0.77)	(3.55)	(-2.48)	(1.56)	(-0.20)	(1.66)	(2.71)	(0.88)
R^2	0.037	0.284	0.12	0.135	0.063	0.094	0.036	0.109

Table 3.9: Flow-performance sensitivity – 12 months, EU

This table examines the flow-performance sensitivity of conventional and ESG active funds, in the EU (Panel A), for a sample period ranges from January 1996 to December 2022. Performance is measured by raw return or past 60-month four-factor alpha. Fund performance is ranked from zero to one according to their 12-month raw return within the same investment objective (Growth, Value, or Blend), or Carhart (1997) four-factor alpha. Then, the performance rank is classified into ranked into three-performance ranked portfolios. Low quintile portfolio representing the bottom 20% performed funds (Low). Mid quantile portfolio composes of the three middle 20% performed funds. The high quintile portfolio includes the top 20% performed funds. The control variables include one-month lagged: raw return, flow, log total net assets, return volatility, expense ratio, and current age. Panel B repeats the same analysis for conventional and ESG passive funds in the EU. Reported are the time-series average coefficients and *t-statistics* (in parentheses) are calculated with Newey-West robust standard errors. ∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Active - EU	**Conventional**				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low	-0.002	-0.001	**-0.351****	**-0.329****	-0.002	0.002	**-0.263*****	-0.148
	(-0.26)	(-0.05)	(-2.47)	(-2.12)	(-0.24)	(0.15)	(-2.69)	(-1.58)
Mid	**0.075*****	**0.049***	0.106	-0.021	**0.050*****	**0.023***	0.088	-0.030
	(2.90)	(1.67)	(0.96)	(-0.18)	(3.37)	(1.66)	(1.35)	(-0.39)
High	**0.013*****	0.006	-0.022	0.189	**0.009****	0.005	-0.011	0.088
	(2.58)	(1.08)	(-0.21)	(1.45)	(2.01)	(1.02)	(-0.23)	(0.81)
Lag return		0.028		0.028		0.004		0.006
		(1.36)		(1.20)		(0.32)		(0.55)
Lag flow		0.139		-0.150		**0.34*****		0.098
		(0.89)		(-1.00)		(5.02)		(1.05)
Lag net assets		-0.001		-0.009		-0.002		0.000
		(-0.33)		(-1.22)		(-0.65)		(0.09)
Lag return volatility		-0.036		0.027		-0.013		**0.093***
		(-0.57)		(0.34)		(-0.35)		(1.66)
Lag expense ratio		**-0.242****		0.061		**-0.324*****		0.011
		(-2.43)		(0.56)		(-2.95)		(0.07)
Age		0.000		0.000		0.000		0.000
		(0.98)		(0.29)		(0.07)		(0.47)
Intercept	0.001	0.049	**-0.006*****	0.149	**0.002****	0.074	**-0.004****	-0.024
	(0.45)	(0.88)	(-2.71)	(0.99)	(2.21)	(1.56)	(-2.52)	(-0.32)
R^2	0.060	0.151	0.072	0.127	0.036	0.247	0.096	0.134

Table 3.9: continued

Panel B: Passive - EU

	Conventional				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low	-0.002	0.018	0.124	-0.096	-0.001	0.006	0.128	-0.121
	(-0.14)	(1.07)	(0.93)	(-0.56)	(-0.04)	(0.34)	(1.00)	(-0.73)
Mid	-0.001	-0.004	-0.069	-0.022	-0.001	-0.007	-0.100	0.000
	(-0.04)	(-0.19)	(-0.82)	(-0.21)	(-0.03)	(-0.29)	(-1.25)	(0.00)
High	0.006	0.001	-0.020	-0.052	0.009	0.005	-0.020	-0.030
	(0.85)	(0.11)	(-0.47)	(-0.89)	(1.03)	(0.51)	(-0.46)	(-0.51)
Lag return		0.001		**0.033***		0.030		0.030
		(0.03)		(1.74)		(1.34)		(1.50)
Lag flow		0.077		0.063		0.060		0.073
		(0.52)		(1.02)		(0.96)		(1.27)
Lag net assets		-0.001		-0.008		0.001		-0.005
		(-0.24)		(-1.53)		(0.38)		(-1.11)
Lag return volatility		**0.100***		-0.060		0.069		0.025
		(1.71)		(-0.82)		(1.22)		(0.32)
Lag expense ratio		-0.026		0.068		0.066		0.074
		(-0.13)		(0.51)		(0.53)		(0.72)
Age		-0.001		0.003		-0.001		0.002
		(-0.56)		(1.61)		(-0.46)		(1.32)
Intercept	**0.007*****	0.031	0.004	0.102	**0.005****	-0.020	0.005	0.059
	(3.19)	(0.41)	(1.33)	(1.32)	(2.24)	(-0.37)	(1.60)	(0.82)
R^2	0.002	0.037	0.004	0.039	0.003	0.024	0.006	0.032

Table 3.10: Flow-performance sensitivity – 36 months, EU

This table examines the flow-performance sensitivity of conventional and ESG active funds, in the EU (Panel A), for a sample period ranges from January 1996 to December 2022. Performance is measured by raw return or past 60-month four-factor alpha. Fund performance is ranked from zero to one according to their 36-month raw return within the same investment objective (Growth, Value, or Blend), or Carhart (1997) four-factor alpha. Then, the performance rank is classified into ranked into three-performance ranked portfolios. Low quintile portfolio representing the bottom 20% performed funds (Low). Mid quantile portfolio composes of the three middle 20% performed funds. The high quintile portfolio includes the top 20% performed funds. The control variables include one-month lagged: raw return, flow, log total net assets, return volatility, expense ratio, and current age. Panel B repeats the same analysis for conventional and ESG passive funds in the EU. Reported are the time-series average coefficients and *t-statistics* (in parentheses) are calculated with Newey-West robust standard errors. ∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Active - EU

	Conventional				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low	0.059	**0.103****	-0.252	**-0.542****	**0.046***	0.050	-0.320	**-0.307****
	(1.29)	(2.16)	(-1.07)	(-2.48)	(1.67)	(1.28)	(-1.31)	(-1.98)
Mid	-0.144	**-0.254****	-0.045	-0.036	**-0.087****	**-0.122****	0.062	-0.057
	(-1.46)	(-2.57)	(-0.37)	(-0.25)	(-2.23)	(-2.08)	(0.69)	(-0.60)
High	0.002	**-0.032****	0.060	0.046	-0.004	**-0.014***	-0.021	0.023
	(0.15)	(-2.20)	(0.43)	(0.37)	(-0.55)	(-1.65)	(-0.28)	(0.25)
Lag return		**0.042****		0.021		0.013		0.006
		(1.99)		(1.17)		(0.99)		(0.58)
Lag flow		0.123		-0.141		**0.338*****		**0.161***
		(0.77)		(-1.04)		(5.17)		(1.83)
Lag net assets		0.002		-0.007		-0.001		-0.004
		(0.55)		(-1.53)		(-0.23)		(-1.05)
Lag return volatility		**-0.140***		**0.127*****		**-0.076***		**0.083*****
		(-1.77)		(3.27)		(-1.88)		(2.83)
Lag expense ratio		**-0.31****		0.005		**-0.334*****		-0.021
		(-2.45)		(0.04)		(-2.86)		(-0.25)
Age		0.000		0.000		0.000		0.001
		(-0.24)		(0.45)		(-0.47)		(0.90)
Intercept	0.006	0.015	-0.005	0.102	**0.006*****	0.066	-0.004	0.055
	(1.63)	(0.22)	(-1.44)	(1.22)	(3.36)	(1.44)	(-1.46)	(0.84)
R^2	0.020	0.160	0.017	0.117	0.012	0.249	0.024	0.176

Table 3.10: continued

Panel B: Passive - EU

	Conventional				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low	-0.008	-0.011	0.399	-0.277	-0.043	0.078	0.290	-0.392
	(-0.14)	(-0.12)	(1.33)	(-0.65)	(-0.72)	(1.00)	(1.00)	(-0.92)
Mid	-0.054	-0.062	0.057	**0.596****	-0.027	**-0.091***	0.112	**0.707****
	(-1.12)	(-1.15)	(0.32)	(2.21)	(-0.58)	(-1.76)	(0.70)	(2.22)
High	0.010	0.012	0.098	0.081	0.006	0.015	0.100	0.116
	(0.58)	(0.63)	(0.89)	(0.45)	(0.45)	(0.85)	(0.93)	(0.66)
Lag return		0.008		0.030		0.032		0.029
		(0.35)		(1.39)		(1.43)		(1.27)
Lag flow		0.060		0.050		0.029		0.043
		(0.39)		(0.79)		(0.47)		(0.70)
Lag net assets		0.003		**-0.013*****		0.003		**-0.011****
		(0.67)		(-2.67)		(0.76)		(-2.48)
Lag return volatility		0.046		-0.001		0.094		0.023
		(0.71)		(-0.01)		(1.28)		(0.26)
Lag expense ratio		-0.063		0.057		0.062		0.060
		(-0.29)		(0.39)		(0.46)		(0.49)
Age		-0.002		**0.003****		-0.001		**0.003***
		(-0.95)		(2.05)		(-0.65)		(1.88)
Intercept	0.005	-0.030	0.003	**0.173****	0.003	-0.050	0.002	**0.151****
	(1.46)	(-0.44)	(0.81)	(2.27)	(0.86)	(-0.79)	(0.51)	(1.98)
R^2	0.012	0.042	0.027	0.094	0.012	0.048	0.024	0.087

3.5 Matching

Table 3.11 reports the standardised mean difference (SMD) statistics for each covariate, including fund risk exposures such as market, size, value, and momentum, across the treatment and control groups for four different settings: (a) US ESG and matched conventional active funds; (b) US ESG and matched conventional passive funds; (c) EU ESG and matched conventional active funds; (d) EU ESG and matched conventional passive funds, both before and after the PSM. SMD below 0.10 indicates excellent covariate balance (Zhang et al. 2019), while values between 0.10 and 0.25 indicates acceptable balance (Stuart et al. 2013). The post matching results for the US ESG vs. matched conventional active and EU ESG vs. matched conventional passive are of a good quality, with all covariates falling within excellent or acceptable thresholds. The US ESG vs. matched passive and EU ESG vs. conventional active matches are not of a good quality through most of the covariates. It is worth noting that, following Bollen (2007), the purpose of matching is not to eliminate all possible imbalance, but rather to reduce systematic differences between ESG and conventional funds that could confound the estimation of performance and flow sensitivity.

For example, the US ESG vs. conventional passive funds, the SMD of the market factor is approximately 0.2, indicating an acceptable level of balance. The size and momentum factors both improved and are well below 0.2 after matching. Although the value factor shows a higher SMD, suggesting slightly weaker balance, this likely reflects the limited size of the US ESG passive funds rather than a systematic bias. Similarly, for the EU ESG vs. conventional active funds, the SMDs of the market and value factors have declined but remain above 0.2, while the momentum factor improved noticeably, decreasing from –0.333 to –0.195, indicating that matching has generally enhanced comparability across some covariates.

Fund performance

Table 3.12 shows the fund performance and the risk exposure of ESG funds and the respective, matched, conventional funds. The evidence for US funds supports H1 that ESG and conventional active funds yield the same risk-adjusted returns. The difference in performance is sensitive to the controls for fund age, load fees, and portfolio composition. In the EU, the significant coefficients discussed above are maintained in the matched sample. The findings for passive funds across both regions are robust to the unmatched sample.

Fund flow-performance sensitivity

Panel A of Table 3.13 reports the result for the US matched sample over the short-term (12-month). The raw return model exhibits consistent findings with the unmatched sample for conventional active funds, specifically, the sensitivity coefficients are not significant at any of the three portfolios. On the other hand, when alphas are considered, the lowest quintile portfolio is negative and significant at the 5% level, and the middle quintile portfolio is positive and significant at the 5% level. Over the longer period (Panel A of Table 3.14) and after adjusting for control variables, the results are consistent with the unmatched sample based on both performance measures. One exception is that the coefficient for the high quantile portfolio becomes statistically insignificant. The results, even with some variations in significance, consistently with the unmatched sample, supports H2 that the flow-performance sensitivity ESG funds is different from conventional funds after matching the conventional active sample with ESG active sample.

Regarding the EU active funds over the short-run (Panel A of Table 3.15), the matched conventional sample shows no flow-performance sensitivity at any of the three ranked portfolios based on raw returns and after adjusting for control variables. This evidence contradicts the unmatched sample findings, in which the middle-ranked portfolio was significant at the 10% level. On the risk-adjusted basis, the lowest quintile becomes insignificant, which contradicts the unmatched sample finding that it was significant at the 5% level. Over the longer period (Panel A of Table 3.16), the raw return model shows no significant flow-performance sensitivity for all ranked portfolios, which were significant at the 5% level in the unmatched sample. Based on the C-4 model, the coefficient for the lowest quintile becomes positive significant at the 10% level. Overall, after matching there is no difference in flow-performance sensitivity between EU conventional and ESG active funds over 12-month period, which is consistent with the unmatched sample. However, over the longer period, the EU matched conventional active funds show significant difference in flow-performance sensitivity as compared to their ESG peers. Hence, the fund age, loads and portfolio compositions affect the sensitivity relationship over the longer period.

Regarding passive funds the results show no significant sensitivity in flow-performance over both the short and long horizons. Given this result, the differences between flow-performance sensitivity between US conventional and ESG passive funds which was seen in the unmatched sample diminishes.

For the EU conventional passive over the short-term, the lowest quintile portfolio has positive and significant coefficient at the 5% level which was insignificant in the unmatched sample. Based on C-4 alpha, the coefficient for the highest quintile is negative and statistically significant at the 10% level. These differences do not drastically change the conclusions drawn from the unmatched sample in the short run, specifically, there is no difference in flow-performance sensitivity between EU conventional and ESG passive funds. However, the longer horizon results exhibit differences as compared to the unmatched sample. Specifically, based on raw returns, the lowest quintile becomes positive and statistically significant at the 1% level, and the middle portfolio becomes negative and statistically significant at the 5% level. Based on the C-4 model, the coefficient for the middle-portfolio becomes insignificant. These changes confirm a difference in flow-performance sensitivity between EU conventional and ESG passive funds.

Table 3. 11: Matching – Sample comparison

This table reports the standardized mean differences (SMD) statistics for each covariate in the treatment and control groups before and after propensity score matching (PSM). Lower values indicate better covariate balance, with SMD values below 0.1 considered excellent and below 0.25 considered acceptable.

Covariate	SMD before	SMD after
	US ESG – matched conventional active	
MKT	0.187	0.018
SMB	-0.101	0.013
HML	-0.225	-0.071
MOM	0.083	0.013
	US ESG – matched conventional passive	
MKT	0.121	0.240
SMB	-0.395	-0.006
HML	-0.300	-0.522
MOM	-0.291	-0.152
	EU ESG – matched conventional active	
MKT	0.485	0.339
SMB	0.156	0.180
HML	-0.462	-0.435
MOM	-0.333	-0.195
	EU ESG – matched conventional passive	
MKT	0.021	-0.076
SMB	0.144	0.190
HML	-0.324	-0.078
MOM	-0.226	-.0461

Table 3.12: Fund performance and risk exposure – matched conventional vs. ESG

This table reports the estimation from three risk models (CAPM, C-4, and FF6) from January 1996 to December 2022. Reported are the OLS estimates for conventional and ESG funds, both active and passive and within two different regions (US and EU). Difference is calculated by subtracting the mean of ESG from matched conventional fund estimated alphas and risk factors. Panel A shows the results for the Capital Asset Pricing Model (CAPM) when each monthly observation of ESG fund is matched to monthly observation of three conventional funds where the match is based on age size and CAPM market risk factor. Panel B shows the results for the four-factor model which incorporates the size (*SMB*), value (*HML*), and momentum (*MOM*) factors to the CAPM model when each monthly observation of ESG fund is matched to monthly observation of three conventional funds where the match is based on age size and four-factor model's risk factors. Panel C shows the results for the six-factor model which augment the operating profitability (*RMW*) and the investment (*CMA*) factors to the four-factor model when each monthly observation of ESG fund is matched to monthly observation of three conventional funds where the match is based on age size and six-factor model's risk factors. For each fund, regression is estimated with Newey-West robust standard errors. *T-statistics (in parentheses)* calculated with two-tailed student t-test. ∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% level, respectively.

	Active						Passive					
	US			EU			US			EU		
	Conv.	ESG	Difference	Conv.	ESG	Difference	Conv.	ESG	Difference	Conv.	ESG	Difference
Panel A: CAPM												
α_1	-0.012	-0.012	0.0001	-0.019	-0.014	**-0.004*****	-0.005	-0.008	**0.003****	-0.005	-0.005	0.0
			(0.22)			(-10.83)			(2.08)			(-0.02)
β_M	0.880	0.886	-0.006	0.711	0.822	**-0.111*****	0.963	0.966	-0.004	0.913	0.910	0.002
			(-0.28)			(-8.19)			(-0.14)			(0.07)
Panel B: Four-Factor Model												
α_4	-0.011	-0.012	0.0004	-0.019	-0.015	**-0.004*****	-0.005	-0.008	**0.003****	-0.005	-0.005	-0.0002
			(0.95)			(-10.69)			(2.06)			(-0.19)
β_M	0.849	0.866	-0.018	0.711	0.837	**-0.126*****	0.940	0.949	-0.009	0.926	0.916	0.010
			(-0.91)			(-9.6)			(-0.31)			(0.3)
β_{SMB}	0.070	0.068	0.002	0.234	0.255	-0.020	-0.038	-0.035	-0.003	0.072	0.138	-0.066
			(0.08)			(-1.38)			(-0.04)			(-1.32)
β_{HML}	0.028	0.008	0.020	-0.009	-0.094	**0.085*****	0.089	0.029	0.060	-0.114	-0.146	0.033
			(1.29)			(7.49)			(1.53)			(0.79)
β_{MOM}	-0.022	-0.023	0.001	0.062	0.033	**0.029*****	-0.058	-0.061	0.003	-0.002	-0.020	0.018
			(0.08)			(5.28)			(0.13)			(1.2)
Panel C: Six-Factor Model												
α_6	-0.011	-0.012	0.001	-0.019	-0.015	**-0.004*****	-0.005	-0.008	**0.003****	-0.005	-0.005	-0.0003
			(1.34)			(-9.54)			(2.05)			(-0.25)
β_M	0.850	0.861	-0.011	0.718	0.828	**-0.111*****	0.931	0.945	-0.014	0.913	0.901	0.012
			(-0.56)			(-9.02)			(-0.49)			(0.36)
β_{SMB}	0.099	0.091	0.008	0.217	0.229	-0.012	-0.005	0.001	-0.006	0.043	0.107	-0.064
			(0.39)			(-0.82)			(-0.09)			(-1.3)
β_{HML}	0.012	0.002	0.01	-0.091	-0.106	0.015	0.068	0.012	0.056*	-0.082	-0.122	0.040
			(0.8)			(1.04)			(1.81)			(0.94)
β_{MOM}	-0.020	-0.018	-0.002	0.063	0.045	**0.019*****	-0.061	-0.057	-0.004	0.013	-0.003	0.015
			(-0.31)			(3.53)			(-0.2)			(1.03)
β_{RMW}	0.038	0.039	-0.001	-0.174	-0.116	**-0.06*****	0.039	0.051	-0.013	-0.063	-0.101	0.039
			(-0.06)			(-3.51)			(-0.38)			(0.82)
β_{CMA}	-0.025	-0.039	0.014	-0.007	-0.125	**0.118*****	0.051	0.029	0.022	-0.148	-0.159	0.012
			(1.26)			(6.77)			(0.74)			(0.23)

Table 3.13: Flow-performance sensitivity – 12 months, US, matched

This table examines the flow-performance sensitivity of matched conventional and ESG, both active and passive funds, in the US (Panel A), for a sample period ranges from January 1996 to December 2022). Each monthly observation of ESG (passive) fund is matched to monthly observation of three conventional (active) funds where the match is based on age size and four-factor model's risk factors. Performance is measured by raw return or past 60-month four-factor alpha. Fund performance is ranked from zero to one according to their 12-month raw return within the same investment objective (Growth, Value, or Blend), or Carhart (1997) four-factor alpha. Then, the performance rank is classified into ranked into three-performance ranked portfolios. Low quintile portfolio representing the bottom 20% performed funds (Low). Mid quantile portfolio composes of the three middle 20% performed funds. The high quintile portfolio includes the top 20% performed funds. The control variables include one-month lagged: raw return, flow, log total net assets, return volatility, expense ratio, and current age. Panel B repeats the same analysis for matched active and passive, both conventional and ESG funds in the US. Reported are the time-series average coefficients and *t-statistics* (in parentheses) are calculated with Newey-West robust standard errors. ∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: ESG match – Active

	Matched conventional				**ESG**			
	Raw Return		Four-factor alpha		Raw Return		Four-factor alpha	
Low	0.007	0.009	**-0.262*****	**-0.230****	-0.012	-0.005	0.087	0.011
	(1.10)	(1.49)	(-3.26)	(-2.51)	(-1.10)	(-0.46)	(1.00)	(0.10)
Mid	**0.049***	0.013	**0.337*****	**0.190****	0.025	0.001	-0.081	0.015
	(1.89)	(0.71)	(4.55)	(2.23)	(1.40)	(0.06)	(-0.95)	(0.14)
High	0.003	0.005	-0.062	-0.090	**0.022*****	**0.013*****	**0.209*****	0.116
	(0.27)	(0.60)	(-0.97)	(-1.19)	(4.40)	(2.69)	(3.20)	(1.12)
Lag return		**0.023****		**0.024****		**0.041*****		0.018
		(2.04)		(2.12)		(3.20)		(1.44)
Lag flow		**0.119***		**0.167****		**0.210*****		0.063
		(1.71)		(2.08)		(3.12)		(0.73)
Lag net assets		**-0.007****		-0.004		-0.002		-0.004
		(-2.17)		(-1.37)		(-0.60)		(-0.93)
Lag return volatility		**-0.082****		**-0.082****		-0.023		-0.022
		(-2.32)		(-2.24)		(-0.65)		(-0.50)
Lag expense ratio		0.067		**0.423****		0.043		**0.348*****
		(0.44)		(2.49)		(0.29)		(3.42)
Age		**-0.001*****		0.000		-0.001		**0.001***
		(-3.31)		(0.31)		(-1.17)		(1.88)
Intercept	**0.018*****	**0.166****	-0.003**	0.039	0.002	0.049	**-0.003***	0.011
	(16.71)	(2.31)	(-2.13)	(0.57)	(1.56)	(0.86)	(-1.84)	(0.16)
R^2	0.020	0.468	0.129	0.289	0.055	0.232	0.051	0.115

Table 3.12: continued								
Panel B: ESG match – Passive								
	Matched conventional				**ESG**			
	Raw Return		Four-factor alpha		Raw Return		Four-factor alpha	
Low	-0.032	0.007	-0.153	-0.222	**0.041****	**0.042***	**-0.881*****	**-0.293***
	(-1.40)	(0.24)	(-1.39)	(-1.09)	(2.02)	(1.77)	(-4.00)	(-1.92)
Mid	0.055	-0.009	0.149	-0.061	0.016	0.021	**0.879****	0.038
	(0.86)	(-0.19)	(0.74)	(-0.24)	(0.40)	(0.56)	(2.80)	(0.18)
High	0.023	0.003	0.091	0.665	**0.035***	-0.002	**-0.665****	-0.082
	(0.93)	(0.22)	(0.32)	(1.54)	(1.70)	(-0.12)	(-2.39)	(-0.33)
Lag return		0.014		0.008		0.001		0.028
		(0.39)		(0.26)		(0.03)		(0.86)
Lag flow		**0.100***		0.032		0.218		**0.150***
		(1.78)		(0.28)		(1.49)		(1.93)
Lag net assets		-0.009		-0.002		-0.008		-0.005
		(-1.19)		(-0.47)		(-0.95)		(-1.38)
Lag return volatility		0.053		0.034		0.026		-0.062
		(0.49)		(0.37)		(0.20)		(-0.46)
Lag expense ratio		-0.044		-0.279		-0.012		-0.034
		(-0.17)		(-0.66)		(-0.14)		(-0.51)
Age		-0.001		-0.001		0.002		0.001
		(-0.59)		(-0.76)		(0.81)		(1.14)
Intercept	**0.015*****	0.196	-0.002	0.064	**0.017*****	0.131	0.002	0.076
	(4.75)	(1.42)	(-1.43)	(0.66)	(3.83)	(1.06)	(1.01)	(1.35)
R^2	0.008	0.105	0.009	0.030	0.035	0.072	0.091	0.060

Table 3.14: Flow-performance sensitivity – 36 months, US, matched

This table examines the flow-performance sensitivity of matched conventional and ESG, both active and passive funds, in the US (Panel A), for a sample period ranges from January 1996 to December 2022). Each monthly observation of ESG (passive) fund is matched to monthly observation of three conventional (active) funds where the match is based on age size and four-factor model's risk factors. Performance is measured by raw return or past 60-month four-factor alpha. Fund performance is ranked from zero to one according to their 36-month raw return within the same investment objective (Growth, Value, or Blend), or Carhart (1997) four-factor alpha. Then, the performance rank is classified into ranked into three-performance ranked portfolios. Low quintile portfolio representing the bottom 20% performed funds (Low). Mid quantile portfolio composes of the three middle 20% performed funds. The high quintile portfolio includes the top 20% performed funds. The control variables include one-month lagged: raw return, flow, log total net assets, return volatility, expense ratio, and current age. Panel B repeats the same analysis for matched active and passive, both conventional and ESG funds in the US. Reported are the time-series average coefficients and *t-statistics* (in parentheses) are calculated with Newey-West robust standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: ESG match - Active

	Matched conventional				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low	**-0.078*** **	-0.009	-0.141	**-0.456** **	-0.038	-0.028	0.040	-0.114
	(-4.42)	(-0.44)	(-1.11)	(-2.13)	(-0.77)	(-0.66)	(0.22)	(-0.65)
Mid	**-0.155***	0.030	-0.014	0.309	0.001	-0.001	-0.127	0.242
	(-1.84)	(0.44)	(-0.12)	(1.43)	(0.03)	(-0.03)	(-0.86)	(1.27)
High	**0.152*** **	0.000	**0.329*** **	0.084	**0.017***	-0.006	**0.328*** **	0.059
	(3.51)	(-0.01)	(3.54)	(0.84)	(1.91)	(-0.65)	(3.15)	(0.32)
Lag return		**0.027** **		**0.018***		**0.043*** **		**0.022***
		(2.51)		(1.82)		(3.49)		(1.79)
Lag flow		**0.125***		0.098		**0.23*** **		0.056
		(1.82)		(1.26)		(3.30)		(0.45)
Lag net assets		-0.004		-0.003		0.003		-0.003
		(-0.99)		(-1.03)		(0.63)		(-0.58)
Lag return volatility		**-0.110*** **		**-0.108*** **		-0.017		-0.004
		(-3.04)		(-2.85)		(-0.52)		(-0.12)
Lag expense ratio		0.202		**0.703*** **		0.073		**0.406*** **
		(1.32)		(3.36)		(0.48)		(3.16)
Age		**-0.001** **		**0.003** **		-0.001		**0.003** **
		(-2.36)		(2.16)		(-1.05)		(2.32)
Intercept	0.004	0.082	**-0.01*** **	-0.053	0.001	-0.044	**-0.006** **	-0.047
	(1.23)	(1.03)	(-5.52)	(-0.80)	(0.43)	(-0.58)	(-2.48)	(-0.67)
R^2	0.068	0.463	0.166	0.283	0.018	0.219	0.061	0.155

Table 3.14: continued

Panel B: ESG match - Passive

	Matched conventional				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low	0.007	-0.036	-0.080	-0.187	0.020	0.037	-0.738	-0.023
	(0.13)	(-0.48)	(-0.47)	(-0.49)	(0.30)	(0.50)	(-1.54)	(-0.07)
Mid	**-0.155****	-0.097	0.177	0.715	**0.164****	0.137	**1.071***	**0.826***
	(-2.38)	(-1.13)	(0.50)	(0.95)	(2.10)	(1.56)	(1.69)	(1.67)
High	0.026	0.015	**2.391*****	0.936	**0.049****	0.041	-0.134	-0.230
	(0.74)	(0.36)	(3.61)	(1.13)	(2.38)	(0.84)	(-0.15)	(-0.21)
Lag return		0.026		-0.001		0.009		0.054
		(0.80)		(-0.04)		(0.27)		(1.47)
Lag flow		0.094		-0.035		0.164		0.132
		(1.57)		(-0.34)		(1.08)		(1.03)
Lag net assets		-0.012		**-0.011****		-0.016		-0.004
		(-1.49)		(-2.15)		(-1.53)		(-0.85)
Lag return volatility		-0.086		-0.096		0.047		**-0.349*****
		(-0.88)		(-0.85)		(0.35)		(-2.85)
Lag expense ratio		-0.102		-0.462		**-0.248***		-0.150
		(-0.35)		(-1.04)		(-1.88)		(-1.60)
Age		0.001		0.002		0.004		0.003
		(0.90)		(1.45)		(1.17)		(1.32)
Intercept	**0.011*****	**0.254***	-0.001	**0.207****	-0.001	**0.273***	**0.005*****	0.063
	(4.76)	(1.65)	(-0.46)	(2.15)	(-0.20)	(1.66)	(2.71)	(0.88)
R^2	0.017	0.087	0.043	0.056	0.063	0.094	0.036	0.109

Table 3.15: Flow-performance sensitivity – 12 months, EU, matched

This table examines the flow-performance sensitivity of matched conventional and ESG, both active and passive funds, in the EU (Panel A), for a sample period ranges from January 1996 to December 2022). Each monthly observation of ESG (passive) fund is matched to monthly observation of three conventional (active) funds where the match is based on age size and four-factor model's risk factors. Performance is measured by raw return or past 60-month four-factor alpha. Fund performance is ranked from zero to one according to their 12-month raw return within the same investment objective (Growth, Value, or Blend), or Carhart (1997) four-factor alpha. Then, the performance rank is classified into ranked into three-performance ranked portfolios. Low quintile portfolio representing the bottom 20% performed funds (Low). Mid quantile portfolio composes of the three middle 20% performed funds. The high quintile portfolio includes the top 20% performed funds. The control variables include one-month lagged: raw return, flow, log total net assets, return volatility, expense ratio, and current age. Panel B repeats the same analysis for matched active and passive, both conventional and ESG funds in the EU. Reported are the time-series average coefficients and *t-statistics* (in parentheses) are calculated with Newey-West robust standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: ESG match - Active

	Matched conventional active				**ESG**			
	Raw Return		Four-factor alpha		Raw Return		Four-factor alpha	
Low	0.110	0.099	**0.506*** **	-0.052	-0.002	0.002	**-0.263*** **	-0.148
	(1.64)	(1.32)	(3.49)	(-0.26)	(-0.24)	(0.15)	(-2.69)	(-1.58)
Mid	0.253	0.295	**0.189** **	-0.058	**0.05*** **	**0.023***	0.088	-0.030
	(1.35)	(1.27)	(2.11)	(-0.48)	(3.37)	(1.66)	(1.35)	(-0.39)
High	-0.021	0.001	-0.084	0.154	**0.009** **	0.005	-0.011	0.088
	(-0.57)	(0.02)	(-1.12)	(1.01)	(2.01)	(1.02)	(-0.23)	(0.81)
Lag return		-0.044		**0.212*** **		0.004		0.006
		(-0.53)		(3.35)		(0.32)		(0.55)
Lag flow		0.108		**0.252** **		**0.34*** **		0.098
		(0.57)		(2.07)		(5.02)		(1.05)
Lag net assets		-0.016		-0.004		-0.002		0.000
		(-1.59)		(-0.63)		(-0.65)		(0.09)
Lag return volatility		0.772		-0.376		-0.013		**0.093***
		(1.00)		(-1.45)		(-0.35)		(1.66)
Lag expense ratio		0.423		0.247		**-0.324*** **		0.011
		(1.43)		(0.38)		(-2.95)		(0.07)
Age		0.003		-0.002		0.000		0.000
		(1.51)		(-1.48)		(0.07)		(0.47)
Intercept	**0.051*** **	0.223	**0.026*** **	0.065	**0.002** **	0.074	**-0.004** **	-0.024
	(3.20)	(1.38)	(5.03)	(0.39)	(2.21)	(1.56)	(-2.52)	(-0.32)
R^2	0.043	0.122	0.095	0.232	0.036	0.247	0.096	0.134

Table 3.15: continued

Panel B: ESG match - Passive

	Matched conventional				**ESG**			
	Raw Return		Four-factor alpha		Raw Return		Four-factor alpha	
Low	0.008	**0.046****	**0.784****	0.301	-0.001	0.006	0.128	-0.121
	(0.28)	(2.14)	(2.20)	(0.83)	(-0.04)	(0.34)	(1.00)	(-0.73)
Mid	-0.059	0.016	0.044	0.076	-0.001	-0.007	-0.100	0.000
	(-0.78)	(0.35)	(0.19)	(0.27)	(-0.03)	(-0.29)	(-1.25)	(0.00)
High	-0.010	-0.001	-0.200	-0.500*	0.009	0.005	-0.020	-0.030
	(-0.75)	(-0.08)	(-0.58)	(-1.85)	(1.03)	(0.51)	(-0.46)	(-0.51)
Lag return		-0.030		0.041		0.030		0.030
		(-0.88)		(1.02)		(1.34)		(1.50)
Lag flow		0.009		-0.038		0.060		0.073
		(0.16)		(-0.42)		(0.96)		(1.27)
Lag net assets		**-0.021****		**-0.019****		0.001		-0.005
		(-2.40)		(-2.21)		(0.38)		(-1.11)
Lag return volatility		-0.118		**-0.398****		0.069		0.025
		(-0.8)		(-2.09)		(1.22)		(0.32)
Lag expense ratio		0.229		-0.019		0.066		0.074
		(0.46)		(-0.05)		(0.53)		(0.72)
Age		0.003		**0.005*****		-0.001		0.002
		(1.43)		(2.60)		(-0.46)		(1.32)
Intercept	**0.021*****	**0.354*****	**0.014*****	**0.293****	**0.005****	-0.020	0.005	0.059
	(7.55)	(2.73)	(2.61)	(2.09)	(2.24)	(-0.37)	(1.60)	(0.82)
R^2	0.003	0.105	0.045	0.132	0.003	0.024	0.006	0.032

Table 3.16: Flow-performance sensitivity – 36 months, EU, matched

This table examines the flow-performance sensitivity of matched conventional and ESG, both active and passive funds, in the EU (Panel A), for a sample period ranges from January 1996 to December 2022). Each monthly observation of ESG (passive) fund is matched to monthly observation of three conventional (active) funds where the match is based on age size and four-factor model's risk factors. Performance is measured by raw return or past 60-month four-factor alpha. Fund performance is ranked from zero to one according to their 36-month raw return within the same investment objective (Growth, Value, or Blend), or Carhart (1997) four-factor alpha. Then, the performance rank is classified into ranked into three-performance ranked portfolios. Low quintile portfolio representing the bottom 20% performed funds (Low). Mid quantile portfolio composes of the three middle 20% performed funds. The high quintile portfolio includes the top 20% performed funds. The control variables include one-month lagged: raw return flow, log total net assets, return volatility, expense ratio, and current age. Panel B repeats the same analysis for matched active and passive, both conventional and ESG funds in the EU. Reported are the time-series average coefficients and *t-statistics* (in parentheses) are calculated with Newey-West robust standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: ESG match – Active

	Matched conventional				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low	**-0.261***	-0.095	**0.478***	**0.460***	**0.046***	0.050	-0.320	**-0.307****
	(-1.81)	(-1.18)	(1.82)	(1.66)	(1.67)	(1.28)	(-1.31)	(-1.98)
Mid	-0.065	-0.046	0.348	0.114	**-0.087****	**-0.122****	0.062	-0.057
	(-0.30)	(-0.35)	(1.37)	(0.26)	(-2.23)	(-2.08)	(0.69)	(-0.60)
High	**0.336****	0.302	-0.289	0.448	-0.004	**-0.014***	-0.021	0.023
	(2.57)	(1.22)	(-1.19)	(0.50)	(-0.55)	(-1.65)	(-0.28)	(0.25)
Lag return		**0.100****		**0.208*****		0.013		0.006
		(1.98)		(2.94)		(0.99)		(0.58)
Lag flow		0.186		0.136		**0.338*****		**0.161***
		(0.20)		(0.89)		(5.17)		(1.83)
Lag net assets		-0.058		**-0.052*****		-0.001		-0.004
		(-1.25)		(-3.11)		(-0.23)		(-1.05)
Lag return volatility		-0.350		**-0.800*****		**-0.076***		**0.083*****
		(-0.98)		(-3.75)		(-1.88)		(2.83)
Lag expense ratio		-0.269		**0.594*****		**-0.334*****		-0.021
		(-0.44)		(2.68)		(-2.86)		(-0.25)
Age		0.008		**-0.004*****		0.000		0.001
		(1.23)		(-3.66)		(-0.47)		(0.90)
Intercept	0.005	1.038	**0.020*****	**0.922*****	**0.006*****	0.066	-0.004	0.055
	(0.20)	(1.22)	(2.81)	(2.94)	(3.36)	(1.44)	(-1.46)	(0.84)
R^2	0.048	0.272	0.034	0.362	0.012	0.249	0.024	0.176

Table 3.16: continued

Panel B: ESG match – Passive

	Matched conventional				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low	**0.092***	**0.180*****	0.915	0.512	-0.043	0.078	0.290	-0.392
	(1.66)	(2.59)	(1.57)	(0.70)	(-0.72)	(1.00)	(1.00)	(-0.92)
Mid	-0.483	**-0.516****	0.339	0.127	-0.027	**-0.091***	0.112	**0.707****
	(-1.56)	(-2.27)	(1.07)	(0.29)	(-0.58)	(-1.76)	(0.70)	(2.22)
High	0.117	0.053	-0.623	-0.762	0.006	0.015	0.100	0.116
	(1.25)	(0.86)	(-1.20)	(-1.17)	(0.45)	(0.85)	(0.93)	(0.66)
Lag return		0.004		0.006		0.032		0.029
		(0.14)		(0.15)		(1.43)		(1.27)
Lag flow		-0.029		-0.077		0.029		0.043
		(-0.46)		(-0.72)		(0.47)		(0.70)
Lag net assets		**-0.063*****		**-0.021****		0.003		**-0.011****
		(-4.01)		(-2.17)		(0.76)		(-2.48)
Lag return volatility		**-0.473*****		-0.368		0.094		0.023
		(-3.65)		(-1.59)		(1.28)		(0.26)
Lag expense ratio		**-1.801*****		-0.088		0.062		0.060
		(-2.58)		(-0.22)		(0.46)		(0.49)
Age		**0.007*****		**0.005***		-0.001		**0.003***
		(2.72)		(1.84)		(-0.65)		(1.88)
Intercept	**0.016*****	**1.199*****	0.015	**0.342****	0.003	-0.050	0.002	**0.151****
	(4.51)	(4.18)	(1.49)	(2.40)	(0.86)	(-0.79)	(0.51)	(1.98)
R^2	0.030	0.188	0.023	0.095	0.012	0.048	0.024	0.087

3.6 Conclusion

The aim of this study is to empirically examine whether there exists a difference in performance and flow-performance sensitivity between ESG and conventional funds, and whether these differences vary across regions. The findings contribute to the literature on two fronts. First, providing the first evidence for the performance and the flow-performance sensitivity of ESG funds based on monthly frequency data from the US and EU. Second, the contribution to the flow-performance sensitivity literature about the behaviour of ESG passive investors and the exploration into their utility of the socially responsible attribute.

First, the findings of Hypotheses 1 and 3, which evaluate the performance of ESG and conventional funds, show no difference in performance between US ESG active funds and their matched conventional peers, which supports Hypothesis 1 and the evidence from earlier literature (Statman 2000; Bauer et al. 2005; Geczy et al. 2005; Renneboog et al. 2008a; Renneboog et al. 2008b). This result may indicate that the advantages of US ESG active funds are offset by associated costs (Statman and Glushkov 2016) or that ESG factors are not priced into the US market, such that firms are neither rewarded nor penalised for their ESG performance (Hamilton et al. 1993). This contradicts the findings from the unmatched sample which suggest US EG active funds underperform their unmatched conventional peers. This implies that age, load fees, and portfolio composition affect fund performance.

On the other hand, US ESG passive funds underperform their conventional peers in both the matched and the unmatched samples. This finding may suggest that the strong demand for ESG passive funds drives up their valuations, thereby lowering expected return and the cost of capital (Bauer et al. 2005). It further implies that US ESG passive investors are willing to accept lower returns in order to hold ESG assets. Consistent with Pástor et al. (2021), such investor preferences create pricing pressure, which elevates firms' valuations while reducing their expected return.

In contrast to the above evidence, European ESG active funds outperform their conventional active peers in both the matched and unmatched samples. This outperformance may reflect the ability of EU ESG firms to develop competitive advantages that enhance long-term profitability and performance (Cummings 2000).

Moreover, it suggests that ESG screening can effectively identify value-relevant information, enabling investors to construct superior risk-return profiles (Rennboog et al. 2008a). Yet, there is no difference in risk-adjusted returns between ESG and conventional passive funds. These findings suggest that the outperformance of ESG active funds in the EU might be attributable to a superiority of ESG active management or may be driven by regulatory and tax reasons.

Second, the results of Hypotheses 2 and 4 which evaluate the flow-performance sensitivity of ESG and conventional funds across regions. In this study, the sample monthly observations were employed, as opposed to prior literature which focuses on annual (Bollen 2007) and quarterly observations (Benson and Humphrey 2008). Moreover, this chapter extends the literature by examining the flow sensitivity to the past 36-month of monthly raw returns and Carhart (1997) four-factor alpha for both ESG and conventional funds. Finally, this study extends existing literature by providing additional evidence on fund performance and flow-performance sensitivity across two dimensions (a) management styles (active vs. passive) and (b) regions (US and EU).

The results using the matched sample suggest that over the short-term (12-month), US ESG active funds are more sensitive to the highest 20% raw return quintile than their conventional active peers consistent with the unmatched sample. However, on a risk-adjusted basis, the results suggest matched conventional active funds are negatively sensitive to the lowest 20% performers and positively sensitive to the mid performers. On the other hand, no difference in flow-performance sensitivity between ESG and unmatched conventional active funds, except for a marginal sensitivity to the mid-ranked conventional active funds.

For the EU active funds, the results suggest that over the short-term the matched conventional active funds are not sensitive to any of the three ranked portfolios, whereas ESG active funds are sensitive to the mid-ranked portfolio but at a weak significance level. The unmatched sample, on the contrary, show that both conventional and ESG funds are sensitive to the middle portfolio, yet at only a weak statistical significance level. After adjusting for risk factors (C-4 model), both matched conventional and ESG active funds show no flow sensitivity to the past 12-month risk-adjusted alpha. This contrasts with the unmatched sample, where EU conventional active funds exhibit sensitivity to underperforming portfolios, while ESG active funds show no flow-performance sensitivity across any of the three ranked portfolios.

Over the longer term (36-month), the findings show no significance variations between US ESG, and conventional active funds based on raw returns, in both the unmatched and matched samples. On the other hand, based on the risk-adjusted model a high negative sensitivity to underperformers of US matched conventional active funds is observed. The results show that the US ESG active funds exhibit no flow-performance sensitivity. This finding is robust for the unmatched sample except for a high positive sensitivity to the outperformers of unmatched conventional active funds. For EU active funds, based on raw returns, matched conventional active funds show no sensitivity to the past 36-month raw return, while ESG active funds have negative sensitivity to the mid- and high-ranked raw return. This contrast unmatched conventional active funds that are negatively sensitivity to the mid-and high-ranked raw return and positively sensitive to the low-ranked past 36-month raw return. On a risk-adjusted basis, matched conventional funds are positively sensitive to underperformers, whereas ESG active funds are negatively sensitive to underperformers. By contrast, in the unmatched sample, both ESG and conventional active funds display negative sensitivity to underperformers.

While EU conventional active investors show positive sensitivity to underperformers over the short-term, EU ESG active investors show no sensitivity to underperformers, on a risk-adjusted basis. This result might be driven by investor expectations of the poor conventional active funds to perform better in the future, and the vice versa for top performers. The results also show that EU ESG active investors value the non-financial aspects of their ESG investment more than US investors. Over the longer term, both EU ESG and conventional active investors are negatively sensitive to underperformers. This similarity in behaviour between EU ESG and conventional active investors over the long term might be explained by shared goals between ESG and non-ESG investors or that ESG and conventional funds follow the same portfolio compositions.

Over the short-term, the comparative results from passive funds indicate that US matched conventional passive investors show no sensitivity to past performance based on both measures of performance, while ESG passive investors reward low ranked funds (raw return) and penalise them based on C-4 alpha. This finding contradicts the unmatched sample that reports positive sensitivity of conventional passive investors to the top-ranked funds (raw return) and negative sensitivity based on C-4 alpha. Over the long-term, both ESG and matched conventional funds show no sensitivity to the 36-months past performance, based on both measures. One exception is that US ESG passive investors are positively sensitive to mid-performers based on C-4 alpha. On the other hand, unmatched conventional passive investors are more sensitive to top performers (raw return), penalise underperformers and reward mid performers (C-4 alpha). However, these results should be interpreted with caution as they may lead to a biased estimate, limited generalisability, and challenge the validity of the findings (Faber and Fonseca 2014).

In the EU, over the short term, matched conventional passive investors reward low-ranked funds (raw return) and penalise outperformers (C-4) alpha, whereas ESG passive investors show no sensitivity to past performance under either measure. The unmatched conventional sample exhibits the same lack of sensitivity as ESG passive investors. Over the long term, matched conventional passive investors reward low-ranked funds and penalise the mid-ranked funds based on raw return, while ESG passive investors penalise mid performers (raw return) and reward them based on C-4 alpha. The unmatched conventional sample, however, show that investors are not sensitive to 36-months past raw return but reward funds that underperform the benchmark.

The evidence on the higher sensitivity of the US ESG active funds to the past 12-month raw returns, as compared to their conventional peers is consistent with Bollen (2007) and Benson and Humphrey (2008). Unlike these studies, using the C-4 alpha to measure performance does not give a consistent result with the raw return performance. For example, US matched conventional active investors penalise underperformers and reward outperformers unlike US EGS active investors who are not sensitive to short-term alpha. Over the long term, ESG investors show no sensitivity to past performance, while matched conventional active investors penalise underperformers. This could imply that the other risk factors incorporated in the Fama-French-Carhart four-factor model caused a variation in the behaviour of ESG and conventional active investors in the US. ESG active investors maintain their position in the funds regardless of their performance levels over the two horizons.

The above evidence could be explained in several ways. First, US conventional active investors are more sophisticated than their ESG peers, being more sensitive to the risk-adjusted performance rather than raw return as ESG active investors are. Second, US ESG active investors are chasing high performing funds in the short-term because they derive incremental value from ESG exposure, especially when the funds generated favourable prior returns (Bollen 2007). Third, US ESG investors maintain their positions in underperformers to avoid capital gain taxes (Gruber 1996) or because of the difficulty they face to choose ESG funds that align with their non-financial goals (Benson and Humphrey 2008). This also shows that US ESG active investors value both financial and non-financial aspects of the ESG funds, especially over the short-term.

Unlike the US market, EU active investors exhibit comparable behaviour between ESG and conventional funds, as evidenced by similar patterns of flow-performance sensitivity over the short-term. Over the long-term, EU conventional active investors do not show sensitivity to past raw return, while ESG investors show negative sensitivity to funds ranked in the middle and top quintile, as measured by raw return. Based on C-4 alpha, ESG active investors reward outperformers and ESG active investors penalise underperformers. Overall, both types of investors appear more sensitive to past performance over the long term than the short term, although their responses remain puzzling.

Regarding US passive investors, the absence of flow-performance sensitivity among conventional passive investors is consistent with the evidence that the flow into passive funds is driven by marketing intensity (Elton et al. 2004) or external rating like Morningstar rating (Del Guercio and Tkac 2008; Hartzmark and Sussman 2019; Reuter and Zitzewitz 2021) rather than performance chasing. ESG passive investors, on the other hand, show puzzling behaviour. In the short term, they reward raw ranked funds based on raw return and penalise funds that underperform the benchmark, which may imply their influence by the non-financial aspect of their investment (Hartzmark and Sussman 2019). Over the long-term, they reward mid-performers which suggests a preference to balance between performance with their sustainability preferences.

EU passive investors, the finding is counterintuitive as matched conventional passive investors reward low-ranked funds based on raw return and penalise outperformers (C-4 alpha), suggesting that flows may be driven by other factors other than return such as cost, distribution, marketing (Ferreira et al. 2012). In contrast, ESG passive investors show no sensitivity to past performance, consistent with evidence that ESG investors are motivated by non-financial rather than financial factors. Over the long horizon, conventional passive investors continue to reward underperformers and penalise mid-performers based on raw return, while rewarding mid-performers based on risk-adjusted return. This puzzling behaviour may reflect a preference for funds that generate medium performance than those outperform the market due to their risk management preferences.

Overall, the results suggest a difference in the flow-performance sensitivity of ESG and conventional funds, both active and passive, across the US and EU markets, consistent with Renneboog et al. (2011). The variations in the findings between the matched and unmatched conventional funds, either active or passive, can be explained by fund age, load fees, and portfolio compositions. Moreover, EU ESG active and passive investors value the non-financial aspect of ESG investment more than US peers and US conventional active investors is more sophisticated than their EU peers.

Chapter 4: The ambiguity aversion in ESG mutual funds: Evidence from the US and Europe.

4.1 Introduction

In financial markets, participants have access to plentiful daily information yet with unknown quality (Epstein and Schneider 2008). Judging the quality of information is an important element in investment decision making and the general analysis of financial markets. For example, signals from reliable sources should, theoretically, have a more substantial role in investment decisions than those coming from unreliable sources. In the mutual fund industry, there are different types of funds with different histories of risk-adjusted returns that convey signals about asset managers' skills. The quality of these signals entails a great deal of uncertainty (Li et al. 2017). When investors are faced with uncertainty, they, arguably estimate the probability of the relevant market conditions with incomplete information and make decisions under ambiguity (Gajdos et al. 2008). This part of uncertainty is different from risky situations where investors have objective probabilities (Epstein and Schneider 2008).

Financial literature in decision-making under ambiguity argues that market participants are more sensitive to the worst-case scenario when receiving unknown quality signals (Ju and Miao 2012). In the mutual fund context, this concept implies that ambiguity-averse investors will place greater weight on the worst-case scenario when making an investment decision. Specifically, noisy and ambiguous signals are generated when mutual funds' returns fluctuate substantially over time (Li et al. 2017), and so ambiguity-averse investors should, theoretically, be more sensitive to the worst performance over multiple horizons when evaluating fund performance.

The increasing focus of the mutual fund industry into the Environmental, Social and Governance (ESG) investment theme generated a large amount of new resources from multiple ESG rating providers. This overload of information combined with the difficulty of judging its quality creates ambiguity for investors which can potentially misguide their investment decisions (Tuttle and Burton 1999). Moreover, the lack of standardised ESG disclosures along with the divergence in ESG ratings between providers adds to the difficulty of analysing ESG data. Literature examined the effect of ESG rating disagreement on stock prices, provide mixed evidence (Gibson-Brandon et al. 2021; Avramov et al. 2022; Luo et al. 2023). Arguably, ESG investors face increased ambiguity, potentially more intense than the one faced by conventional investors (Luo et al. 2023).

To date, the only empirical evidence on ambiguity aversion in the mutual fund industry is provided by Li et al. (2017), who document that US active mutual fund investors exhibit ambiguity-averse behaviour. However, no study has yet examined ambiguity aversion in the context of ESG funds. This study aims to fill this gap by investigating the degree of ambiguity aversion among ESG funds relative to conventional funds. In doing so, it contributes to three strands of the literature.

First, it extends the empirical literature on the impact of ambiguity on asset prices (e.g. Anderson et al. 2009; Antoniou et al. 2015; Anantanasuwong et al. 2024) by examining this relationship in the context of ESG investing. Second, it adds to the fund flow–performance sensitivity literature by providing new evidence on how ESG and conventional investors respond to past performance, highlighting the role of ambiguity aversion across management styles and across regions (US and EU). Finally, it contributes to the growing body of work on ESG rating divergence and its implications for asset pricing (Gibson-Brandon et al. 2021; Avramov et al. 2022; Luo et al. 2023). Accordingly, this Chapter addresses the following research question:

Did ESG investors respond differently than conventional investors to ambiguity signalled by the worst performance?

To answer this research question, a fund's minimum historical performance is used as a measure of ambiguity given that it reflects the worst-case realisation of funds returns. By closely following Li et al. (2017), this Chapterproxies ambiguity using the worst performance measure and investigates how investors react to the worst performance through investment flow. Theoretically, worst performance is more ambiguous to investors and thus, acts as an impeding factor to future fund flows. In this context, ambiguity-averse investors are likely to be more responsive to downside scenarios when assessing fund performance. To capture the relationship between fund flows and the minimum performance over multiple horizons, this study employs a panel regression model. To correct for autocorrelation and heteroskedasticity effects, the standard errors are estimated according to Newey and West (1987). The empirical findings suggest that

ESG active investors show no significant response to ambiguity, while US matched conventional active investors display evidence of ambiguity aversion. In Europe, neither ESG nor matched conventional active investors exhibit sensitivity to the minimum rank measure, consistent with the unmatched sample.

For passive investors, the evidence suggests that US ESG investors have become more sensitive to poor past performance, measured by four-factor alpha, though only at a weak level of significance. By contrast, US matched conventional passive funds show no sensitivity to minimum performance, consistent with results from the unmatched sample. In Europe, ESG passive funds also display no reaction to the worst performance, whereas their matched conventional counterparts are averse to ambiguity when measured by risk-adjusted alpha. This is inconsistent with the unmatched sample, where EU conventional passive investors show no sensitivity to the worst performance. However, these results should be interpreted with caution as limited sample size of US ESG index funds may lead to a biased estimate, limited generalisability, and challenge the validity of the findings (Faber and Fonseca 2014).

Overall, the evidence suggests that US and EU ESG active investors derive more utility from the non-financial rather than the financial aspect of investment, as indicated by their neutral response to ambiguity (minimum performance). Conversely, US ESG passive investors behave as if ESG is financially material. Specifically, they are averse to the worst performance measure and hence, they are, evidently, concerned about the financial aspect of their investment. This heterogeneity in ambiguity aversion among ESG active and passive investors could theoretically affect the pricing of ESG assets given that ambiguity seekers and neutral investors determine the asset prices, as opposed to ambiguity averse investors (Anantanasuwong et al. 2024).

4.2 Theoretical foundation

Savage (1954) presented an influential decision-making theory that has three main claims; (1) maximisation of expected utility is a normative approach to decision-making, (2) subjective probabilities are determined based on individuals' preferences, and (3) people's behaviour is explained through the utility theory. In his theory, Savage (1954) developed the concept of subjective probability, yet its measurement is no longer the only popular followed method. Moreover, Savage's (1954) theory is a "descriptive model of choice under uncertainty". To clarify, individuals take decisions in a situation based on utilities and probabilities where probabilities are defined as " the one's best estimate of the likelihood of states of the world" (Frisch and Baron 1988, p.150). Hence, according to Savage's (1954) theory, there is no distinction between risk and uncertainty. But later studies on decision-making under uncertainty implied that risk and uncertainty are distinct. Ellsberg (1961) is the first study to claim against Savage's (1954) axiom and that Bayesian theory is just applied to decision making under only risk, not uncertainty. The limited knowledge during the process to reach an outcome will result in ambiguity which causes problems for probability theories that are based on alternative gambles (Einhorn and Hogarth 1985).

According to Ellsberg (1961), deciding among different gambles is a function of an event's probability, utility, and ambiguity. Ellsberg (1961) assumes that to reach "a best estimate" of the probability of the event's occurrence, decision makers evaluate the distribution of each event through the use of all available information. Therefore, to prove his assumption that uncertainty involves aspects which are captured by known probabilities and others with unknown probabilities, Ellsberg (1961) designed an experiment: consider two urns from which a ball will be drawn randomly, each one containing red and black balls as follows:Urn1: there are 100 red and black balls, yet their probabilities are unknown; Urn 2: there are 100 balls, with equal distribution of black and red (50 black, 50 red). If the following two gambles were assumed: Bet 1: $100 if a red ball will be drawn from Urn 2, $0 otherwise; Bet 2: $100 if a red ball will be drawn from Urn 1, $0 otherwise.

These two bets have the same expected values, however, bet 2 has a minimum expected value of 0 because there is a worst-case scenario of having no red ball in the Urn. Some participants suggest that the subjective probability to draw a red ball from Urn1 follows the known probability to draw a red ball from Urn 2 which equals 0.5. However, most of the other participants were ambiguity averse and preferred to bet on red or black (Bet1) Urn 2 than Urn 1. The reason is that the paradox considers the participant's confidence associated with the uncertain nature without taking into consideration the non-additivity of complementary probabilities. Thus, Ellsberg's results prove a distinction between risk and uncertainty as participants would be averse to bets with unknown probability, according to their people's level of confidence which challenges Savage (1954)'s theory.

Roberts (1963) opposes Ellsberg's paradox in that his decision rule is more complex compared to Savage's rule and requires the assessment of more quantities. Hence, it is unlikely that people will follow it. Besides, Roberts (1963) added that people who will not follow the Bayesian theory will not follow Ellsberg's reformation of it because it requires formal assessment of things that are difficult to assess using computational or analytical analysis rather would require prohibitive computation or analytical methods.

Unlike Savage (1954) who claims that there is no difference between risk and ambiguity as long as there are known distributions and Ellsberg (1961) who contends ambiguity is determined by the degree of confidence associated with the estimated distribution, Becker and Browson (1964) assume that ambiguity of an alternative is defined by the nature of the distribution of future events' probabilities that is related to this alternative.

In Becker and Browson (1964)'s experiment, which is based on Ellsberg's paradox, imagine two urns with limited information available to the observers; there are a minimum of both black and red balls in each Urn. For an instance, Urn A has at least 40 red and 40 black balls for a total of 100 balls. Ambiguity in this experiment is defined as the "range of the possible distributions" which is 20 in this case. Their experiment uses the difference in behaviour as a function of the different degrees of ambiguity. Hence, they hypothesised that (1) people would pay money to avoid ambiguity, and (2) some people act as if ambiguity is associated with each probability's distribution. Their evidence confirmed that ambiguity-averse people are willing to pay more money to avoidance of ambiguity, especially if the situation has the same expected value as that of the unambiguous situation.

In order to test Becker and Browson's (1964) evidence that the ambiguity in decision-making is minimised to the range of the induced second-order distribution, Yates and Zukowski (1976) designed an experiment with three different games: Game 1 "G1": one bookbag with red and blue chips inside. Equally distributed chips (50% red and 50% blue); Game 2 "G2": number of x chips were drawn randomly from the bookbag. In order to induce second-order distribution, the bookbag was refilled with x chips of a certain colour and 10-x chips f the other colour; Game 3 "G3": the bookbag was refilled again, but now with unknown distribution of the blue and red chips.

They propose a presence of ambiguity in G3, yet the gambler might use subjective second-order distribution. Their finding shows that people are ambiguity averse since G1 was preferred to G2 with no proof of G1 preference over G3. Thus, they concluded that this "not only constitutes evidence against the ranging hypothesis for ambiguity characterization but is damaging for variance and another dispersion hypothesis as well" (Yates and Zukowski 1976, p.24-25).

However, Gärdenfors and Sahlin (1983) argued against Yates and Zukowski (1976)'s claim that the game construction (G2) does not involve second-order distribution among the participants. They believe that G1 does not add to the experiment, especially when examining the impact of unreliable probabilities in decision-making. Hence, they developed a model of decision-making that is a generalisation of Bayesian theory, taking into consideration the reliability of probability judgements. They implicitly refer to ambiguity in the model through a related term "epistemic reliability". They emphasise that the distribution will be less epistemically reliable if the agent has limited information relevant to the state of nature. They argue that two gambles could have different "epistemic riskiness," but will be equivalent, according to the standard utility theory. Furthermore, they explained two types of risks in their model: (1) risk results from uncertainty about which set of possible "states of nature" will obtain (same as standard utility theory); and (2) risk results from the decision maker's limited knowledge of every possible state of the world. Their model predicts that probability distribution depends on the size of evidence which means if evidence (perceived size of possible loss) increases, the threshold of including probability distribution decreases.

Einhorn and Hogarth (1985) assume that ambiguity influences probability judgement which in turn affects people's choices. Based on this assumption, Einhorn and Hogarth (1985) developed "a descriptive model of subjective probability" in which the event's subjective probability is a function of the perceived ambiguity, judgement, and optimism-pessimism stance. The perceived ambiguity is determined based on the available evidence, the limited knowledge of the process, and the degree of reliability of sources. Moreover, they argue that the uncertainty which is accompanied by identifying the appropriate set of distribution in a particular situation results in ambiguity. Also, the ambiguity is positively related to the number of implausible distributions which depends on the people's knowledge of the situation. Frisch and Baron (1988) argue that Einhorn and Hogarth's (1985) model is not considered an explanatory theory of ambiguity but rather is a psychological description of ambiguity, providing no explanation of the impacts of ambiguity on judgements and choice.

4.3 Literature review

4.3.1 Ambiguity in the financial markets

Ambiguity has varied definitions in the financial literature as some view ambiguity as avoidance in individual-level decision making while others study the costs and benefits associated with ambiguity (Arend 2020). The concept of ambiguity originates in Knight (1921) who argues that ambiguity consists of two parts; the measurable uncertainty (risk) whereby the outcome probabilities can be quantified and the unmeasurable uncertainty whereby the outcomes are unknown, and the probabilities cannot be objectively identified. Ellsberg (1961) defines ambiguity as the uncertainty due to disagreement, as well as the level of reliability and consistency of information. Frisch and Baron (1988) define ambiguity based on the idea of the weight of evidence. If there is a low weight of evidence, the subjective experience of missing information will be high. Conversely, if there is a high weight of evidence, the subjective experience of missing information will be low.

Several studies examine the potential causes and effects of ambiguity. For example, Einhorn and Hogarth (1985) develop a descriptive model of subjective probability based on the assumption that ambiguity influences the outcome probabilities in decision making which in turn affects choices. They argue that the uncertainty, which is accompanied by identifying the appropriate set of distribution in a particular situation, results in ambiguity. They also state that a positive relationship between ambiguity and the number of implausible distributions, which depends on the people's knowledge of the situation. It should also be noted that critics argue that the model of Einhorn and Hogarth (1985) is not an explanatory theory of ambiguity but is rather a psychological description of ambiguity which provides no explanation about the impacts of ambiguity on judgements and choice (Frisch and Baron 1988).

Curley et al. (1986) suggest that one of the causes of ambiguity is the probability of negative evaluation by others leading to an increased ambiguity effect. This is because people evaluate missing information as if they had known it before the decision was made, so they avoid taking decisions in ambiguous situations (Baron and Hershey 1988). A second cause of ambiguity is the sample size and the source of reliability as stated by Einhorn and Hogarth (1985). Specifically, ambiguity increases when the sample is small, and the source is unreliable. A third cause of ambiguity is self-evaluation based on past decisions (Ellsberg 1961). In this situation, the decision-makers' anxiety and fear of regret would lead to avoidance of taking decisions. Finally, the fear of uncertainty in general causes ambiguity. As Curley et al. (1986) state that people tend to avoid all facets of uncertainty and hence, avoid both risky and ambiguous situations.

Considering the effects of ambiguity, Epstein and Schneider (2008) state two effects of ambiguous information. First, investors react asymmetrically to ambiguous information given the context it conveys. For example, an ambiguous signal of bad news is perceived as more reliable than an ambiguous signal of good news, which reflects investors' asymmetric reaction to uncertainty. Given the above, shocking news has a more substantial effect on conditional actions, such as portfolio decisions, than good news. As such investors evaluate information based on conditional probability, which minimises the utility of this information. Second, non-Bayesian investors avoid making investment decisions if the information is expected to be of a low quality. Specifically, they do not update their beliefs but rather consider ambiguous information to be unreliable, unlike Bayesian investors who update their beliefs based on the quality and the likelihood of future information.

To directly quantify ambiguity is a challenge in finance, mainly because of the difficulty in obtaining investors' preferences parameters, especially worldwide (Breuer et al. 2017). Hence, studies commonly employ proxies as measures of ambiguity to test its effects in asset pricing models. For example, Gilboa and Schmeidler (1989) developed a model for ambiguity-aversion which assumes that investor preferences are represented by the min-max expected utility over multiple possible distributions. Epstein and Wang (1995) evaluate the impact of Knightian uncertainty (Knight 1921) on asset pricing based on an intemporal utility model of aversion and suggest that ambiguity drives the booms and crashes in asset prices. Epstein and Schneider (2003) extend the multiple-priors model of Gilboa and Schmeidler (1989), which is applied recursively based on the minimum expected utility of an individual. Their model allows investors to account for ambiguity while making dynamic investment decisions.

Izhakian and Benninga (2011) study the effect of ambiguity on asset prices as an uncertainty premium which includes a risk premium and an ambiguity premium. They conclude that the ambiguity premium could also explain the equity premium puzzle. Unlike traditional risk models, they show that a higher risk aversion leads to a lower ambiguity premium and a lower uncertainty premium. In another study, Izhakian (2017) proposed a decision-making model based on a theoretical framework of expected utility with uncertain probabilities (EUUP) to measure ambiguity separately from risk. Based on EUUP, ambiguity preferences are defined based on mean-preserving spreads in probabilities. As such, ambiguity is measured using the volatility of probabilities.

Rather than being content with a theoretical model some studies test ambiguity aversion empirically. For instance, Epstein and Schneider (2008) propose a model for ambiguity-averse investors based on the axiom of recursive multiple priors' utility and signals from uncertain information quality. Their model assumes that investors are pessimistic and evaluate potential actions based on worst-case scenarios. Agents which receive signals of uncertain information update their beliefs following a multiple priors' utility function instead of the Bayesian approach. They find evidence of ambiguity premia and return skewness induced by ambiguity aversion.

Easley and O'Hara (2009) study the implications of ambiguity aversion on the performance and regulation of markets. Their results show that ambiguity aversion can be a significant factor in investor decision-making, which ultimately affects the performance of assets as evaluated by traditional factor models. In another study, Easley and O'Hara (2010) examine whether the market freeze during the financial crisis of 2008 was caused by ambiguity aversion. Based on Bewley (2002) model of Knightian uncertainty, they report uncertainty to be a factor of market liquidity which makes bid and ask prices inappropriate measures of asset fair values. Their study documents that the market freeze was caused due to traders receiving incomplete information over portfolios.

In an experimental setting, Bossaerts et al. (2010) examine ambiguity aversion and its impact on investor portfolio choices and asset prices. They document a significant percentage of agents do not hold an ambiguous portfolio (ambiguity-averse agents) and find heterogeneity across ambiguity-averse investors. Similarly, Illeditsch (2011) studies the effect of risk and ambiguity on optimal portfolios and concludes that ambiguity aversion leads to portfolio inertia and excess volatility. Furthermore, Brenner and Izhakian (2018) study the effect of risk and ambiguity on expected returns based on a theoretically developed measure of ambiguity defined as the expected volatility of probabilities across the relevant outcomes. Using intraday data of the SPDR ETF[23], they find a positive and significant ambiguity risk premium which indicates that ambiguity is priced by the equity market.

Other studies use proxies to measure the degree of ambiguity (Anderson et al. 2009; Antoniou et al. 2015; Li et al. 2017). Anderson et al. (2009) investigate asset pricing model performance by testing the risk-return trade-off and the uncertainty-return trade-off based on the model of Merton (1973). They measure risk based on return volatility and uncertainty using the degree of disagreement of professional forecasters. They employ an aggregate measure of professional forecast disagreement instead of an individual stock or portfolio-based measure. They find a strong correlation between the uncertainty measure and excess returns, while the risk measure is not highly correlated with excess returns and hence, they argue that uncertainty drives excess returns. What is more, they find a significant ambiguity aversion during periods of market high uncertainty and that the market excess return increases with increased ambiguity.

Based on the aggregate dispersion of the forecast measure proposed by Anderson et al. (2009), Antoniou et al. (2015) examine stock market participation by testing the hypothesis stemming from the theoretical models of portfolio choice which include ambiguity. This hypothesis states that investors' desire to invest in equity decreases with the increase in ambiguity. Using US data of fund flows from the Investment Company Institute they measure stock market participation as the capital flows into equity mutual funds. They confirm the hypothesis that ambiguity is associated with lower capital

[23] Sample period spanning from February 1993 to December 2016.

inflows which means weaker stock market participation. They also find that the ambiguity effect is more evident in aggressive growth and growth funds that have holdings of assets of companies that pay no dividends and rely mainly on capital gains.

Moreover, Li et al. (2017) examine investor decision-making under ambiguity via their response to multiple signals of past performance that are measured over different time horizons. Their sample includes mutual fund data from the Centre for Research on Security Prices (CRSP) during the period between January 1993 to December 2014. They suggest that fund flows respond to multiple performance signals (one year, three years, 6-years) with different sensitivity and with more weight on the worst performance signal. They control for fund characteristics, such as strategy change, flow volatility, family size and investment style and find high ambiguity aversion for funds with small fund families, more aggressive strategy changes, and high volatile past fund flows.

Using a large sample of investors, including company stock, local stock index, foreign stock index, and bitcoin, Anantanasuwong et al. (2024) investigate ambiguity aversion and perceived ambiguity. They find that 58% of investors are ambiguity-averse, 30% are ambiguity-seeking, and 12% are ambiguity-neutral. Their findings suggest a consistency of ambiguity-aversion across different assets suggesting that ambiguity is an investor trait and not specific to the invested asset. Investor perception of ambiguity is influenced by education and financial literacy and varies by asset class. Lastly, they document a correlation between ambiguity attitude and investment choices.

4.3.2 Ambiguity in ESG investment

With the rapid growth in ESG-related options, investors allocate capital into ESG mutual funds, mainly following ESG ratings (Hartzmark and Sussman 2019). Investors use ratings from third-party providers to assess ESG risk and related opportunities (Berg et al. 2022a). Hence, ratings providers play a crucial role as information intermediaries between corporations and investors as the target consumers of ESG information. Despite the shared aim of ESG rating agencies, the methodologies based on which they estimate ratings diverge significantly (Berg et al. 2022a).

This divergence in ESG ratings complicate the ability to assess ESG performance of companies, funds, and portfolios and potentially undermines the objective of promoting ESG-inclined investing behaviour (Berg et al. 2022a) and introduces a barrier to sustainable investing (Avramov et al. 2022). The uncertainty hinders investors from reliably evaluating a company's ESG performance which ultimately impacts their investment decisions (Luo et al. 2023). As such, the divergence in ratings could be viewed as an uncertainty factor consistent with the notion of Knightian uncertainty, whereby risk cannot be quantified, leading to an uncertainty premium (Gibson-Brandon et al. 2021).

The literature further examines the causes and implications of divergence in ESG ratings. Chatterji et al. (2016) report two drivers; the use of different activities in evaluating a company's ESG score and the adoption of different methodologies which they call commensurability. Conversely, Eccles and Stroehle (2018) advocate for the influence of varied cultural, regulatory, and economic environments on the development of the ESG metrics. Lastly, Billio et al. (2021) suggest that divergence among ESG ratings is due to heterogeneity in ESG definitions and reporting standards.

Berg et al. (2022b) use a sample of six different ESG rating providers: KLD, Sustainalytics, Moody's ESG, Refinitiv, MSCI, and S&P Global. They find that ratings divergence is driven mostly by three factors. First, scope which describes how different agencies use different attributes in evaluating ESG performance. Second, measurement which refers to how different indicators are used to measure the same attribute. Third, weight which to discrepancies in the assessment of the different attributes. Furthermore, Christensen et al. (2022) suggest that disclosure plays a substantial role in driving ESG rating divergence. The richer the disclosures the wider the ESG rating disagreement is among agencies. Unlike financial disclosures, ESG disclosures entail no widespread agreement about the meaning of the non-financial variables. Hence, the lack of common understanding of ESG metrics makes it hard for agents to evaluate the ESG performance of corporations (Christensen et al. 2022).

Going further, literature also examines the effect of ESG rating disagreement on stock prices. Gibson-Brandon et al. (2021) document a positive relationship between stock return and ESG rating disagreement. Avramov et al. (2022) examine the impact of ESG rating disagreement on asset pricing. They report a negative association between expected returns and ESG ratings, specifically in the case of narrow ESG disagreement. Luo et al. (2023) argue that the heterogeneity in the ESG rating system have caused uncertainty of ESG performance which challenged investors' ability to evaluate ESG performance objectively. They suggest that ESG-sensitive investors are averse to ambiguity of ESG ratings, which lowers the aggregate demand for such products.

This Chapter follows this line of literature and examines the behaviour of ESG investors when faced with ambiguity and compare this to investors who focus on conventional funds. The only empirical evidence from the mutual fund industry is provided by Li et al. (2017) who examined ambiguity aversion using a sample of US active mutual funds. Their findings suggest that US active investors are ambiguity averse. Literature in the flow-performance sensitivity of ESG funds compared to conventional funds document that investors value the non-financial, as well as the financial aspect of their investments. On the other hand, Starks (2023) argues that investors focus on both the financial and non-financial aspect of ESG-related investments. Specifically, they explain that investors consider ESG as a risk management process which mitigates ESG risks that could affect the financial performance.

As discussed in the literature review, return volatility leads to noisy signals which are perceived as ambiguous by investors, and these are widely documented in the literature. On the other hand, measures of downside deviation, such as minimum performance rank, are also perceived as ambiguity but are not that widely studied yet. These represent an assessment of the worst-case scenario for an investor. This chapter proxies ambiguity using the worst performance measure. Investors respond to ambiguity by altering investment flows in funds. Different investors are expected to alter their flows with different intensity, which is called their fund flow sensitivity. For example, ESG investors might perceive ambiguity as bad risk management and thus, decrease their flow of capital into funds with ambiguous information. On the other hand, they might be willing to take the ambiguity without requiring additional risk premium. To uncover how ESG investors behave towards ambiguity, one has to compare them to conventional investors. Given this discussion, this chapter tests the following hypotheses:

H1: *ESG investors are ambiguity-averse and thus, exhibit significant fund flow sensitivity to increasing ambiguity as this is measured by the minimum performance.*

4.4 Data and research methodology
4.4.1 Data

Data was sourced from Refinitiv Lipper and Morningstar Direct. These databases are survivorship bias-free as they provide data for active and defunct funds. According to Brown et al. (1992), non-surviving mutual funds are the funds that are ceased to exist, usually due to poor performance. Thus, controlling for funds' survivorship bias in the data ensures that performance persistence is not overstated due to the exclusion of defunct funds (Wermers 1997). The dataset is composed of ESG and conventional mutual funds, managed actively and passively. These vary by size (small, medium, and large cap) and investment objective (value, growth, and blended). Moreover, the sample includes funds domiciled in the US and the EU to aid comparison between the two investment regions. Lastly, the dataset has been limited to equity-only funds and excludes the following categories: income balanced, allocation, international equity, specialised sector, and money market funds. The sample period spans the months from the January 1996 until December 2022.

The same filtering criteria as in the previous chapter are applied here too. For instance, the sample excludes small-sized funds of less than fifteen million USD in total net assets as of December 2022 and young funds of less than six years old as of the end of the sample in December 2022. The final US sample includes 4,171 conventional active funds, 236 ESG active funds, 193 conventional passive funds and 19 ESG passive funds domiciled. The final EU sample includes 2,525 conventional active funds, 1380 ESG active funds, 170 conventional passive funds, and 132 ESG passive funds. The limited dataset consisting of just 19 US ESG index funds may lead to a biased estimate, limited generalisability, and challenge the validity of the findings (Faber and Fonseca 2014). The US defunct funds include 1,485 conventional active, 134 ESG active, 23 conventional passive and 1 ESG passive. The EU defunct funds include 5,085 conventional active, 885 ESG active, 94 conventional passive, and 36 ESG passive.

All information for the funds, such as net return, total net assets, inception date, FirmID, turnover, and expense ratio, were extracted from Morningstar Direct and combined with Refinitiv Lipper data using the ISIN identifiers. To measure the fund performance based on risk-adjusted return, the Fama and French (1993) and momentum factors for the US and EU markets were extracted from Kenneth French's website [24].

4.4.2 Methodology

This chapter examines the behaviour of ESG investors in comparison to conventional investors under the assumption that both are ambiguity averse. To test whether either investor category is ambiguity-averse, the flow sensitivity to the worst performance is tested over multiple horizons using the following panel regression model. To avoid autocorrelation in the cross-sectional flow-performance estimation, the Newey and West (1987) autocorrelation and heteroskedasticity consistent standard errors is used.

$$Flow_{i,t} = \alpha + \beta_1 \; Min\ Rank_{i,t} \; + \; \beta_2 \, X_{i,t-n} + \delta_i + \epsilon_{i,t} \qquad (4.1)$$

$\boldsymbol{Flow_{i,t}}$ is the percentage flows into fund i in month t (Sirri and Tufano 1998; Del Guercio and Tkac 2002; Bollen 2007; Renneboog et al. 2011). $\boldsymbol{Min\ Rank_{i,t}}$ is then captured by taking the minimum of the performance rank over 1-, 2-, and 3-year horizons as follows: $\boldsymbol{Min\ Rank_{i,t} = \mathrm{Min}\left(Perf - 1Yr_{i,t}\, , Perf - 2Yr_{i,t}\, , Perf - 3Yr_{i,t}\right)}$ (Hendricks et al.1993; Huang et al. 2007; Li et al. 2017). δ_i represents funds fixed effects to control for the varying flow between different funds, and $\epsilon_{i,t}$ is the error term. To account for cross-sectional and cross-time dependence, the standard errors are clustered by funds and months.

As discussed in the literature review, investors face uncertainty when receiving signals of unknown quality. These signals might be relevant to their investment decisions or noisy and irrelevant. In this context, ambiguity-averse investors place a higher weight on the worst-case scenario, which is receiving a bad news signal with high precision. Following Li et al. (2017), the minimum performance rank over one-, two- and three-year horizons is used to measure ambiguity. It is worth noting that the relative performance ranking is used instead of the absolute figure to control for any influences of common factors affecting performance within a fund category and because investors react to

[24] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

different performance signals with different sensitivity based on their beliefs about which time horizon best reflect future performance (Li et al. 2017).

Performance is measured in two forms. First, by raw returns and second, by the returns adjusted by Carhart (1997) four factors. Under the assumption that ESG investors are allocating their capital based on a risk-return optimisation strategy, traditional asset pricing models should sufficiently capture the rationale behind investment decisions (Bollen 2007). Subsequently, funds are ranked based on their raw return and four-factor alpha over the past 12- 24-, and 36- months. The ranking is done within each investment objective category (Growth, value, blend) to control for the effects of different objectives. $\boldsymbol{X}_{i,t-n}$ is a vector of control variables that may drive the fund flows: one-month lagged: raw return, flow, log total net assets, return volatility, expense ratio, and current age. $\epsilon_{i,t}$ is the error term of fund i at time t.

4.4.3 Complementary ambiguity proxies

Following Li et al. (2017), the hypothesis is also tested using three different proxies of ambiguity. Specifically, fund flow volatility, family size and strategy change. It should be noted that these measures are used to check the robustness of the results and not to compare which measure is the best proxy to measure for the fund's ambiguity.

Flow volatility

Li et al. (2017) argue that mutual funds with high flow volatility are associated with high ambiguity. Therefore, investors expected to show higher marginal sensitivity to the minimum performance of such funds. In this case, this chapter examines the interaction between the two ambiguity measures. Specifically, it studies how the volatility of fund flows (Li et al. 2017) interacts with the minimum performance rank and what effect this has on fund flows. Flow volatility is calculated as the standard deviation of the past 12 months capital flows into a fund. At each monthly period the volatility of fund flows is ranked into terciles. The first tercile embodies the low flow volatility funds, the middle tercile includes the medium flow volatility funds, and the top tercile represents the high flow volatile funds. Again, the measures are computed for each investment objective category (Growth, value, blend, etc.). Finally, the minimum rank of performance over 1-, 2-, and 3- year horizons is interacted with the three tercile ranks of flow volatility.

Family size

Drawing inspiration from firm-level literature, which suggests negative relation between family size and ambiguity (Antoniou et al. 2015), Li et al. (2017) assume that funds belonging to large family sizes (i.e. large net asset base) have a good reputation and are managed by a skilled manager. Thus, ambiguity-averse investors might evaluate the past performance of these funds more favourably as compared to funds belonging to small family sizes. This implies that investors will be more ambiguous about funds with small family sizes than funds with large family sizes. Given this argument, ambiguity-averse investors expect to exhibit added sensitivity to the minimum performance rank of the small family sized funds.

To calculate family size, the funds are grouped according to their Family ID and summed total net assets for funds within the same fund family. Then, at each monthly period and for each investment style category the fund family size is ranked into tercile ranks. The bottom tercile contains the small family size funds, the middle tercile includes the medium family size funds, and the top tercile represents the large family size funds. Finally, the minimum rank of performance over 1-, 2-, and 3- year horizons is interacted with the three tercile ranks of family size.

Strategy change

Another driver of ambiguity is a strategy change (Li et al. 2017). Brown et al. (2009) document that, on average, funds with high consistent investment styles outperformed less consistent investment styles. The higher the style consistency, the less the portfolio turnover and fewer asset and security allocation errors. In short, investors will be capable of evaluating the funds' performance if it has high style consistency. According to Lynch and Musto (2003), it is difficult to evaluate the past performance of funds with aggressive strategy change. These funds are more ambiguous for investors. Therefore, ambiguity-averse investors are expected to show added sensitivity to the minimum performance rank of funds that change their strategy aggressively.

Strategy change is measured in two ways. First, the R-squared calculated from the a time series regression under the four-factor model, following Lynch and Musto (2003) and Li et al. (2017). The rationale behind this is that a low R-squared value suggests that the four-factor model is ineffective in explaining the fund performance. One possible explanation is that the factor loadings fluctuate over time, reflecting shifts in investment style. Such variability can make it more challenging for investors to interpret past performance signals and accordingly face a prominent level of ambiguity. Second, at each month *t*, the funds' *i*'s factor loadings of the four-factor model are computed over two non-overlapping periods; the prior 1- to 30 month and 31- to 60-month periods. Then, the average absolute change in the factor loadings between these periods as follows:

$$LDEL_{i,t} = \frac{\sum|\beta^{f}_{i,1-30} - \beta^{f}_{i,31-60}|}{4} \qquad (4.2)$$

where *f* represents the four factors of the C-4 model: *market (MKT), size (SMB),* value *(HML),* and momentum *(MOM).*

Subsequently, at each monthly period and for each investment style category the fund strategy change is ranked into tercile ranks. The bottom tercile contains the funds with low strategy change (large R^2, small $LDEL_{i,t}$), the middle tercile includes the funds with medium strategy change, and the top tercile represents funds with more frequent strategy change (small R^2, large $LDEL_{i,t}$). Finally, the minimum rank of performance over 1-, 2-, and 3- year horizons is interacted with the three tercile ranks of strategy change.

The following panel regression model is estimated for each of the three different ambiguity proxies mentioned above separately, to test the main hypothesis stating that ESG investors are ambiguity-averse and thus, exhibit significant fund flow sensitivity to increasing ambiguity as this is measured by the minimum performance.

$$Flow_{i,t} = \alpha + \beta_1\ Low\ ambiguity_{i,t} * Min\ Rank_{i,t} + \beta_2\ Mid\ ambiguity_{i,t} * Min\ Rank_{i,t} + \beta_3\ High\ ambiguity_{i,t} * Min\ Rank_{i,t} + X_{i,t-n} + \delta_i + \epsilon_{i,t} \qquad (4.3)$$

where $\boldsymbol{Low\ ambiguity_{i,t}}$, $\boldsymbol{Mid\ ambiguity_{i,t}}$, $\boldsymbol{High\ ambiguity_{i,t}}$ represent a dummy variable that equals 1 if the funds fall within the low, medium, and top tercile ranks of fund flows volatility, family size, and strategy change, respectively. $Min - Rank_{i,t}$ is the minimum of the performance rank over 1-, 2-, and 3-year horizons. $\boldsymbol{X_{i,t-n}}$ is a vector of control variables that may drive the fund flow: one-month lagged: raw return, flow, log total net assets, return volatility, expense ratio, and current age. δ_i represents funds fixed effects to control for the varying flow between different funds, and $\epsilon_{i,t}$ is the error term. To account for cross-sectional and cross-time dependence, the standard errors are clustered by funds and months.

4.5 Empirical results

4.5.1 The funds' return volatility

As discussed earlier, uncertainty encompasses a measurable part (risk) and an unmeasurable part (ambiguity), which is the main concern in this paper. This section visualises the funds' average risk (the measurable part) over the sample period, using the standard deviation of monthly raw returns during the prior 12 months in Figures 4.2 (US) and 4.2 (EU). The funds' volatility heightens investors' uncertainty about their historical performance (Li et al. 2017). In both regions, all funds' categories exhibit fluctuations in their past performance throughout the sample period. Interestingly, they all reached their highest level of volatility in 2009, in both regions. This period of high volatility was primarily a result of the impact of the 2008 financial crisis, which increased investment risk and certainly reduced investors' confidence. During this period of high volatility, investors are expected to be ambiguity-averse because of the difficulty of predicting future return (Huang et al. 2022). Moreover, as shown from both graphs, there is a subtle variation in volatility levels among fund categories, within each period. This implies that investors' perception of risk and ambiguity aversion are not drastically different between the funds' categories, and across regions.

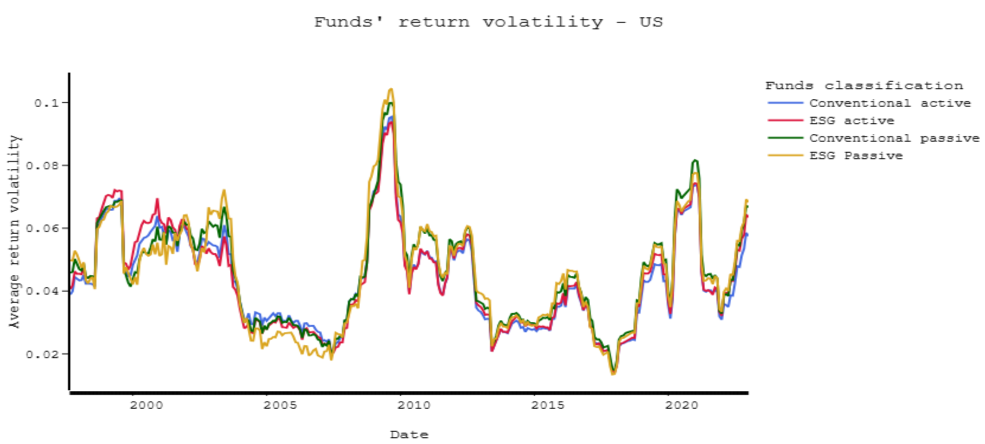


Figure 4.1:The funds 'return volatility-US.
The figure shows the return volatility averaged over the US funds in each fund category (conventional active, ESG active, conventional passive, ESG passive). Return volatility is calculated as the standard deviation of the funds' prior 12 months raw return. The X-axis shows the timeline from 1996 to 2022, and the Y-Axis shows the funds' average return volatility.

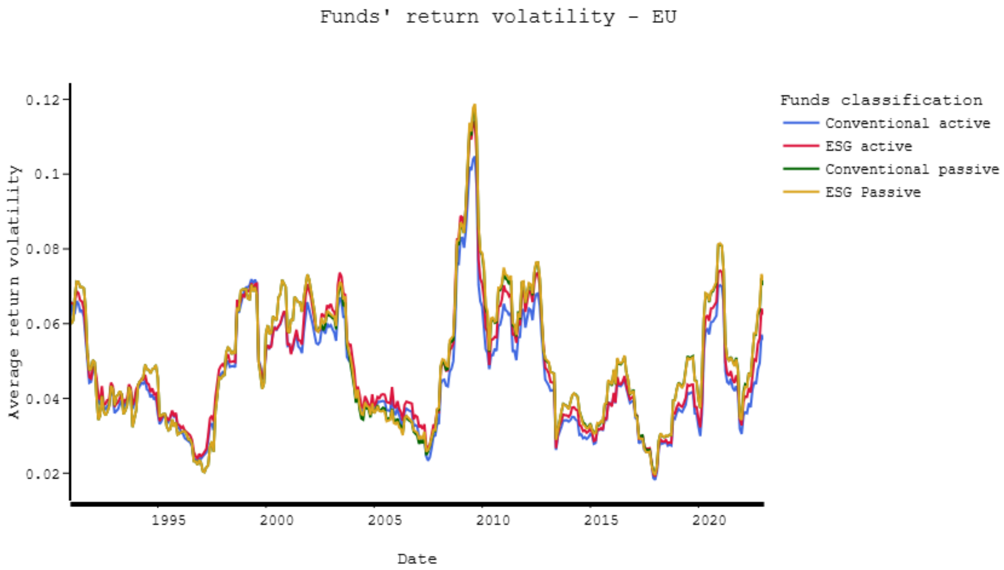


Figure 4.2: The funds 'return volatility-EU.
The figure shows the return volatility averaged over the EU funds in each fund category (conventional active, ESG active, conventional passive, ESG passive). Return volatility is calculated as the standard deviation of the funds' prior 12 months raw return. The X-axis shows the timeline from 1996 to 2022, and the Y-Axis shows the funds' average return volatility.

4.5.2 Empirical findings: Ambiguity aversion

Minimum rank

In this section, the hypothesis is examined in the context of active and passive funds and across regions for more comprehensive analysis. To test this prediction, equation 4.1 is estimated for conventional and ESG funds domiciled in the US (Table 4.1) and the EU (Table 4.2), whether active (panel A) or passive (panel B), using raw return and the Carhart (1997) four-factor alpha. The results suggest no difference in US and EU ESG and conventional active investors' flow sensitivity to the worst performance, as both are ambiguity neutral.

Tables 4.1 and 4.2 present the results of the ambiguity aversion using the minimum rank of performance measured over 1-, 2-, and 3-year horizons for conventional and ESG funds in the US and the EU, respectively. It is expected to see a positive and significant coefficient on the $\boldsymbol{Min\,Rank_{i,t}}$ for ESG and conventional funds. Panel A of Table 4.1 shows the result for US conventional and ESG active funds' ambiguity aversion. About US conventional active funds, the coefficient for the $\boldsymbol{Min\,Rank_{i,t}}$ is negative and statistically insignificant, as measured by raw return. Adjusting the model for other fund characteristics, the coefficient becomes positive, but still statistically insignificant. These finding highlights that other fund characteristics rather than the minimum performance rank explains US conventional active fund flows. For example, there is a positive relationship between fund flow and one-month lagged return, flow, and expense ratio, consistent with Benson and Humphrey (2008). Additionally, fund flow is higher for small sized and less volatile funds.

On the other hand, on a risk-adjusted basis, there is a positive and statistically significant coefficient for the $\boldsymbol{Min\ Rank_{i,t}}$ at the 1% level (0.021). Considering other fund characteristics, this coefficient becomes negative and statistically insignificant. Other fund characteristics show some variations compared to the model using raw return. In this case, the fund inflow is higher for larger and more volatile funds. This change in result could mean that funds' size and volatility may have captured the effect of risk factors before accounting for them. Thus, while investors favour small and less volatile funds when considering raw return, they may favour large and more volatile funds when measuring performance using four-factor alpha. This also suggests that US conventional active investors respond differently to absolute versus risk-adjusted performance when making their investment decisions.

In case of US ESG active funds, as seen from Table 4.1, the coefficient for the $\boldsymbol{Min\ Rank_{i,t}}$ is negative and statistically insignificant, using raw return. These results remain unchanged when adjusting for other funds' characteristics. The results also show a positive and statically significant relationship between US ESG active fund flows and one-month lagged return and flow. On a risk adjusted basis, the results hold, which means that US ESG active investors show no added flow sensitivity to the minimum performance. As to fund characteristics, the fund inflows is higher for large-sized US ESG active funds, which is statistically significant at the 5% level.

Panel A of Table 4.2 reports the results for EU conventional and ESG active funds. Based on a raw return, the coefficient for the $\boldsymbol{Min\ Rank_{i,t}}$ is positive and statistically significant at the 5% level. This coefficient becomes statistically insignificant after adjusting for other funds' characteristics. The results also show that EU conventional active fund inflows are higher for older funds with low expense ratio. On a risk-adjusted basis, the coefficient on the $\boldsymbol{Min\ Rank_{i,t}}$ is positive and statistically insignificant. With control variables considered, the coefficient becomes negative but still statistically insignificant. As to other fund characteristics, there is a positive and statistically significant (5%) relationship between fund flows and lagged volatility.

Focusing on EU ESG active funds, the $\boldsymbol{Min\ Rank_{i,t}}$ coefficient is positive and statistically significant at the 10% level, on a raw return basis. However, it becomes statistically insignificant after controlling for other funds' characteristics. The results show a positive and statistically significant relationship between EU ESG active fund flows and one-month lagged flow, which implies their flow persistence. On the other hand, there is a negative and statistically significant (10%) between fund flows and their lagged expense ratio. On a risk-adjusted basis, the $\boldsymbol{Min\ Rank_{i,t}}$ coefficient is negative and statistically insignificant. It becomes positive but still statistically insignificant after adding other funds' characteristics. For the funds' characteristics, the result shows a negative and statistically significant relationship between fund flows and their one-month lagged total net assets (1% level) and expense ratio (5% level). Additionally, EU ESG active fund inflow is higher for funds generating positive return.

Panel B of Table 4.1 reports the result for US passive funds, conventional and ESG. On a raw return basis, there is a positive and statistically significant (1% level) coefficient on the $\boldsymbol{Min\ Rank_{i,t}}$ variable. This coefficient becomes statistically insignificant when considering other funds' characteristics. Similar to US conventional active funds, US conventional passive fund inflow is higher for small sized and less volatile funds, captured by a negative and statically significant coefficients on one-month lagged funds' size and volatility. The result also shows a negative and statistically significant relationship between fund flows and one-month lagged expense ratio. On a risk adjusted basis, the coefficient on the $\boldsymbol{Min\ Rank_{i,t}}$ is positive and statistically insignificant, regardless of whether control variables are included. The result also shows that US conventional passive fund inflows is higher for young funds and the ones attracting more capital. For US ESG passive funds, the coefficient on the $\boldsymbol{Min\ Rank_{i,t}}$ is positive and statistically significant at the 1% level, based on a raw return. The result remains unchanged with including other fund characteristics, yet the strength of the significancy level declines (10% level). On a risk adjusted basis, the coefficient on the $\boldsymbol{Min\ Rank_{i,t}}$ is positive and statistically insignificant. However, it becomes statistically significant at the 10% level when adjusting for other funds' characteristics. The results also indicate that US ESG passive fund inflows increases when the funds' expense ratio decreases.

Panel B of Table 4.2 reports the results of EU conventional and ESG passive funds. The $\boldsymbol{Min\ Rank_{i,t}}$ coefficient is negative and statistically significant at the 10% level, based on raw return. This means that EU conventional passive investors are not ambiguity averse as these fund inflows increases when their minimum performance rank over multiple years decreases. However, this coefficient becomes statistically insignificant after controlling for other fund characteristics. This result holds when measuring performance using four-factor alpha. The EU conventional passive fund flow is negatively related to their one-month lagged volatility at a 5% statistically significant level. Focusing on EU ESG passive funds, the result is consistent with EU conventional passive funds, on a raw and risk-adjusted return basis.

In sum, these findings highlight that, after adjusting for other funds' characteristics, both US conventional and ESG active funds show no added flow sensitivity to the minimum performance rank, whether using a raw or risk-adjusted returns. The result for EU active funds is robust to those of US active funds. These findings do not support the argument that ESG investors are ambiguity-averse and thus, exhibit significant fund flow sensitivity to increasing ambiguity as this is measured by the minimum performance (H1). This is also inconsistent with Li et al. (2017) finding who confirm that US active investors' added sensitivity to the minimum performance as measured by raw return and four-factor alpha. This result implies that US and EU investors are not ambiguity averse and that their flow sensitivity is based on other fund characteristics not for the ambiguity which is captured by the minimum performance when fund's past performance is measured across multiple horizons.

In the case of passive funds, US ESG passive investors show added flow sensitivity to the minimum performance rank, on a raw and risk-adjusted return basis. In other words, US ESG passive investors invest in poor performing funds when their performance improves, which indicates their aversion to ambiguity. However, the evidence supporting this result is not strongly significant. Conversely, US conventional passive funds are not sensitive to the worst performance. This result highlights a slightly higher flow sensitivity to the worst performance from US ESG passive investors as compared to their conventional peers. For EU passive funds, both conventional and ESG passive investors do not show added flow sensitivity to the worst performance, which implies that they are not ambiguity averse.

Table 4.1: Ambiguity - minimum performance - US

This table analyses the investors' ambiguity aversion of conventional and ESG active funds during the period of January 1996 – December 2022 by examining how investors' fund flow responds to the minimum performance. The minimum performance rank is used as a proxy measure of ambiguity. Funds' performance are ranked from the worst(zero) to best (one) according to their average raw return in the past 12, 24, and 36 months relative to other funds within the same investment objective (Growth, Value, or Blend), or according to their average Carhart (1997) four-factor alphas in the past 12, 24, and 36 months. Min rank is defined as the lowest performance rank achieved across the three horizons. The control variables include one-month lagged: return, flow, log total net assets, return volatility, expense ratio, and current age. Panel B repeats the same analysis for conventional and ESG passive funds in the US. Reported are the time-series averages of coefficients and *t-statistics* (in parentheses) are calculated with Newey-West robust standard errors. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Active - US

	Conventional				ESG			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Min rank	-0.0001	0.002	**0.021***	-0.003	-0.001	-0.007	0.005	0.000
	(-0.05)	(0.83)	(5.97)	(-0.60)	(-0.36)	(-1.64)	(0.91)	(-0.00)
Lag return		**0.022***		**0.016**		**0.021*		0.010
		(2.60)		(2.14)		(1.80)		(0.86)
Lag flow		**0.257***		**0.187**		**0.178**		0.145
		(4.01)		(2.29)		(2.23)		(1.60)
Lag net assets		**-0.008**		**0.006***		0.007		**0.006**
		(-2.34)		(2.72)		(1.42)		(2.45)
Lag return volatility		**-0.054**		**0.067***		-0.022		0.004
		(-2.07)		(3.19)		(-0.74)		(0.18)
Lag expense ratio		**0.369***		**0.507***		0.138		-0.148
		(2.79)		(5.12)		(1.03)		(-1.62)
Age		0.000		**0.001*		0.001		0.000
		(-0.32)		(1.88)		(1.15)		(0.03)
Intercept	**0.002***	0.123	**-0.011***	**-0.183***	**0.002**	**-0.163*	**-0.006***	**-0.114***
	(2.76)	(1.61)	(-8.82)	(-4.47)	(2.40)	(-1.82)	(-3.04)	(-3.33)
R^2	0.00001	0.469	0.116	0.492	0.0005	0.117	0.004	0.117

Table 4.1: continued

Panel B: Passive - US

	Conventional				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Min rank	**0.011*****	0.005	0.010	0.001	**0.021*****	**0.023***	0.015	**0.020***
	(2.58)	(0.76)	(1.59)	(0.21)	(4.09)	(1.93)	(1.17)	(1.71)
Lag return		-0.001		-0.013		-0.002		-0.013
		(-0.07)		(-0.90)		(-0.07)		(-0.46)
Lag flow		0.112		**0.233*****		0.028		-0.031
		(1.55)		(3.28)		(0.47)		(-0.63)
Lag net assets		**-0.009****		-0.002		-0.002		-0.009
		(-2.30)		(-0.99)		(-0.55)		(-1.63)
Lag return volatility		**-0.194*****		-0.020		0.014		-0.17
		(-3.46)		(-0.38)		(0.13)		(-1.58)
Lag expense ratio		**-0.679****		-0.192		-0.111		**-0.923*****
		(-2.01)		(-0.42)		(-1.33)		(-2.73)
Age		**-0.001*****		**-0.001****		0.000		-0.002
		(-3.53)		(-2.57)		(-0.35)		(-0.75)
Intercept	0.000	**0.233*****	**-0.007*****	0.074	0.003	0.051	0.004	**0.260****
	(-0.27)	(2.63)	(-3.21)	(1.26)	(1.29)	(0.81)	(0.92)	(2.57)
R^2	0.031	0.194	0.016	0.155	0.026	0.033	0.011	0.184

Table 4.2: Ambiguity - minimum performance - EU

This table analyses the investors' ambiguity aversion of conventional and ESG active funds during the period of January 1996 – December 2022 by examining how investors' fund flow responds to the minimum performance. The minimum performance rank is used as a proxy measure of ambiguity. Funds' performance are ranked from the worst(zero) to best (one) according to their average raw return in the past 12, 24, and 36 months relative to other funds within the same investment objective (Growth, Value, or Blend), or according to their average Carhart (1997) four-factor alphas in the past 12, 24, and 36 months. Min rank is defined as the lowest performance rank achieved across the three horizons. The control variables include one-month lagged: return, flow, log total net assets, return volatility, expense ratio, and current age. Panel B repeats the same analysis for conventional and ESG passive funds in the EU. Reported are the time-series averages of coefficients and *t-statistics* (in parentheses) are calculated with Newey-West robust standard errors. ∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Active - EU	**Conventional**				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Min Rank	**0.009****	0.002	0.002	-0.005	**0.005***	0.003	-0.001	0.004
	(2.55)	(0.61)	(0.45)	(-0.87)	(1.73)	(1.11)	(-0.24)	(0.55)
Lag return		0.029		0.026		-0.002		**0.020****
		(1.32)		(1.16)		(-0.23)		(1.99)
Lag flow		-0.015		-0.184		**0.291*****		-0.003
		(-0.09)		(-1.15)		(3.46)		(-0.05)
Lag net assets		-0.006		-0.010		-0.005		**-0.011*****
		(-1.58)		(-1.52)		(-1.36)		(-2.90)
Lag return volatility		-0.029		**0.095****		0.033		0.054
		(-0.52)		(2.17)		(1.03)		(1.58)
Lag expense ratio		**-0.210*****		-0.206		**-0.135***		**-0.211****
		(-2.66)		(-1.51)		(-1.77)		(-2.27)
Age		**0.001*****		-0.001		0.001		-0.000
		(2.90)		(-0.67)		(1.27)		(-0.33)
Intercept	-0.001	**0.119***	-0.001	**0.232***	0.001	**0.092***	0.001	**0.236*****
	(-0.44)	(1.78)	(-0.68)	(1.78)	(1.36)	(1.70)	(0.41)	(3.35)
R^2	0.023	0.070	0.000	0.114	0.013	0.160	0.000	0.171

Table 4.2: continued								
Panel B: Passive - EU								
	Conventional				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Min rank	**-0.009***	-0.002	-0.010	-0.022	**-0.012****	-0.004	-0.009	-0.028
	(-1.70)	(-0.26)	(-0.72)	(-0.95)	(-2.50)	(-0.59)	(-0.74)	(-1.01)
Lag return		0.007		0.063		0.012		0.058
		(0.36)		(1.57)		(0.60)		(1.47)
Lag flow		0.083		0.052		0.013		0.046
		(1.47)		(0.84)		(0.21)		(0.78)
Lag net assets		0.001		-0.009		0.002		-0.006
		(0.34)		(-1.11)		(0.66)		(-0.64)
Lag return volatility		-0.005		**-0.282****		0.050		**-0.216***
		(-0.08)		(-2.10)		(0.77)		(-1.65)
Lag expense ratio		0.132		-0.019		0.120		0.002
		(0.94)		(-0.11)		(1.14)		(0.01)
Age		0.000		0.003		0.000		0.003
		(0.24)		(1.25)		(0.02)		(1.20)
Intercept	**0.007*****	-0.028	0.006	0.133	**0.007*****	-0.036	0.005	0.077
	(3.45)	(-0.65)	(1.38)	(1.06)	(3.53)	(-0.97)	(1.34)	(0.47)
R^2	0.011	0.019	0.002	0.051	0.023	0.024	0.002	0.040

Flow volatility

In this subsection, the hypothesis is examined using fund flows volatility as a proxy for funds' ambiguity. It is expected that the flow sensitivity to the minimum performance increases to those funds with more volatile past flow. The coefficient for $\boldsymbol{Low\ ambiguity_{i,t} * Min\ Rank_{i,t}}$ captures the additional flow sensitivity to the $Min\ Rank_{i,t}$ for funds with low past flow volatility, which is expected to be small. The $\boldsymbol{Mid\ ambiguity_{i,t} * Min\ Rank_{i,t}}$ coefficient captures the additional flow sensitivity to the $Min\ Rank_{i,t}$ for funds with medium past flow volatility. Finally, the coefficient on the $\boldsymbol{High\ ambiguity_{i,t} * Min\ Rank_{i,t}}$ captures the additional flow sensitivity to the $Min\ Rank_{i,t}$ for funds with high past flow volatility, which is expected to be large and positive.

Panel A of Table 4.3 presents the result for US conventional and ESG active funds. Concerning US conventional active funds, The coefficients on the $\boldsymbol{Low\ ambiguity_{i,t} * Min\ Rank_{i,t}}$ and the $\boldsymbol{Mid\ ambiguity_{i,t} * Min\ Rank_{i,t}}$ are negative and statistically significant at the 1% level. While the coefficient on the $\boldsymbol{High\ ambiguity_{i,t} * Min\ Rank_{i,t}}$ is positive and statistically significant at the 1% level. As expected, US conventional active investors with more volatile flows are more ambiguous to investors. However, this result is no longer significant after adjusting for control variables. This finding is robust in the specifications using the risk-adjusted return.

Focusing on US ESG active funds, the coefficients for the $\boldsymbol{Mid\ ambiguity_{i,t} * Min\ Rank_{i,t}}$ **is** negative and statistically significant at the 1%. Unlike US conventional active investors, US ESG active investors are not ambiguity averse to the worst performance of the high flow volatile funds. This result becomes statistically insignificant after adjusting for other funds' characteristics. On a risk-adjusted basis, the result is statistically insignificant, regardless of the control variables.

Panel A of Table 4.4 reports the result for EU conventional and ESG active funds. For conventional active funds, the coefficients on the three interaction terms are statistically insignificant on a raw return basis, irrespective of other funds' characteristics. On a risk-adjusted basis, there is a negative and statistically significant (5% level) coefficient on the interaction term $\boldsymbol{High\ ambiguity_{i,t} * Min\ Rank_{i,t}}$. However, adjusting for funds' characteristics diminishes this statistical significance. Regarding EU ESG active investors, the coefficient on the interaction term of the low flow volatile funds is positive and statistically significant at the 10% level based on a raw return. After adjusting for risk using the C-4 alpha, the coefficient on the interaction term indicating low flow volatile funds becomes statistically significant at the 1% level, while the coefficient on the high ambiguity interaction term is negative and statistically significant at the 5% level. This result becomes insignificant after adjusting for other funds' characteristics, whether on a raw or risk-adjusted return basis.

Looking at passive funds, Panel B of Table 4.3 presents US conventional and ESG passive funds' ambiguity aversion. For US conventional passive funds, the three interaction terms are not statistically different from zero based on raw return. However, after controlling for other funds' characteristics, the coefficient for the interaction term of the funds ranked as low flow volatile is positive and statistically significant at the 1% level. The interaction term capturing the medium flow volatility is negative and statistically significant at the 10% level. This result indicates that, on a raw return basis, US conventional passive investors are only averse to funds with low flow volatility and show no sensitivity to the ambiguous funds (high flow volatility). On a risk adjusted basis, the three interaction terms are statistically insignificant regardless of the funds' other characteristics.

In the case of US ESG passive funds, the three interaction terms are not statistically significant based on raw return. However, on a risk adjusted basis, the coefficient on the $\boldsymbol{Low\ ambiguity_{i,t} * Min\ Rank_{i,t}}$ is positive and statistically significant at the 1% level and the $\boldsymbol{Mid\ ambiguity_{i,t} * Min\ Rank_{i,t}}$ is negative and statistically significant at the 5% level. Adjusting for other funds' characteristics, the interaction term for the low volatile ranked funds remains positive with a weaker statistically significant level at the 5%. The $\boldsymbol{High\ ambiguity_{i,t} * Min\ Rank_{i,t}}$coefficient becomes negative and statistically significant at the 10% level.

About EU passive funds, Panel B of Table 4.4 reports no statistically significant result for the three interaction terms based on raw return, irrespective of the adjustment of the control variables. However, on a risk adjusted basis, the coefficients on the $\boldsymbol{Low\ ambiguity_{i,t} * Min\ Rank_{i,t}}$ and the $\boldsymbol{High\ ambiguity_{i,t} * Min\ Rank_{i,t}}$ are negative and statistically significant at the 1% level. Adjusting for other funds' characteristics, only the coefficient for the funds ranked with the high flow volatile tercile remains negative with a weaker statistically significant at the 5% level. This result holds for EU ESG passive funds.

Overall, once accounting for other funds' characteristics, US and EU conventional and ESG active investors do not show added flow sensitivity to the minimum performance rank of the funds with high past flow volatility. Hence, they are not ambiguity averse to ambiguous funds according to past flow volatility. This result is consistent with the findings of the minimum rank for both US and conventional active investors. As to US and EU conventional and ESG passive funds, the findings highlight that US conventional passive investors are not behaving in a linear way to the worst performance of funds with different level of flow volatility, based on raw return. While they find funds with low flow volatility to be ambiguous, the funds with medium and high flow volatility do not appear ambiguous to them. Similarly, US ESG passive investors show non-linear sensitivity to the worst performance of funds with different levels of flow volatility, on a risk-adjusted basis. For instance, they are confident in funds with low flow volatility, but flow into high flow volatile funds when their poor performance improves. Regarding EU passive investors, both conventional and ESG passive investors are not averse to ambiguity, indicated by negative response to the worst performance of high flow volatile funds when performance is measured by risk-adjusted return.

Table 4.3: Ambiguity – flow volatility - US

This table analyses the investors' ambiguity aversion of conventional and ESG active funds during the period of January 1996 – December 2022 by examining how investors' fund flow responds to the minimum performance across different levels of flow volatility. The flow volatility is used as a proxy measure of ambiguity. Flow volatility is the standard deviation of the funds' prior 12-month flow. Each month, three dummy variables representing flow volatility levels across terciles (low, mid, and high ambiguity equals 1 if the fund flows volatility fall in the bottom, medium, and top terciles, respectively). Funds' performance are ranked from the worst (zero) to best (one) according to their average raw return in the past 12, 24, and 36 months relative to other funds within the same investment objective (Growth, Value, or Blend), or according to their average Carhart (1997) four-factor alpha in the past 12, 24, and 36 months. Min rank is defined as the lowest performance rank achieved across the three horizons. A panel OLS regression is estimated by regressing funds' monthly net flow on the interaction between funds' minimum performance interacted with the three dummy variables of the fund flows volatility tercile ranks. The control variables include one-month lagged: return, flow, log total net assets, return volatility, expense ratio, and current age. Panel B repeats the same analysis for conventional and ESG passive funds in the US. Reported are the time-series averages of coefficients and *t-statistics* (in parentheses) are calculated with Newey-West robust standard errors. ∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Active - US

	Conventional				ESG			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low ambiguity * Min Rank	**-0.107*****	-0.048	**-0.086*****	0.036	-0.057	0.002	0.021	0.015
	(-4.66)	(-1.63)	(-2.22)	(0.99)	(-2.65)	(0.07)	(1.18)	(0.90)
Mid ambiguity * Min Rank	**-0.160*****	0.067	**-0.138****	-0.042	**0.068*****	0.028	0.004	-0.003
	(-2.46)	(0.85)	(-2.71)	(-0.88)	(2.25)	(0.74)	(0.23)	(-0.16)
High ambiguity * Min Rank	**0.293*****	-0.012	**0.293*****	0.000	-0.005	-0.043	0.001	-0.004
	(5.67)	(-0.16)	(6.10)	(0.00)	(-0.19)	(-1.29)	(0.05)	(-0.28)
Lag return		**0.019****		**0.016****		**0.020***		0.008
		(2.12)		(2.12)		(1.68)		(0.68)
Lag flow		**0.237*****		**0.186****		**0.175****		0.159
		(3.60)		(2.18)		(1.96)		(1.64)
Lag net assets		-0.001		**0.006*****		0.002		**0.006*****
		(-0.10)		(2.81)		(0.38)		(2.74)
Lag return volatility		0.009		**0.066*****		-0.031		0.004
		(0.20)		(3.09)		(-0.80)		(0.14)
Lag expense ratio		**0.506*****		**0.496*****		**0.219****		**-0.221****
		(4.20)		(3.94)		(2.12)		(-2.25)
Age		0.001		**0.001****		0.001		0.000
		(0.75)		(2.36)		(1.28)		(-0.64)
Intercept	**-0.002*****	-0.043	**-0.014*****	**-0.201*****	0.000	-0.065	**-0.008*****	**-0.103*****
	(-2.69)	(-0.31)	(-11.17)	(-4.49)	(0.28)	(-0.75)	(-4.54)	(-3.19)
R^2	0.193	0.454	0.242	0.489	0.026	0.121	0.016	0.110

Table 4.3: Continued

Panel B: Passive - US	**Conventional**				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low ambiguity * Min Rank	0.018	**0.128*** **	0.010	-0.004	0.036	0.000	**0.107*** **	**0.114** **
	(0.46)	(2.94)	(0.51)	(-0.13)	(1.46)	(-0.01)	(3.62)	(2.22)
Mid ambiguity * Min Rank	0.008	**-0.071***	-0.004	-0.016	0.082	0.072	**-0.043** **	0.106
	(0.15)	(-1.66)	(-0.19)	(-0.63)	(1.07)	(1.17)	(-2.03)	(1.48)
High ambiguity * Min Rank	0.001	-0.068	0.019	0.018	-0.039	0.052	-0.038	**-0.130***
	(0.01)	(-1.38)	(0.84)	(0.66)	(-0.60)	(1.41)	(-1.14)	(-1.95)
Lag return		0.001		-0.004		0.025		-0.025
		(0.05)		(-0.33)		(0.72)		(-0.60)
Lag flow		0.091		**0.146***		0.047		-0.128
		(1.21)		(1.93)		(0.46)		(-1.18)
Lag net assets		**-0.006***		-0.003		-0.004		**-0.026***
		(-1.91)		(-1.01)		(-0.31)		(-1.90)
Lag return volatility		**-0.200*** **		-0.062		-0.052		-0.013
		(-3.54)		(-1.0)		(-0.30)		(-0.08)
Lag expense ratio		**-0.538***		-0.621		-0.374		0.372
		(-1.65)		(-1.56)		(-0.94)		(0.59)
Age		**-0.001*** **		**-0.001** **		-0.001		**0.010***
		(-4.34)		(-2.08)		(-0.16)		(1.71)
Intercept	-0.001	**0.164** **	**-0.007*** **	0.105	0.001	0.108	0.001	0.288
	(-0.35)	(2.42)	(-4.54)	(1.44)	(0.31)	(0.53)	(0.13)	(1.60)
R^2	0.025	0.221	0.016	0.154	0.038	0.053	0.080	0.193

Table 4.4: Ambiguity – flow volatility – EU

This table analyses the investors' ambiguity aversion of conventional and ESG active funds during the period of January 1996 – December 2022 by examining how investors' fund flow responds to the minimum performance across different levels of flow volatility. The flow volatility is used as a proxy measure of ambiguity. Flow volatility is the standard deviation of the funds' prior 12-month flow. Each month, three dummy variables representing flow volatility levels across terciles (low, mid, and high ambiguity equals 1 if the fund flows volatility fall in the bottom, medium, and top terciles, respectively). Funds' performance are ranked from the worst (zero) to best (one) according to their average raw return in the past 12, 24, and 36 months relative to other funds within the same investment objective (Growth, Value, or Blend), or according to their average Carhart (1997) four-factor alphas in the past 12, 24, and 36 months. Min rank is defined as the lowest performance rank achieved across the three horizons. A panel OLS regression is estimated by regressing funds' monthly net flow on the interaction between funds' minimum performance interacted with the three dummy variables of the fund flows volatility tercile ranks. The control variables include one-month lagged: return, flow, log total net assets, return volatility, expense ratio, and current age. Panel B repeats the same analysis for conventional and ESG passive funds in the EU. Reported are the time-series averages of coefficients and *t-statistics* (in parentheses) are calculated with Newey-West robust standard errors. ∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Active – EU

	Conventional				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low ambiguity * Min Rank	0.032	0.018	0.051	0.020	**0.046***	0.017	**0.082*****	0.050
	(0.97)	(0.37)	(1.34)	(0.36)	(1.82)	(0.84)	(2.86)	(1.48)
Mid ambiguity * Min Rank	0.010	-0.019	0.032	0.043	0.026	0.035	0.003	0.033
	(0.28)	(-0.45)	(0.76)	(0.91)	(0.64)	(0.67)	(0.12)	(1.09)
High ambiguity * Min Rank	-0.024	0.003	**-0.096****	-0.080	-0.060	-0.046	**-0.082****	-0.045
	(-0.47)	(0.04)	(-2.65)	(-1.09)	(-1.38)	(-0.89)	(-2.53)	(-1.46)
Lag return		0.027		0.022		-0.001		0.013
		(1.08)		(0.96)		(-0.08)		(1.11)
Lag flow		-0.007		-0.151		**0.251*****		0.015
		(-0.04)		(-0.87)		(2.76)		(0.28)
Lag net assets		-0.008		-0.008		-0.005		**-0.012*****
		(-1.15)		(-1.27)		(-1.37)		(-3.14)
Lag return volatility		-0.013		0.074		0.027		0.047
		(-0.25)		(1.12)		(0.77)		(1.53)
Lag expense ratio		**-0.192****		-0.194		**-0.161****		**-0.185***
		(-2.36)		(-1.24)		(-2.25)		(-1.72)
Age		0.001		-0.001		0.000		0.000
		(1.14)		(-0.63)		(0.80)		(-0.51)
Intercept	0.000	0.157	0.002	0.190	**0.002****	**0.105***	0.000	**0.254*****
	(0.20)	(1.31)	(0.60)	(1.54)	(2.28)	(1.82)	(0.02)	(3.44)
R^2	0.017	0.058	0.028	0.094	0.023	0.168	0.049	0.175

Table 4.4: Continued

Panel B: Passive - EU	**Conventional**				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low ambiguity * Min Rank	-0.026	-0.016	**-0.085*****	-0.044	-0.004	0.002	**-0.065****	-0.038
	(-1.40)	(-0.51)	(-2.88)	(-1.40)	(-0.13)	(0.09)	(-2.37)	(-1.17)
Mid ambiguity * Min Rank	0.023	0.029	0.056	0.035	0.019	0.054	0.060	0.045
	(1.01)	(0.85)	(1.19)	(0.66)	(0.55)	(1.28)	(1.29)	(0.77)
High ambiguity * Min Rank	-0.005	0.021	**-0.166*****	**-0.134****	-0.040	-0.042	**-0.138****	**-0.130****
	(-0.25)	(0.45)	(-3.02)	(-2.12)	(-1.30)	(-0.99)	(-2.76)	(-2.13)
Lag return		0.015		**0.082***		0.016		**0.081***
		(0.92)		(1.91)		(0.93)		(1.86)
Lag flow		0.038		0.001		0.047		-0.010
		(0.59)		(0.01)		(0.72)		(-0.14)
Lag net assets		-0.003		-0.007		-0.001		-0.007
		(-1.14)		(-0.86)		(-0.47)		(-0.78)
Lag return volatility		0.027		-0.126		0.069		-0.096
		(0.41)		(-0.94)		(1.01)		(-0.66)
Lag expense ratio		**0.261****		-0.243		0.104		**-0.412****
		(2.22)		(-1.47)		(1.16)		(-1.96)
Age		**0.003****		0.001		0.001		0.000
		(2.36)		(0.32)		(1.41)		(-0.16)
Intercept	**0.003***	0.008	**0.023****	0.148	**0.005*****	-0.010	**0.018****	0.192
	(1.84)	(0.19)	(2.44)	(1.18)	(2.63)	(-0.29)	(2.06)	(1.14)
R^2	0.011	0.037	0.103	0.115	0.018	0.036	0.082	0.111

Family size

In this subsection, the hypothesis is examined using funds' family size as a proxy for funds' ambiguity. It is expected that the flow sensitivity to the minimum performance increases to small sized (high ambiguous) funds. The coefficient for $\boldsymbol{Low\ ambiguity_{i,t} * Min\ Rank_{i,t}}$ captures the additional flow sensitivity to the $Min\ Rank_{i,t}$ for large funds, which is expected to be small. The $\boldsymbol{Mid\ ambiguity_{i,t} * Min\ Rank_{i,t}}$ coefficient captures the additional flow sensitivity to the $Min\ Rank_{i,t}$ for medium-sized funds. Finally, the coefficient on the $\boldsymbol{High\ ambiguity_{i,t} * Min\ Rank_{i,t}}$ captures the additional flow sensitivity to the $Min\ Rank_{i,t}$ for small-sized funds, which is expected to be large and positive.

Panel A of Table 4.5 presents the result for US conventional and ESG active funds. Based on raw return, the coefficient for the $\boldsymbol{Mid\ ambiguity_{i,t} * Min\ Rank_{i,t}}$ is negative and statistically significant at the 5% level. While the $\boldsymbol{High\ ambiguity_{i,t} * Min\ Rank_{i,t}}$ is positive and statistically significant at the 1% level. After adjusting for funds' characteristics, these coefficients become statistically insignificant, suggesting that US conventional active investors are not ambiguity averse consistent with prior results. On a risk-adjusted basis, the coefficient for the interaction term between low ambiguity (large-sized funds) and minimum rank is positive and statistically significant at the 1% level, while the coefficient for the $\boldsymbol{Mid\ ambiguity_{i,t} * Min\ Rank_{i,t}}$ is negative and statistically significant at the 1% level. Considering other funds' characteristics, the coefficient for the $\boldsymbol{Low\ ambiguity_{i,t} * Min\ Rank_{i,t}}$ remains positive but significant at the 5% level and the $\boldsymbol{High\ ambiguity_{i,t} * Min\ Rank_{i,t}}$ is negative but only statistically significant at the 10% level.

Concerning US ESG active investors, the coefficients for both interaction terms of the low and high ambiguity are statistically significant at the 1% level based on raw return, yet the first one has a positive sign, and the latter has a negative sign. This result remains unchanged after adjusting for control variables, however the coefficient for the interaction term between minimum rank and low ambiguity becomes statistically significant at the 5% level. On a risk-adjusted basis, the coefficients on the $\boldsymbol{Low\ ambiguity_{i,t} * Min\ Rank_{i,t}}$ and the $\boldsymbol{Mid\ ambiguity_{i,t} * Min\ Rank_{i,t}}$ are positive and statistically significant at the 5% and 1% level, respectively. While the

$\boldsymbol{High\ ambiguity_{i,t} * Min\ Rank_{i,t}}$ is negative and statistically significant at the 1% level. These coefficients become statistically insignificant when controlling for other funds' characteristics.

Panel A of Table 4.6 presents the results for EU conventional and ESG active funds. Based on raw return, there is a positive and statistically significant coefficient for the $\boldsymbol{Low\ ambiguity_{i,t} * Min\ Rank_{i,t}}$ after adjusting for funds' attributes. Based on C-4 alpha, this coefficient remains statistically significant, while the coefficient on the $\boldsymbol{Mid\ ambiguity_{i,t} * Min\ Rank_{i,t}}$ is negative and only statistically significant at the 10% level. After adjusting for control variables, these coefficients become statistically insignificant. About EU ESG active funds, the three interaction terms are not statistically different from zero considering controlling variables and whether performance is measured using raw or risk-adjusted return.

Regarding US conventional passive investors, panel B of Table 4.5 reports statistically significant coefficients on the $\boldsymbol{Low\ ambiguity_{i,t} * Min\ Rank_{i,t}}$ and the $\boldsymbol{Mid\ ambiguity_{i,t} * Min\ Rank_{i,t}}$, on a raw return basis. Yet, the former is positive, while the latter is negative. These coefficients become statistically insignificant after adjusting for other funds' characteristics. On a risk-adjusted basis, there is a negative and statistically significant coefficient for the $\boldsymbol{Low\ ambiguity_{i,t} * Min\ Rank_{i,t}}$ interaction term**,** considering control variables. Regarding US ESG passive funds, after adjusting for funds' characteristics, the $\boldsymbol{Mid\ ambiguity_{i,t} * Min\ Rank_{i,t}}$ is positive and statistically significant at the 1% and 10% level based on a raw and risk-adjusted return, respectively. For EU passive investors, Panel B of Table 4.6 shows that both conventional and ESG passive investors do not show added flow sensitivity to the minimum performance rank or the funds' family size, whether on a raw or risk-adjusted basis.

These results suggest that, after controlling for other funds' characteristics, US conventional active investors react differently to different levels of ambiguity as reflected by the funds' family size. For example, on a risk adjusted basis, US conventional active investors are confident in poor performing funds that belong to large size family, but flow into funds belonging to small size family (high ambiguity) only when their poor performance improves. Similarly, US ESG active investors show the same behaviour but when performance is measured using raw return. Regarding EU active investors, the result suggest that EU conventional active investors show added sensitivity to only the worst performance of funds belonging to large sized family, based on raw return.

As to passive investors, on a risk-adjusted basis, US conventional passive investors flow into funds belonging to large size family (high ambiguity) only when their poor performance improves. US ESG passive investors are only averse to funds belong to medium sized family (medium ambiguity), on a raw and risk-adjusted basis. For EU passive investors, based on raw return, conventional passive funds with poor performance and belonging to small family size (high ambiguous) do not appear ambiguous to investors.

Table 4.5: Ambiguity – family size - US

This table analyses the investors' ambiguity aversion of conventional and ESG active funds during the period of January 1996 – December 2022 by examining how investors' fund flow responds to the minimum performance across different levels of funds' family size. The family size is used as a proxy measure of ambiguity. Family size is the summed total net assets of funds that belong to the same fund family. Each month, three dummy variables representing family size levels across terciles (Low, mid, and high ambiguity equals 1 if the funds' family size fall in the top, medium, and bottom terciles, respectively). Funds' performance are ranked from the worst (zero) to best (one) according to their average raw return in the past 12, 24, and 36 months relative to other funds within the same investment objective (Growth, Value, or Blend), or according to their average Carhart (1997) four-factor alphas in the past 12, 24, and 36 months. Min rank is defined as the lowest performance rank achieved across the three horizons. A panel OLS regression is estimated by regressing funds' monthly net flow on the interaction between funds' minimum performance interacted with the three dummy variables of the funds' family size tercile ranks. The control variables include one-month lagged: return, flow, log total net assets, return volatility, expense ratio, and current age. Panel B repeats the same analysis for conventional and ESG passive funds in the US. Reported are the time-series averages of coefficients and *t-statistics* (in parentheses) are calculated with Newey-West robust standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Active - US

	Conventional				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low ambiguity * Min Rank	-0.023	0.001	**0.277*** **	**0.097** **	**0.078*** **	**0.065** **	**0.064** **	0.028
	(-0.38)	(0.02)	(6.18)	(2.15)	(3.25)	(2.52)	(2.49)	(0.88)
Mid ambiguity * Min Rank	**-0.158** **	0.046	**-0.155*** **	-0.022	0.017	0.018	**0.043*** **	-0.003
	(-2.14)	(1.01)	(-6.86)	(-0.74)	(0.73)	(0.76)	(3.41)	(-0.19)
High ambiguity * Min Rank	**0.189*** **	-0.040	-0.050	**-0.102* **	**-0.088*** **	**-0.084*** **	**-0.097*** **	-0.019
	(3.23)	(-0.92)	(-1.00)	(-1.81)	(-3.34)	(-3.34)	(-5.31)	(-0.84)
Lag return		**0.022*** **		**0.015** **		**0.026** **		0.010
		(2.67)		(2.01)		(2.21)		(0.87)
Lag flow		**0.262*** **		**0.176** **		0.126		0.138
		(4.02)		(2.16)		(1.56)		(1.48)
Lag net assets		**-0.009** **		**0.005** **		0.004		**0.007*** **
		(-2.50)		(2.19)		(0.78)		(2.61)
Lag return volatility		**-0.065** **		**0.084*** **		0.008		0.004
		(-2.21)		(3.88)		(0.27)		(0.19)
Lag expense ratio		**0.313** **		**0.492*** **		0.104		**-0.185** **
		(2.13)		(3.78)		(0.81)		(-2.02)
Age		0.000		0.000		0.000		0.000
		(-0.74)		(0.60)		(0.62)		(-0.47)
Intercept	0.001	**0.167* **	**-0.011*** **	**-0.149*** **	0.001	-0.093	**-0.004** **	**-0.12*** **
	(1.48)	(1.86)	(-6.85)	(-3.35)	(0.88)	(-1.05)	(-2.23)	(-3.14)
R²	0.039	0.471	0.333	0.503	0.055	0.152	0.148	0.123

Table 4.5: Continued

Panel B: Passive - US

	Conventional				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low ambiguity * Min Rank	**0.141****	0.042	0.017	**-0.085*****	0.011	-0.079	0.088	0.032
	(2.90)	(0.72)	(1.08)	(-3.38)	(0.33)	(-0.57)	(1.77)	(0.72)
Mid ambiguity * Min Rank	**-0.130****	-0.063	**0.050***	0.005	0.018	**0.051*****	**-0.063***	**0.056***
	(-2.10)	(-1.19)	(1.77)	(0.19)	(0.40)	(2.85)	(-1.77)	(1.91)
High ambiguity * Min Rank	0.038	0.036	-0.032	0.038	0.023	0.078	**0.072****	-0.010
	(0.73)	(0.63)	(-1.19)	(1.48)	(0.73)	(1.17)	(2.84)	(-0.36)
Lag return		-0.002		-0.014		0.025		-0.030
		(-0.13)		(-1.05)		(0.76)		(-0.85)
Lag flow		0.105		**0.189****		0.033		-0.100
		(1.49)		(2.51)		(0.28)		(-1.01)
Lag net assets		**-0.009***		-0.003		-0.016		-0.012
		(-1.87)		(-1.24)		(-1.41)		(-1.61)
Lag return volatility		**-0.195*****		0.003		-0.087		**-0.344****
		(-3.62)		(0.07)		(-0.64)		(-2.39)
Lag expense ratio		**-0.643****		-0.053		-0.043		**-1.372****
		(-2.03)		(-0.12)		(-0.21)		(-1.96)
Age		**-0.001*****		**-0.002*****		0.003		-0.001
		(-2.76)		(-3.92)		(0.88)		(-0.23)
Intercept	-0.001	**0.234****	**-0.007*****	**0.101***	0.004	0.263	-0.003	**0.327****
	(-0.95)	(2.21)	(-3.19)	(1.80)	(1.20)	(1.60)	(-0.65)	(2.21)
R^2	0.065	0.201	0.024	0.204	0.018	0.061	0.072	0.177

Table 4.6: Ambiguity – family size - EU

This table analyses the investors' ambiguity aversion of conventional and ESG active funds during the period of January 1996 – December 2022 by examining how investors' fund flow responds to the minimum performance across different levels of funds' family size. The family size is used as a proxy measure of ambiguity. Family size is the summed total net assets of funds that belong to the same fund family. Each month, three dummy variables representing family size levels across terciles (Low, mid, and high ambiguity equals 1 if the funds' family size fall in the top, medium, and medium terciles, respectively). Funds' performance are ranked from the worst (zero) to best (one) according to their average raw return in the past 12, 24, and 36 months relative to other funds within the same investment objective (Growth, Value, or Blend), or according to their average Carhart (1997) four-factor alphas in the past 12, 24, and 36 months. Min rank is defined as the lowest performance rank achieved across the three horizons. A panel OLS regression is estimated by regressing funds' monthly net flow on the interaction between funds' minimum performance interacted with the three dummy variables of the funds' family size tercile ranks. The control variables include one-month lagged: return, flow, log total net assets, return volatility, expense ratio, and current age. Panel B repeats the same analysis for conventional and ESG passive funds in the EU. Reported are the time-series averages of coefficients and *t-statistics* (in parentheses) are calculated with Newey-West robust standard errors. ∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Active - EU

	Conventional				ESG			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low ambiguity * Min Rank	0.017	**0.085****	**0.065****	-0.014	0.011	0.036	0.031	0.035
	(1.15)	(2.00)	(2.63)	(-0.28)	(0.45)	(0.90)	(1.97)	(1.43)
Mid ambiguity * Min Rank	0.008	0.009	**-0.040***	-0.004	-0.026	-0.039	**-0.039****	0.015
	(0.33)	(0.34)	(-1.78)	(-0.15)	(-0.87)	(-1.07)	(-2.63)	(0.58)
High ambiguity * Min Rank	0.002	-0.089	0.013	-0.002	0.027	0.010	0.014	-0.028
	(0.08)	(-1.56)	(0.68)	(-0.07)	(1.12)	(0.26)	(0.83)	(-1.32)
Lag return		0.030		0.026		-0.002		**0.022****
		(1.39)		(1.17)		(-0.20)		(2.21)
Lag flow		-0.044		-0.184		**0.273*****		-0.023
		(-0.25)		(-1.14)		(3.50)		(-0.34)
Lag net assets		-0.004		-0.011		**-0.006****		**-0.013*****
		(-0.94)		(-1.41)		(-1.98)		(-3.32)
Lag return volatility		-0.052		**0.095****		0.021		0.031
		(-0.89)		(2.05)		(0.65)		(0.90)
Lag expense ratio		**-0.279****		-0.194		-0.092		**-0.400*****
		(-2.61)		(-1.64)		(-0.98)		(-2.96)
Age		0.000		-0.001		0.001		-0.001
		(0.81)		(-0.68)		(1.41)		(-0.89)
Intercept	-0.001	0.106	**-0.004****	0.237	**0.002***	**0.119****	0.000	**0.297*****
	(-0.44)	(1.55)	(-2.13)	(1.58)	(1.69)	(2.23)	(-0.24)	(4.09)
R^2	0.024	0.096	0.024	0.114	0.018	0.167	0.025	0.186

Table 4.6: Continued

Panel B: Passive- EU	**Conventional**				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low ambiguity * Min Rank	-0.017	0.057	-0.015	0.096	-0.005	0.052	-0.005	0.031
	(-0.54)	(1.38)	(-0.36)	(1.10)	(-0.15)	(0.93)	(-0.20)	(0.42)
Mid ambiguity * Min Rank	0.016	0.024	-0.017	-0.010	0.017	-0.015	0.006	0.022
	(0.45)	(0.76)	(-0.46)	(-0.15)	(0.61)	(-0.47)	(0.16)	(0.29)
High ambiguity * Min Rank	-0.041	**-0.103****	-0.021	-0.032	-0.053	-0.034	-0.024	-0.015
	(-0.79)	(-2.02)	(-0.68)	(-0.46)	(-1.42)	(-0.96)	(-0.95)	(-0.21)
Lag return		0.003		-0.012		0.020		-0.013
		(0.13)		(-0.39)		(0.79)		(-0.39)
Lag flow		-0.035		-0.047		-0.070		-0.035
		(-0.51)		(-0.36)		(-1.01)		(-0.34)
Lag net assets		0.004		0.002		0.001		-0.003
		(0.51)		(0.18)		(0.19)		(-0.26)
Lag return volatility		-0.109		0.018		-0.022		-0.172
		(-1.25)		(0.12)		(-0.27)		(-1.45)
Lag expense ratio		-0.107		-0.411		0.061		**-0.844****
		(-0.31)		(-1.15)		(0.27)		(-2.37)
Age		-0.003		**-0.006***		-0.001		**-0.008****
		(-1.51)		(-1.95)		(-0.51)		(-2.25)
Intercept	**0.009*****	-0.014	0.008	0.095	**0.009*****	-0.008	0.004	0.273
	(4.11)	(-0.1)	(0.88)	(0.47)	(3.94)	(-0.06)	(0.47)	(1.24)
R^2	0.021	0.043	0.005	0.178	0.029	0.027	0.008	0.138

Strategy change

In this subsection, funds' strategy change is used as a proxy for funds' ambiguity. It is expected that the flow sensitivity to the minimum performance increases to the funds that change their strategy too aggressively/frequently. The strategy change is measured by the R-squared calculated from a time series regression of the funds' C-4 model (Tables 4.7 and 4.8) and the funds' average absolute change in its factor loadings (4.9 and 4.10). The coefficient for $\boldsymbol{Low\ ambiguity_{i,t} * Min\ Rank_{i,t}}$ captures the additional flow sensitivity to the $Min\ Rank_{i,t}$ for funds with less frequent strategy change, which is expected to be small. The $\boldsymbol{Mid\ ambiguity_{i,t} * Min\ Rank_{i,t}}$ coefficient captures the additional flow sensitivity to the $Min\ Rank_{i,t}$ for funds with medium strategy change frequency. Finally, the coefficient on the $\boldsymbol{High\ ambiguity_{i,t} * Min\ Rank_{i,t}}$ captures the additional flow sensitivity to the $Min\ Rank_{i,t}$ for funds with high frequent strategy change, which is expected to be large and positive.

Panel A of Table 4.7 reports the result of US conventional and ESG active funds' ambiguity aversion using R-square as a proxy. Regarding US conventional active funds, the coefficients on the three interaction terms are statistically significant at the 1% level based on raw return; however, the sign for the $\boldsymbol{Low\ ambiguity_{i,t} * Min\ Rank_{i,t}}$ is negative**,** while the $\boldsymbol{Mid\ ambiguity_{i,t} * Min\ Rank_{i,t}}$ and $\boldsymbol{High\ ambiguity_{i,t} * Min\ Rank_{i,t}}$ are positive. Adjusting for other funds' characteristics, the interaction term for funds with less frequent strategy change remains negative with statistical significance at the 5% level and the interaction term for funds with medium frequent strategy change is robust. On a risk -adjusted basis, there is no statistical evidence that US conventional active investors are ambiguity-averse when considering the funds' strategy change, regardless of the control variables. As for US ESG active funds, on a raw return basis and with considering control variables, the coefficients on the medium and high ambiguity interaction terms are statistically significant at the 1% level; however, the first is positive and the latter is negative. On a risk-adjusted basis, only the coefficient for the low ambiguity interaction term is negative and statistically significant at the 5% level.

Panel A of Table 4.8 shows the result for EU conventional and ESG active funds. Based on raw return and after adjusting for control variables, only the coefficient for the high ambiguity of the EU conventional active funds is negative and statistically significant at the 1% level. On a risk -adjusted basis, the coefficients for the three interaction terms are statistically insignificant. For EU ESG active funds, the coefficients for the three interaction terms are not statistically significant when performance is measured using raw return. Relative to risk-adjusted performance, the coefficient on the interaction term for the low ambiguity is positive and statistically significant at the 5% level.

Regarding passive funds, Panel B of Table 4.7 presents the result for the US conventional and ESG passive funds. On a raw return basis and after adjusting for funds 'characteristics, the coefficient on the medium ambiguity interaction term is positive and statistically significant at the 5% level. The coefficient on the high ambiguity interaction term is negative and statistically significant at the 1% level. On a risk-adjusted basis, the coefficient on the medium ambiguity interaction term holds, while the coefficient on the low ambiguity interaction term is negative and becomes statistically significant at the 10% level. For US ESG passive funds, the coefficients on the three interaction terms are not statistically significant relative to both performance measures. Panel B of Table 4.8 reports a negative and statistically significant coefficient (5% level) for the low ambiguity interaction term and a positive coefficient on the medium ambiguity interaction term, which is statistically significant at the 10% level based on a raw return. About EU ESG passive funds, the three coefficients on the three interaction terms are not statistically significant after adjusting for control variables and whether the performance is measured by raw or risk-adjusted return.

These results suggest that, and measuring performance based on raw return, US conventional active investors are ambiguity averse to the minimum performance of funds with medium strategy change as measured by R-square. However, they flow into funds with low frequency strategy change when they perform worse. This implies US conventional active are averse to low and medium ambiguity, but they do not show sensitivity to funds with high ambiguity. US ESG active investors are averse to funds with medium strategy change. Most interestingly, they tolerate the worst performance of funds with high strategy change frequency. After adjusting for risk factors, US ESG active investors tolerate the poor performer of funds with less strategy change frequency (low ambiguity). For EU active funds, EU conventional active investors are not ambiguity averse. Conversely, EU ESG active investors are averse to the funds' worst performance when they have less frequent strategy change (low ambiguity) when considering other risk factors.

US conventional passive investors show ambiguity aversion to the funds with medium strategy change; they tend to tolerate the poor performance of the funds with high frequent strategy change when performance is measured based on raw return. On a risk-adjusted basis, they tolerate the poor performance of the funds with low ambiguity. On the other hand, US ESG passive investors are not averse to ambiguity. EU conventional and ESG passive investors are not averse to ambiguity, whether on a raw or risk-adjusted return basis. One exception is that, based on raw return, EU conventional passive investors are averse to the worst performance of funds with medium strategy change. Yet, at a weak statistical significance.

Panel A of Table 4.9 presents the result for US conventional and ESG active funds' ambiguity aversion using the change in factor loading as a proxy of strategy change. After adjusting for other funds' characteristics, the results show that US conventional active investors flow into the poor performers with low loading change (less aggressive strategy change), capture by positive and statistically significant coefficient for the low ambiguity interaction term. For EU investors (panel A of Table 4.10), EU conventional active investors do not show added sensitivity to the worst performance. On the other hand, EU ESG active investors are tolerating ambiguity, indicated by a positive coefficient for the low loading change interaction term and a negative coefficient on the high factor loading interaction term with statistical significance at the 10% and 5% level, respectively.

Panel B of Tables 4.9 and 4.10 report conventional and ESG passive funds' ambiguity aversion using the change in factor loading as a proxy of strategy change in the US and the EU, respectively. For US conventional passive funds, investors show added flow sensitivity to the minimum raw return of funds with less aggressive strategy change, captured by positive and statistically significant coefficient at the 10% level. However, on a risk-adjusted basis, their flow sensitivity decreases when the funds with less aggressive strategy change improve their performance, indicated by negative and statistically significant coefficient at the 1% level. They also show added sensitivity to the minimum risk-adjusted performance of funds with medium loading changes, captured by positive and statistically significant coefficient at the 5% level. For US ESG passive funds, investors show added flow sensitivity to the minimum raw return of funds with less aggressive strategy change. Based on a risk-adjusted return, show added sensitivity to the minimum risk-adjusted performance of funds with medium loading changes, captured by positive and statistically significant coefficient at the 10% level. Panel B of Table 4.10 shows that EU conventional and ESG passive investors do not show added sensitivity to the worst performance, whether measured by raw return or C-4 alpha.

In sum, using strategy change as a proxy for ambiguity, conventional and ESG investors do not respond to ambiguity in a linear way. Using R-squared to measure strategy change, US conventional active investors flow into poor performing funds with less frequent strategy change (low ambiguity) when their performance increases, but averse to those funds with medium strategy change, based on raw return. For ESG active investors, they are averse to the worst performer funds with medium strategy change, but they do not consider funds with more frequent strategy change as ambiguous. On a risk-adjusted basis, US ESG active investors only flow into poor performing funds with less frequent strategy change (low ambiguity) when their performance improves. Using the factor loading to measure strategy change, this result becomes insignificant. Only US conventional active fund flow is sensitive to the worst performance of funds with less strategy change, on a risk-adjusted basis.

Regarding EU conventional and ESG active funds, EU conventional active investors are not averse to the poor performers of funds with more frequent strategy change based on raw return. However, based on the factor loading as a proxy for strategy change, EU conventional investors do not show sensitivity to the worst performance. Looking at EU ESG active funds, investors are averse to worst performance (risk-adjusted return) of funds with less frequent/aggressive strategy change. This result holds for both measures of strategy change, however US ESG active investors do not consider funds with more aggressive strategy change (factor loading) as ambiguous.

About passive funds, US conventional passive investors are averse to the worst performance of funds with medium strategy change, based on raw and risk-adjusted return. Interestingly, they are not averse to the funds with more frequent strategy change based on raw return and the ones with less frequent strategy change based on risk-adjusted return. US ESG passive investors do not show sensitivity to the worst performance of funds with strategy change at any level. However, when strategy change is measured using change in factor loading, the results are not robust. US conventional passive investors are averse to funds with less aggressive strategy change based on raw return. However, when performance is measured using C-4 alpha, investors show confidence in funds with less strategy change and becomes averse to the ones with medium strategy change. As to US ESG passive funds, investors are averse to funds with less strategy change based on raw return and funds with medium strategy change based on risk-adjusted return.

For EU passive funds, EU conventional passive investors are confident in funds with less frequent strategy change but averse to the funds with medium strategy change based on raw return and R-squared measure of strategy change. Based on change in factor loading, this result becomes insignificant. Based on the change in factor loading measure, both EU conventional and ESG passive investors do not show added sensitivity to the worst performance.

Table 4.7: Ambiguity – strategy change (R-squared) - US

This table analyses the investors' ambiguity aversion of conventional and ESG active funds during the period of January 1996 – December 2022 by examining how investors' fund flow responds to the minimum performance across different levels of funds' strategy change. The strategy change is used as a proxy measure of ambiguity. Strategy change is measured by the funds' Carhart (1997) four-factor model's R-squared. Each month, three dummy variables representing strategy change levels across terciles (low, mid, and high ambiguity equals 1 if the funds' strategy change fall in the top, medium, and bottom terciles, respectively). Funds' performance are ranked from the worst (zero) to best (one) according to their average raw return in the past 12, 24, and 36 months relative to other funds within the same investment objective (Growth, Value, or Blend), or according to their average Carhart (1997) four-factor alphas in the past 12, 24, and 36 months. Min rank is defined as the lowest performance rank achieved across the three horizons. A panel OLS regression is estimated by regressing funds' monthly net flow on the interaction between funds' minimum performance interacted with the three dummy variables of the funds' strategy change tercile ranks. The control variables include one-month lagged: return, flow, log total net assets, return volatility, expense ratio, and current age. Panel B repeats the same analysis for conventional and ESG passive funds in the US. Reported are the time-series averages of coefficients and *t-statistics* (in parentheses) are calculated with Newey-West robust standard errors. ∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Active - US

	Conventional				ESG			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low ambiguity * Min Rank	**-0.110*****	**-0.057****	-0.005	-0.037	-0.028	-0.023	-0.072	**-0.041****
	(-5.33)	(-2.55)	(-0.23)	(-1.17)	(-1.22)	(-0.66)	(-4.52)	(-1.97)
Mid ambiguity * Min Rank	**0.093*****	**0.110*****	0.050	-0.016	0.03	**0.120*****	0.020	0.032
	(3.05)	(3.31)	(1.35)	(-0.40)	(0.95)	(3.23)	(0.99)	(1.51)
High ambiguity * Min Rank	**0.033*****	-0.026	0.017	0.021	0.004	**-0.108*****	0.014	0.002
	(3.13)	(-1.53)	(1.21)	(1.12)	(0.33)	(-4.01)	(1.93)	(0.20)
Lag return		**0.027*****		**0.017****		0.015		0.010
		(3.58)		(2.20)		(1.47)		(0.91)
Lag flow		**0.167****		**0.174****		-0.134		0.135
		(2.39)		(2.10)		(-1.11)		(1.50)
Lag net assets		-0.004		0.002		**0.017*****		**0.006****
		(-1.40)		(0.85)		(2.84)		(2.11)
Lag return volatility		0.010		**0.059*****		**0.081****		0.009
		(0.45)		(2.66)		(2.03)		(0.37)
Lag expense ratio		**0.637*****		**0.651*****		-0.003		-0.238**
		(4.51)		(4.90)		(-0.02)		(-2.29)
Age		0.000		0.001		**-0.002***		0.000
		(-0.11)		(1.31)		(-1.71)		(-0.15)
Intercept	**-0.004*****	0.013	**-0.011*****	**-0.125****	**-0.003*****	**-0.310*****	0.000	**-0.093****
	(-4.62)	(0.29)	(-6.52)	(-2.29)	(-2.68)	(-3.21)	(-0.05)	(-2.39)
R^2	0.238	0.497	0.120	0.502	0.012	0.199	0.090	0.133

Table 4.7: Continued

Panel B: Passive - US

	Conventional				ESG			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low ambiguity * Min Rank	**-0.064***** (-3.49)	-0.033 (-0.75)	-0.019 (-0.85)	**-0.064*** (-1.95)	0.127 (2.79)	-0.094 (-1.06)	**-0.108**** (-2.35)	-0.002 (-0.04)
Mid ambiguity * Min Rank	**0.067**** (2.23)	**0.103**** (2.22)	0.042 (1.46)	**0.082**** (2.32)	**-0.103**** (-2.07)	0.125 (1.44)	0.033 (1.11)	0.034 (0.8)
High ambiguity * Min Rank	-0.013 (-0.75)	**-0.084***** (-2.73)	**0.033*** (1.76)	-0.005 (-0.19)	0.026 (1.14)	0.034 (0.65)	**0.074***** (3.39)	0.037 (1.18)
Lag return		**0.034*** (1.76)		-0.017 (-1.14)		-0.043 (-1.21)		-0.039 (-1.11)
Lag flow		0.045 (0.78)		**0.192***** (2.67)		-0.028 (-0.34)		-0.092 (-0.97)
Lag net assets		**-0.005**** (-2.09)		-0.001 (-0.51)		-0.006 (-0.59)		**-0.012*** (-1.78)
Lag return volatility		**-0.153**** (-2.00)		0.026 (0.48)		**-0.262*** (-1.93)		-0.236 (-1.49)
Lag expense ratio		-0.751 (-1.05)		-0.522 (-1.05)		**-0.579*** (-1.95)		**-0.931*** (-1.66)
Age		-0.001 (-1.46)		**-0.001**** (-2.36)		0.001 (0.39)		0.000 (0.18)
Intercept	0.000 (0.07)	**0.159**** (2.29)	**-0.01***** (-3.29)	0.058 (0.97)	0.001 (0.25)	0.133 (0.94)	0.007 (1.58)	**0.282**** (2.36)
R^2	0.034	0.137	0.028	0.194	0.101	0.215	0.11	0.171

Table 4.8: Ambiguity – strategy change (R-squared) - EU

This table analyses the investors' ambiguity aversion of conventional and ESG active funds during the period of January 1996 – December 2022 by examining how investors' fund flow responds to the minimum performance across different levels of funds' strategy change. The strategy change is used as a proxy measure of ambiguity. Strategy change is measured by the funds' Carhart (1997) four-factor model's R-squared. Each month, three dummy variables representing strategy change levels across terciles (low, mid, and high ambiguity equals 1 if the funds' strategy change fall in the top, medium, and bottom terciles, respectively). Funds' performance are ranked from the worst (zero) to best (one) according to their average raw return in the past 12, 24, and 36 months relative to other funds within the same investment objective (Growth, Value, or Blend), or according to their average Carhart (1997) four-factor alphas in the past 12, 24, and 36 months. Min rank is defined as the lowest performance rank achieved across the three horizons. A panel OLS regression is estimated by regressing funds' monthly net flow on the interaction between funds' minimum performance interacted with the three dummy variables of the funds' strategy change tercile ranks. The control variables include one-month lagged: return, flow, log total net assets, return volatility, expense ratio, and current age. Panel B repeats the same analysis for conventional and ESG passive funds in the EU. Reported are the time-series averages of coefficients and *t-statistics* (in parentheses) are calculated with Newey-West robust standard errors. ∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Active - EU

	Conventional				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low ambiguity * Min Rank	**0.059***	0.032	0.001	0.006	0.029	0.022	0.007	**0.074****
	(1.92)	(1.04)	(0.03)	(0.18)	(1.57)	(0.83)	(0.31)	(2.47)
Mid ambiguity * Min Rank	-0.064	0.000	0.067	-0.016	-0.026	-0.023	0.017	0.024
	(-1.17)	(0.00)	(2.13)	(-0.42)	(-0.75)	(-0.54)	(0.64)	(0.72)
High ambiguity * Min Rank	-0.021	**-0.095*****	**-0.063****	0.001	-0.034	-0.020	-0.024	-0.030
	(-0.53)	(-3.25)	(-2.40)	(0.03)	(-1.37)	(-0.77)	(-1.27)	(-1.08)
Lag return		0.010		0.026		0.006		**0.021****
		(0.45)		(1.16)		(0.54)		(2.18)
Lag flow		-0.146		-0.184		**0.200****		-0.038
		(-1.17)		(-1.14)		(2.36)		(-0.56)
Lag net assets		0.010		-0.011		-0.003		**-0.012*****
		(1.16)		(-1.44)		(-0.59)		(-2.72)
Lag return volatility		**0.091*****		**0.096****		0.034		0.038
		(2.58)		(2.12)		(1.08)		(1.07)
Lag expense ratio		-0.004		-0.214		-0.099		**-0.415*****
		(-0.04)		(-1.52)		(-1.37)		(-3.83)
Age		0.001		-0.001		0.000		-0.001
		(1.16)		(-0.86)		(0.15)		(-1.33)
Intercept	**0.003****	-0.198	-0.001	**0.237***	**0.004*****	0.060	0.000	**0.296*****
	(2.09)	(-1.22)	(-0.40)	(1.67)	(3.00)	(0.81)	(0.21)	(3.69)
R^2	0.036	0.130	0.020	0.114	0.054	0.163	0.009	0.199

Table 4.8: Continued

Panel B: Passive - EU

	Conventional				ESG			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low ambiguity * Min Rank	**-0.072****	**-0.096****	-0.009	-0.042	**-0.087****	-0.07	-0.016	-0.032
	(-2.27)	(-2.45)	(-0.33)	(-0.49)	(-2.43)	(-1.44)	(-0.66)	(-0.38)
Mid ambiguity * Min Rank	0.006	**0.062***	-0.04	-0.021	0.020	0.044	-0.029	-0.059
	(0.20)	(1.81)	(-1.23)	(-0.19)	(0.73)	(0.93)	(-0.90)	(-0.55)
High ambiguity * Min Rank	**0.052****	0.035	0.001	-0.001	0.057	0.038	0.002	-0.011
	(2.03)	(1.10)	(0.03)	(-0.05)	(1.47)	(0.87)	(0.08)	(-0.34)
Lag return		**0.037***		0.062		0.025		0.056
		(1.75)		(1.59)		(1.08)		(1.43)
Lag flow		0.023		0.048		0.027		0.041
		(0.32)		(0.76)		(0.40)		(0.66)
Lag net assets		**-0.012*****		-0.008		**-0.012****		-0.004
		(-2.66)		(-1.03)		(-2.45)		(-0.41)
Lag return volatility		0.048		**-0.253****		0.100		-0.182
		(0.57)		(-2.06)		(1.09)		(-1.52)
Lag expense ratio		0.015		-0.143		0.021		-0.075
		(0.11)		(-0.70)		(0.19)		(-0.36)
Age		0.003		0.002		**0.004****		0.002
		(1.57)		(0.63)		(2.25)		(0.69)
Intercept	0.002	**0.176****	0.007	0.148	0.003	**0.153***	0.006	0.062
	(0.92)	(2.46)	(1.46)	(1.17)	(0.99)	(1.89)	(1.42)	(0.36)
R^2	0.074	0.116	0.008	0.054	0.058	0.098	0.008	0.045

Table 4.9: Ambiguity – strategy change (change in factor loadings) - US

This table analyses the investors' ambiguity aversion of conventional and ESG active funds during the period of January 1996 – December 2022 by examining how investors' fund flow responds to the minimum performance across different levels of funds' strategy change. The strategy change is used as a proxy measure of ambiguity. Strategy change is measured by the funds' average absolute change in the funds' Carhart (1997) factor loadings between the previous 1-30 and 31-60 months. Each month, three dummy variables representing strategy change levels across terciles (low, mid, and high ambiguity equals 1 if the funds' strategy change fall in the bottom, medium, and top terciles, respectively). Funds' performance are ranked from the worst (zero) to best (one) according to their average raw return in the past 12, 24, and 36 months relative to other funds within the same investment objective (Growth, Value, or Blend), or according to their average Carhart (1997) four-factor alphas in the past 12, 24, and 36 months. Min rank is defined as the lowest performance rank achieved across the three horizons. A panel OLS regression is estimated by regressing funds' monthly net flow on the interaction between funds' minimum performance interacted with the three dummy variables of the funds' strategy change tercile ranks. The control variables include one-month lagged: return, flow, log total net assets, return volatility, expense ratio, and current age. Panel B repeats the same analysis for conventional and ESG passive funds in the US. Reported are the time-series averages of coefficients and *t-statistics* (in parentheses) are calculated with Newey-West robust standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Active - US

	Conventional				ESG			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low ambiguity * Min Rank	-0.001	0.060	0.042	**0.064*** **	**-0.026***	0.004	**-0.061*** **	-0.008
	(-0.02)	(1.13)	(1.11)	(2.65)	(-1.81)	(0.19)	(-2.82)	(-0.39)
Mid ambiguity * Min Rank	-0.035	-0.063	-0.032	-0.040	0.005	-0.018	**0.082*** **	0.021
	(-0.42)	(-1.18)	(-0.92)	(-1.35)	(0.22)	(-0.53)	(2.83)	(0.87)
High ambiguity * Min Rank	0.048	0.022	0.029	0.014	0.031	0.021	0.029	0.025
	(1.36)	(0.72)	(1.37)	(1.27)	(1.65)	(0.75)	(1.49)	(1.42)
Lag return		**0.020***		-0.001		0.003		0.003
		(1.83)		(-0.09)		(0.26)		(0.23)
Lag flow		0.119		0.150		**0.182***		**0.206****
		(1.13)		(1.19)		(1.90)		(2.24)
Lag net assets		-0.001		**0.005****		0.003		**0.007****
		(-0.28)		(2.38)		(1.04)		(2.07)
Lag return volatility		0.094		0.006		0.006		-0.046
		(1.37)		(0.13)		(0.12)		(-1.18)
Lag expense ratio		0.146		0.108		0.055		**-0.639*** **
		(0.83)		(0.75)		(0.55)		(-2.61)
Age		**-0.001*** **		0.000		**-0.001*** **		0.000
		(-3.85)		(-0.33)		(-3.37)		(0.97)
Intercept	-0.002	0.024	**-0.009***	**-0.126****	**-0.002***	-0.041	**-0.011*** **	**-0.092***
	(-1.13)	(0.45)	(-1.73)	(-2.52)	(-1.81)	(-0.82)	(-4.10)	(-1.85)
R^2	0.010	0.160	0.050	0.256	0.022	0.180	0.174	0.237

Table 4.9: Continued

Panel B: Passive - US	**Conventional**				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low ambiguity * Min Rank	0.011	**0.059***	**-0.031***	**-0.046*****	0.048	**0.086*****	**0.068*****	-0.009
	(0.29)	(1.95)	(-1.78)	(-2.67)	(1.85)	(3.33)	(2.93)	(-0.25)
Mid ambiguity * Min Rank	-0.030	-0.030	0.037	**0.058****	0.014	-0.031	**0.088*****	**0.149***
	(-0.60)	(-0.82)	(1.59)	(2.05)	(0.27)	(-0.88)	(2.27)	(1.76)
High ambiguity * Min Rank	0.022	-0.014	0.029	0.005	0.011	-0.003	-0.061	0.126
	(1.31)	(-0.55)	(1.13)	(0.16)	(0.18)	(-0.07)	(-1.36)	(1.22)
Lag return		0.010		0.011		-0.017		-0.014
		(0.82)		(0.70)		(-0.38)		(-0.28)
Lag flow		0.140		**0.359*****		0.102		**-0.199***
		(1.44)		(3.11)		(1.08)		(-1.83)
Lag net assets		-0.003		-0.010		0.004		**-0.031****
		(-0.89)		(-1.50)		(0.90)		(-2.47)
Lag return volatility		0.029		-0.063		0.085		0.047
		(0.40)		(-0.98)		(0.71)		(0.22)
Lag expense ratio		-1.065		-1.147		-0.060		**-1.717****
		(-1.34)		(-1.40)		(-0.17)		(-2.53)
Age		**-0.002****		**-0.001****		-0.001		**0.010***
		(-2.52)		(-2.25)		(-0.74)		(1.78)
Intercept	0.000	0.126	**-0.006****	0.266	-0.002	-0.052	-0.003	**0.505*****
	(-0.00)	(1.16)	(-2.19)	(1.59)	(-0.66)	(-0.84)	(-0.69)	(2.71)
R^2	0.008	0.158	0.033	0.268	0.094	0.117	0.178	0.196

Table 4.10: Ambiguity – strategy change (change in factor loadings) - EU

This table analyses the investors' ambiguity aversion of conventional and ESG active funds during the period of January 1996 – December 2022 by examining how investors' fund flow responds to the minimum performance across different levels of funds' strategy change. The strategy change is used as a proxy measure of ambiguity. Strategy change is measured by the funds' average absolute change in the funds' Carhart (1997) factor loadings between the previous 1-30 and 31-60 months. Each month, three dummy variables representing strategy change levels across terciles (low, mid, and high ambiguity equals 1 if the funds' strategy change fall in the bottom, medium, and top terciles, respectively). Funds' performance are ranked from the worst (zero) to best (one) according to their average raw return in the past 12, 24, and 36 months relative to other funds within the same investment objective (Growth, Value, or Blend), or according to their average Carhart (1997) four-factor alphas in the past 12, 24, and 36 months. Min rank is defined as the lowest performance rank achieved across the three horizons. A panel OLS regression is estimated by regressing funds' monthly net flow on the interaction between funds' minimum performance interacted with the three dummy variables of the funds' strategy change tercile ranks. The control variables include one-month lagged: return, flow, log total net assets, return volatility, expense ratio, and current age. Panel B repeats the same analysis for conventional and ESG passive funds in the EU. Reported are the time-series averages of coefficients and *t-statistics* (in parentheses) are calculated with Newey-West robust standard errors. ∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Active - EU								
	Conventional				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low ambiguity * Min Rank	-0.012	-0.006	0.013	0.026	-0.003	-0.017	0.074	**0.096***
	(-0.16)	(-0.33)	(0.32)	(0.67)	(-0.13)	(-0.61)	(1.42)	(1.80)
Mid ambiguity * Min Rank	0.008	0.038	0.064	-0.002	0.027	0.067	0.005	-0.052
	(0.12)	(1.00)	(1.62)	(-0.05)	(0.84)	(1.15)	(0.08)	(-1.04)
High ambiguity * Min Rank	0.019	-0.037	**-0.104****	-0.075	-0.024	-0.043	**-0.115****	**-0.173****
	(0.15)	(-0.89)	(-2.47)	(-1.45)	(-0.60)	(-0.84)	(-2.58)	(-2.42)
Lag return		**0.023****		0.015		0.023		0.012
		(2.15)		(0.97)		(1.64)		(0.60)
Lag flow		-0.061		-0.073		0.031		-0.166
		(-0.56)		(-0.48)		(0.31)		(-0.98)
Lag net assets		**-0.019****		-0.015		-0.011		**-0.021****
		(-2.46)		(-1.50)		(-0.52)		(-2.13)
Lag return volatility		**-0.147*****		-0.029		-0.100		0.050
		(-2.72)		(-0.32)		(-1.00)		(0.44)
Lag expense ratio		-0.251		-0.051		-0.379		**-0.881****
		(-0.83)		(-0.19)		(-0.39)		(-1.96)
Age		-0.001		0.000		-0.001		**0.003****
		(-0.70)		(0.20)		(-0.32)		(2.41)
Intercept	-0.001	**0.400****	0.002	0.287	0.000	0.272	0.004	**0.452****
	(-0.59)	(2.52)	(1.36)	(1.47)	(0.21)	(0.51)	(1.63)	(1.98)
R^2	0.001	0.227	0.114	0.092	0.008	0.264	0.128	0.454

Table 4.10: Continued

Panel B: Passive - EU	**Conventional**				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low ambiguity * Min Rank	-0.030	-0.036	0.069	0.218	-0.068	0.036	-0.010	-0.140
	(-0.85)	(-0.37)	(1.20)	(1.22)	(-1.22)	(0.51)	(-0.20)	(-1.52)
Mid ambiguity * Min Rank	0.071	-0.034	0.247	0.296	0.019	0.082	0.106	-0.010
	(1.33)	(-0.25)	(1.52)	(1.20)	(0.56)	(1.35)	(1.25)	(-0.07)
High ambiguity * Min Rank	0.067	0.114	0.075	0.190	-0.006	-0.014	-0.042	0.138
	(1.30)	(0.78)	(1.06)	(1.11)	(-0.15)	(-0.34)	(-0.51)	(0.90)
Lag return		-0.036		-0.046		0.121		**0.144***
		(-0.44)		(-0.42)		(1.14)		(1.79)
Lag flow		-0.045		-0.068		-0.005		-0.090
		(-0.32)		(-0.39)		(-0.05)		(-1.13)
Lag net assets		0.004		0.009		-0.028		-0.004
		(0.19)		(0.15)		(-1.21)		(-0.12)
Lag return volatility		-0.142		0.604		0.140		**-0.735***
		(-0.60)		(0.46)		(0.37)		(-1.85)
Lag expense ratio		-0.261		-1.710		0.049		0.360
		(-0.48)		(-1.19)		(0.33)		(0.80)
Age		0.000		0.017		0.004		0.003
		(0.18)		(1.14)		(1.37)		(1.41)
Intercept	**-0.010***	-0.059	**-0.038***	-0.588	0.007	0.431	-0.001	0.028
	(-1.73)	(-0.16)	(-1.67)	(-0.45)	(1.16)	(1.16)	(-0.10)	(0.05)
R^2	0.032	0.061	0.074	0.184	0.019	0.078	0.026	0.167

4.6 Matching

The above analysis is conducted further using the matched conventional funds sample from the previous chapter to control for the impact of other variables on the dynamics of fund flows. Tables 4.11 to 4.20 report the results of ambiguity aversion of ESG funds and the respective, matched, conventional funds using the minimum performance rank and the different ambiguity proxies.

Panel A of Table 4.11 reports the result of US active funds using the minimum performance rank. Inconsistent with the unmatched sample, the table shows a positive and statistically significant coefficient for the $\boldsymbol{Min\ Rank_{i,t}}$ at the 5% level, based on raw return and after adjusting for control variables. This result is consistent with Li et al. (2017), suggesting that US conventional active investors are averse to ambiguity of performance over multiple horizons. This result then suggests a difference between US conventional and ESG active investors' ambiguity aversion and that US conventional fund flows is sensitive to the controls for fund age, load fees, and portfolio composition. For US passive funds (Panel B of Table 4.11), the result for the matched conventional passive sample is consistent with the unmatched sample, suggesting no aversion to ambiguity.

For EU funds (Table 4.12), Panel A shows that the result for EU matched conventional active funds is consistent with the unmatched sample, suggesting no added flow sensitivity to the minimum performance rank. As to passive funds (Panel B), after adjusting for other funds' characteristics, the coefficient for the $\boldsymbol{Min\ Rank_{i,t}}$ becomes negative and statistically significant at the 5% level based on raw return and becomes positive and statistically significant at the 10% level on a risk-adjusted basis. This result contradicts the unmatched sample that it was negative and insignificant under both performance measures. Thus, the fund age, loads and portfolio compositions affect EU conventional passive investors' ambiguity aversion. This result confirms that EU conventional passive investors are ambiguity averse only after adjusting for other risk factors and a difference in ambiguity aversion between EU conventional passive and ESG passive investors who do not show any added flow sensitivity to the minimum performance.

Looking at the result using the flow volatility as a proxy for ambiguity, Table 4.13 reports consistent findings with the unmatched sample of US conventional active funds after adjusting for other funds' attributes and based on both performance measures. Panel B reports the result for US matched conventional passive funds, the coefficients for the three interaction terms are statistically insignificant using the raw return model. This result is inconsistent with the unmatched sample which was positive and significant (1% level) for the interaction term between minimum rank and the low flow volatility and negative and statistically significant (10% level) for the interaction term for the funds ranked with medium flow volatility tercile.

Regarding EU funds (Table 4.14), Panel A reports the result for EU conventional active funds. Based on a raw return and after adjusting for control variables, the coefficient for the $\boldsymbol{Low\ ambiguity_{i,t}} * \boldsymbol{Min\ Rank_{i,t}}$ is positive and significant at the 5% level. The coefficients for the $\boldsymbol{Mid\ ambiguity_{i,t}} * \boldsymbol{Min\ Rank_{i,t}}$ and $\boldsymbol{High\ ambiguity_{i,t}} * \boldsymbol{Min\ Rank_{i,t}}$ are negative and statistically significant at the 10% and 5% levels. This finding contradicts the unmatched sample where the three interaction terms are statistically insignificant. For EU passive investors, Panel B reports a positive and statistically significant coefficient (5% level) for the $\boldsymbol{Low\ ambiguity_{i,t}} * \boldsymbol{Min\ Rank_{i,t}}$ based on risk-adjusted return and after adjusting for control variables. This coefficient was insignificant under the unmatched sample. The coefficient for the $\boldsymbol{High\ ambiguity_{i,t}} * \boldsymbol{Min\ Rank_{i,t}}$ becomes statistically insignificant.

Tables 4.15 and 4.16 report the result using the family size proxy of ambiguity for US and EU funds, respectively. The result for US matched conventional active and passive funds (Table 4.15) exhibit differences as compared to the unmatched sample after adjusting for other funds' characteristics. Specifically, based on raw return, the coefficients on the interaction terms for mid and high ambiguity levels become statistically significant at the 5% level. Yet, the former has a negative sign, and the latter has a positive sign. On a risk-adjusted basis, the coefficients for the interaction terms for the low and high ambiguity become statistically insignificant.

Table 4.16 reports the result for EU funds, the findings for matched conventional active and passive funds contradicts the unmatched sample. For instance, based on a raw return and after controlling for other funds' characteristics, the coefficient for $\boldsymbol{Low\ ambiguity_{i,t}} * \boldsymbol{Min\ Rank_{i,t}}$ of EU matched conventional active funds becomes statistically insignificant. For passive funds, the coefficient for the $\boldsymbol{Mid\ ambiguity_{i,t}} * \boldsymbol{Min\ Rank_{i,t}}$ becomes negative and statistically significant at the 5% level based on raw return and after adjusting for other funds' characteristics. The coefficient for the $\boldsymbol{High\ ambiguity_{i,t}} * \boldsymbol{Min\ Rank_{i,t}}$ becomes statistically insignificant. Based on risk-adjusted return, the coefficients for the $\boldsymbol{Low\ ambiguity_{i,t}} * \boldsymbol{Min\ Rank_{i,t}}$ and $\boldsymbol{High\ ambiguity_{i,t}} * \boldsymbol{Min\ Rank_{i,t}}$ become positive and statistically significant at the 5% and 1 % level.

Table 4.17 presents the result using strategy change proxy as measured by R-squared. The findings contradict the unmatched sample based on both performance measures. Based on raw return and after controlling for other funds' characteristics, the coefficients for the $\boldsymbol{Low\ ambiguity_{i,t}} * \boldsymbol{Min\ Rank_{i,t}}$ and $\boldsymbol{Mid\ ambiguity_{i,t}} * \boldsymbol{Min\ Rank_{i,t}}$ for US matched conventional active funds become statistically insignificant. On a risk-adjusted basis, the $\boldsymbol{Mid\ ambiguity_{i,t}} * \boldsymbol{Min\ Rank_{i,t}}$ and $\boldsymbol{High\ ambiguity_{i,t}} * \boldsymbol{Min\ Rank_{i,t}}$ coefficients become statistically significant at the 5% level, the former is negative and the latter is positive. For passive funds, panel B shows inconsistent result with the unmatched sample. Based on raw return, the mid and high ambiguity interaction terms become statistically insignificant. On a risk-adjusted basis, the coefficients for the low and mid ambiguity become statistically insignificant.

About EU funds (Table 4.18), the only difference between the unmatched and matched samples is based on the raw return model. After adjusting for other funds' attributes, the coefficient for the $\boldsymbol{High\ ambiguity_{i,t}} * \boldsymbol{Min\ Rank_{i,t}}$ of EU matched conventional active funds becomes statistically insignificant. For EU matched conventional passive funds, the $\boldsymbol{Low\ ambiguity_{i,t}} * \boldsymbol{Min\ Rank_{i,t}}$ and $\boldsymbol{Mid\ ambiguity_{i,t}} * \boldsymbol{Min\ Rank_{i,t}}$ coefficients become statistically insignificant, based on raw return and after adjusting for control variables.

Finally, Tables 4.19 and 4.20 report the results for the strategy change proxy using the change in factor loading measure. The finding for the US matched conventional active funds based on risk-adjusted return. Specifically, the $\boldsymbol{Low\ ambiguity_{i,t}} * \boldsymbol{Min\ Rank_{i,t}}$ becomes statistically insignificant and the $\boldsymbol{High\ ambiguity_{i,t}} * \boldsymbol{Min\ Rank_{i,t}}$ becomes positive and statistically significant at the 10% level, taking control variables into considerations. For US conventional passive funds, the findings contradict the unmatched sample based on raw and risk-adjusted return. The $\boldsymbol{Low\ ambiguity_{i,t}} * \boldsymbol{Min\ Rank_{i,t}}$ coefficient becomes statistically insignificant using the raw return model. On a risk-adjusted basis, the $\boldsymbol{Mid\ ambiguity_{i,t}} * \boldsymbol{Min\ Rank_{i,t}}$ and $\boldsymbol{High\ ambiguity_{i,t}} * \boldsymbol{Min\ Rank_{i,t}}$ coefficients become statistically insignificant. For EU matched conventional active and passive funds, the findings are consistent with the unmatched sample, on a raw and risk-adjusted basis.

Table 4.11: Ambiguity - minimum performance, US, matched

This table analyses the investors' ambiguity aversion of matched conventional and ESG, both active and passive funds during the period of January 1996 – December 2022 by examining how investors' fund flow responds to the minimum perfomance. The minimum performance rank is used as a proxy measure of ambiguity. Funds' performance are ranked from the worst(zero) to best (one) according to their average raw return in the past 12, 24, and 36 months relative to other funds within the same investment objective (Growth, Value, or Blend), or according to their average Carhart (1997) four-factor alphas in the past 12, 24, and 36 months. Min rank is defined as the lowest performance rank achieved across the three horizons. The control variables include one-month lagged: return, flow, log total net assets, return volatility, expense ratio, and current age. Panel B repeats the same analysis for matched active and passive, both conventional and ESG funds in the US. Reported are the time-series averages of coefficients and *t-statistics* (in parentheses) are calculated with Newey-West robust standard errors. ∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: ESG match - Active	**Matched conventional**				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Min Rank	**-0.008****	**0.008****	**0.012*****	0.001	-0.001	-0.007	0.005	0.000
	(-2.50)	(2.19)	(3.40)	(0.14)	(-0.36)	(-1.64)	(0.91)	(-0.00)
Lag return		**0.035*****		**0.016***		**0.021***		0.010
		(3.45)		(1.68)		(1.80)		(0.86)
Lag flow		0.055		0.115		**0.178****		0.145
		(0.80)		(1.33)		(2.23)		(1.60)
Lag net assets		**-0.015*****		0.001		0.007		**0.006****
		(-4.52)		(0.35)		(1.42)		(2.45)
Lag return volatility		**-0.097*****		-0.045		-0.022		0.004
		(-3.50)		(-1.61)		(-0.74)		(0.18)
Lag expense ratio		0.175		0.436		0.138		-0.148
		(1.09)		(1.61)		(1.03)		(-1.62)
Age		**-0.002*****		0.001		0.001		0.000
		(-2.70)		(0.57)		(1.15)		(0.03)
Intercept	**0.016*****	**0.301*****	-0.008***	-0.079	**0.002****	**-0.163***	**-0.006*****	**-0.114*****
	(12.19)	(4.53)	(-6.52)	(-1.01)	(2.4)	(-1.82)	(-3.04)	(-3.33)
R^2	0.019	0.391	0.038	0.201	0.0005	0.117	0.004	0.117

Table 4.11: Continued

Panel A: ESG match - passive

	Matched conventional				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Min Rank	-0.013	-0.005	0.008	-0.003	**0.021*** **	**0.023***	0.015	**0.020***
	(-1.48)	(-0.33)	(1.30)	(-0.34)	(4.09)	(1.93)	(1.17)	(1.71)
Lag return		-0.012		-0.010		-0.002		-0.013
		(-0.31)		(-0.26)		(-0.07)		(-0.46)
Lag flow		0.082		-0.119		0.028		-0.031
		(1.01)		(-1.03)		(0.47)		(-0.63)
Lag net assets		0.003		**-0.019****		-0.002		-0.009
		(0.25)		(-2.48)		(-0.55)		(-1.63)
Lag return volatility		-0.050		-0.105		0.014		-0.17
		(-0.41)		(-0.94)		(0.13)		(-1.58)
Lag expense ratio		0.182		-0.911		-0.111		**-0.923*****
		(0.49)		(-1.49)		(-1.33)		(-2.73)
Age		-0.001		**0.005****		0.000		-0.002
		(-0.28)		(2.17)		(-0.35)		(-0.75)
Intercept	**0.011*****	-0.044	**-0.006*****	**0.342****	0.003	0.051	0.004	**0.260****
	(3.53)	(-0.24)	(-3.63)	(2.49)	(1.29)	(0.81)	(0.92)	(2.57)
R^2	0.010	0.016	0.008	0.090	0.026	0.033	0.011	0.184

Table 4.12: Ambiguity - minimum performance, EU, matched

This table analyses the investors' ambiguity aversion of matched conventional and ESG, both active and passive funds during the period of January 1996 – December 2022 by examining how investors' fund flow responds to the minimum performance. The minimum performance rank is used as a proxy measure of ambiguity. Funds' performance are ranked from the worst(zero) to best (one) according to their average raw return in the past 12, 24, and 36 months relative to other funds within the same investment objective (Growth, Value, or Blend), or according to their average Carhart (1997) four-factor alphas in the past 12, 24, and 36 months. Min rank is defined as the lowest performance rank achieved across the three horizons. The control variables include one-month lagged: return, flow, log total net assets, return volatility, expense ratio, and current age. Panel B repeats the same analysis for matched active and passive, both conventional and ESG funds in the EU. Reported are the time-series averages of coefficients and *t-statistics* (in parentheses) are calculated with Newey-West robust standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: ESG match - Active	**Matched conventional**				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Min Rank	**0.053*** **	0.102	-0.004	0.071	**0.005***	0.003	-0.001	0.004
	(2.67)	(1.30)	(-0.20)	(1.18)	(1.73)	(1.11)	(-0.24)	(0.55)
Lag return		**0.117***		0.153		-0.002		**0.020****
		(1.80)		(1.10)		(-0.23)		(1.99)
Lag flow		0.248		-0.073		**0.291*****		-0.003
		(0.33)		(-0.36)		(3.46)		(-0.05)
Lag net assets		-0.041		-0.042		-0.005		**-0.011*****
		(-1.06)		(-0.76)		(-1.36)		(-2.90)
Lag return volatility		0.449		-0.526		0.033		0.054
		(0.65)		(-0.86)		(1.03)		(1.58)
Lag expense ratio		-0.021		-0.149		**-0.135***		**-0.211****
		(-0.08)		(-0.54)		(-1.77)		(-2.27)
Age		0.006		0.000		0.001		-0.000
		(1.05)		(-0.41)		(1.27)		(-0.33)
Intercept	-0.002	0.646	-0.005	0.786	0.001	**0.092***	0.001	**0.236*****
	(-0.15)	(1.11)	(-0.63)	(0.75)	(1.36)	(1.70)	(0.41)	(3.35)
R^2	0.041	0.213	0.000	0.091	0.013	0.160	0.000	0.171

Table 4.12: Continued

Panel B: ESG match - Passive

	Matched conventional				ESG			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Min Rank	-0.017	**-0.054****	0.266	**0.097***	**-0.012****	-0.004	-0.009	-0.028
	(-1.02)	(-2.23)	(1.38)	(1.83)	(-2.50)	(-0.59)	(-0.74)	(-1.01)
Lag return		-0.026		0.017		0.012		0.058
		(-0.68)		(0.30)		(0.60)		(1.47)
Lag flow		0.023		0.083		0.013		0.046
		(0.32)		(0.71)		(0.21)		(0.78)
Lag net assets		0.014		-0.025**		0.002		-0.006
		(1.42)		(-2.23)		(0.66)		(-0.64)
Lag return volatility		**-0.329****		-0.265		0.050		**-0.216***
		(-2.35)		(-0.73)		(0.77)		(-1.65)
Lag expense ratio		0.185		-0.189		0.120		0.002
		(0.55)		(-0.35)		(1.14)		(0.01)
Age		-0.002		**0.006***		0.000		0.003
		(-1.19)		(1.66)		(0.02)		(1.20)
Intercept	**0.021*****	-0.182	-0.078	0.354**	**0.007*****	-0.036	0.005	0.077
	(3.70)	(-1.22)	(-1.31)	(2.15)	(3.53)	(-0.97)	(1.34)	(0.47)
R^2	0.007	0.059	0.159	0.124	0.023	0.024	0.002	0.040

Table 4.13: Ambiguity – flow volatility, US, matched

This table analyses the investors' ambiguity aversion of matched conventional and ESG, both active and passive funds during the period of January 1996 – December 2022 by examining how investors' fund flow responds to the minimum performance across different levels of flow volatility. The flow volatility is used as a proxy measure of ambiguity. Flow volatility is the standard deviation of the funds' prior 12-month flow. Each month, three dummy variables representing flow volatility levels across terciles (low, mid, and high ambiguity equals 1 if the fund flows volatility fall in the bottom, medium, and top terciles, respectively). Funds' performance are ranked from the worst (zero) to best (one) according to their average raw return in the past 12, 24, and 36 months relative to other funds within the same investment objective (Growth, Value, or Blend), or according to their average Carhart (1997) four-factor alphas in the past 12, 24, and 36 months. Min rank is defined as the lowest performance rank achieved across the three horizons. A panel OLS regression is estimated by regressing funds' monthly net flow on the interaction between funds' minimum performance interacted with the three dummy variables of the fund flows volatility tercile ranks. The control variables include one-month lagged: return, flow, log total net assets, return volatility, expense ratio, and current age. Panel B repeats the same analysis for matched active and passive, both conventional and ESG funds in the US. Reported are the time-series averages of coefficients and *t-statistics* (in parentheses) are calculated with Newey-West robust standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: ESG match - Active	**Matched conventional**				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low ambiguity * Min Rank	**0.095*****	0.039	-0.033	-0.014	-0.057	0.002	0.021	0.015
	(2.85)	(0.74)	(-1.49)	(-0.47)	(-2.65)	(0.07)	(1.18)	(0.90)
Mid ambiguity * Min Rank	**-0.121*****	-0.066	-0.011	-0.011	**0.068*****	0.028	0.004	-0.003
	(-3.18)	(-1.25)	(-0.34)	(-0.30)	(2.25)	(0.74)	(0.23)	(-0.16)
High ambiguity * Min Rank	-0.004	0.045	**0.102*****	0.025	-0.005	-0.043	0.001	-0.004
	(-0.17)	(1.05)	(3.46)	(0.68)	(-0.19)	(-1.29)	(0.05)	(-0.28)
Lag return		**0.029*****		0.009		**0.020***		0.008
		(2.93)		(0.86)		(1.68)		(0.68)
Lag flow		0.116		0.096		**0.175****		0.159
		(1.51)		(1.02)		(1.96)		(1.64)
Lag net assets		**-0.012*****		**0.006***		0.002		**0.006*****
		(-2.78)		(1.78)		(0.38)		(2.74)
Lag return volatility		**-0.089****		-0.019		-0.031		0.004
		(-2.01)		(-0.66)		(-0.8)		(0.14)
Lag expense ratio		0.211		**0.726*****		**0.219****		**-0.221****
		(0.83)		(2.66)		(2.12)		(-2.25)
Age		-0.001		**0.003****		0.001		0.000
		(-1.57)		(2.17)		(1.28)		(-0.64)
Intercept	**0.016*****	**0.245****	**-0.012*****	**-0.245*****	0.000	-0.065	**-0.008*****	**-0.103*****
	(12.66)	(2.33)	(-7.36)	(-2.59)	(0.28)	(-0.75)	(-4.54)	(-3.19)
R^2	0.052	0.374	0.112	0.249	0.026	0.121	0.016	0.110

Panel B: ESG match - Passive	Table 4.13: Continued							
	Matched conventional				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low ambiguity * Min Rank	-0.035	-0.037	0.052	0.050	0.036	0.000	**0.107*****	**0.114****
	(-1.05)	(-1.2)	(1.47)	(0.78)	(1.46)	(-0.01)	(3.62)	(2.22)
Mid ambiguity * Min Rank	0.018	0.033	-0.011	-0.083	0.082	0.072	**-0.043****	0.106
	(0.35)	(0.81)	(-0.23)	(-1.34)	(1.07)	(1.17)	(-2.03)	(1.48)
High ambiguity * Min Rank	0.005	0.039	-0.060	-0.043	-0.039	0.052	-0.038	**-0.130***
	(0.16)	(1.33)	(-1.61)	(-0.89)	(-0.60)	(1.41)	(-1.14)	(-1.95)
Lag return		0.011		-0.006		0.025		-0.025
		(0.34)		(-0.12)		(0.72)		(-0.60)
Lag flow		0.056		-0.169		0.047		-0.128
		(0.79)		(-1.47)		(0.46)		(-1.18)
Lag net assets		0.000		**-0.020****		-0.004		**-0.026***
		(-0.05)		(-2.00)		(-0.31)		(-1.90)
Lag return volatility		0.103		-0.073		-0.052		-0.013
		(0.86)		(-0.66)		(-0.30)		(-0.08)
Lag expense ratio		0.518		-0.76		-0.374		0.372
		(1.25)		(-1.54)		(-0.94)		(0.59)
Age		0.000		**0.005***		-0.001		**0.010***
		(0.25)		(1.66)		(-0.16)		(1.71)
Intercept	**0.008****	-0.020	**-0.004***	**0.342****	0.001	0.108	0.001	0.288
	(2.13)	(-0.14)	(-1.87)	(2.05)	(0.31)	(0.53)	(0.13)	(1.60)
R^2	0.004	0.02	0.028	0.078	0.038	0.053	0.080	0.193

Table 4.14: Ambiguity – flow volatility, EU, matched

This table analyses the investors' ambiguity aversion of matched conventional and ESG, both active and passive funds during the period of January 1996 – December 2022 by examining how investors' fund flow responds to the minimum performance across different levels of flow volatility. The flow volatility is used as a proxy measure of ambiguity. Flow volatility is the standard deviation of the funds' prior 12-month flow. Each month, three dummy variables representing flow volatility levels across terciles (low, mid, and high ambiguity equals 1 if the fund flows volatility fall in the bottom, medium, and top terciles, respectively). Funds' performance are ranked from the worst (zero) to best (one) according to their average raw return in the past 12, 24, and 36 months relative to other funds within the same investment objective (Growth, Value, or Blend), or according to their average Carhart (1997) four-factor alphas in the past 12, 24, and 36 months. Min rank is defined as the lowest performance rank achieved across the three horizons. A panel OLS regression is estimated by regressing funds' monthly net flow on the interaction between funds' minimum performance interacted with the three dummy variables of the fund flows volatility tercile ranks. The control variables include one-month lagged: return, flow, log total net assets, return volatility, expense ratio, and current age. Panel B repeats the same analysis for matched active and passive, both conventional and ESG funds in the EU. Reported are the time-series averages of coefficients and *t-statistics* (in parentheses) are calculated with Newey-West robust standard errors. ∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: ESG match - Active	**Matched conventional**				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low ambiguity * Min Rank	**0.177***	**0.208****	-0.060	-0.021	**0.046***	0.017	**0.082*****	0.050
	(1.84)	(2.07)	(-1.36)	(-0.23)	(1.82)	(0.84)	(2.86)	(1.48)
Mid ambiguity * Min Rank	**-0.122*****	**-0.230***	0.075	0.035	0.026	0.035	0.003	0.033
	(-3.24)	(-1.95)	(1.48)	(0.19)	(0.64)	(0.67)	(0.12)	(1.09)
High ambiguity * Min Rank	-0.061	**-0.146****	0.011	-0.011	-0.060	-0.046	**-0.082****	-0.045
	(-0.96)	(-2.46)	(0.46)	(-0.40)	(-1.38)	(-0.89)	(-2.53)	(-1.46)
Lag return		0.032		-0.003		-0.001		0.013
		(0.85)		(-0.06)		(-0.08)		(1.11)
Lag flow		0.049		0.088		**0.251*****		0.015
		(0.29)		(0.88)		(2.76)		(0.28)
Lag net assets		-0.018		-0.032		-0.005		**-0.012*****
		(-1.30)		(-1.01)		(-1.37)		(-3.14)
Lag return volatility		**-0.263****		-0.381		0.027		0.047
		(-2.15)		(-0.87)		(0.77)		(1.53)
Lag expense ratio		0.076		0.217		**-0.161****		**-0.185***
		(0.39)		(0.52)		(-2.25)		(-1.72)
Age		0.000		-0.002		0.000		0.000
		(0.29)		(-0.4)		(0.80)		(-0.51)
Intercept	**0.022*****	0.354	-0.002	0.585	**0.002****	**0.105***	0.000	**0.254*****
	(4.97)	(1.50)	(-0.42)	(0.96)	(2.28)	(1.82)	(0.02)	(3.44)
R^2	0.171	0.259	0.086	0.043	0.023	0.168	0.049	0.175

Table 4.14: continued

Panel B: ESG match - Passive	**Conventional active**				**ESG active**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low ambiguity * Min Rank	0.000	0.115	**0.164****	**0.157****	-0.004	0.002	**-0.065****	-0.038
	(-0.01)	(0.83)	(2.35)	(2.06)	(-0.13)	(0.09)	(-2.37)	(-1.17)
Mid ambiguity * Min Rank	0.005	0.012	0.118	-0.141	0.019	0.054	0.060	0.045
	(0.12)	(0.19)	(1.51)	(-1.05)	(0.55)	(1.28)	(1.29)	(0.77)
High ambiguity * Min Rank	0.005	-0.045	-0.099	-0.021	-0.040	-0.042	**-0.138****	**-0.130****
	(0.07)	(-0.61)	(-1.00)	(-0.28)	(-1.30)	(-0.99)	(-2.76)	(-2.13)
Lag return		0.009		0.022		0.016		**0.081***
		(0.26)		(0.33)		(0.93)		(1.86)
Lag flow		-0.014		0.060		0.047		-0.010
		(-0.23)		(0.49)		(0.72)		(-0.14)
Lag net assets		-0.029		**-0.036***		-0.001		-0.007
		(-1.43)		(-1.80)		(-0.47)		(-0.78)
Lag return volatility		**-0.340***		**-0.509***		0.069		-0.096
		(-1.95)		(-1.68)		(1.01)		(-0.66)
Lag expense ratio		0.415		1.365		0.104		**-0.412****
		(0.72)		(1.62)		(1.16)		(-1.96)
Age		0.006		0.003		0.001		0.000
		(1.34)		(0.70)		(1.41)		(-0.16)
Intercept	**0.009***	0.446	-0.019	**0.543***	**0.005*****	-0.010	**0.018****	0.192
	(1.77)	(1.49)	(-1.10)	(1.78)	(2.63)	(-0.29)	(2.06)	(1.14)
R^2	0.000	0.067	0.092	0.224	0.018	0.036	0.082	0.111

Table 4.15: Ambiguity – family size, US, matched

This table analyses the investors' ambiguity aversion of matched conventional and ESG, both active and passive funds during the period of January 1996 – December 2022 by examining how investors' fund flow responds to the minimum performance across different levels of funds' family size. The family size is used as a proxy measure of ambiguity. Family size is the summed total net assets of funds that belong to the same fund family. Each month, three dummy variables representing family size levels across terciles (Low, mid, and high ambiguity equals 1 if the funds' family size fall in the top, medium, and bottom terciles, respectively). Funds' performance are ranked from the worst (zero) to best (one) according to their average raw return in the past 12, 24, and 36 months relative to other funds within the same investment objective (Growth, Value, or Blend), or according to their average Carhart (1997) four-factor alphas in the past 12, 24, and 36 months. Min rank is defined as the lowest performance rank achieved across the three horizons. A panel OLS regression is estimated by regressing funds' monthly net flow on the interaction between funds' minimum performance interacted with the three dummy variables of the funds' family size tercile ranks. The control variables include one-month lagged: return, flow, log total net assets, return volatility, expense ratio, and current age. Panel B repeats the same analysis for for matched active and passive, both conventional and ESG funds in the US. Reported are the time-series averages of coefficients and *t-statistics* (in parentheses) are calculated with Newey-West robust standard errors. ∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: ESG match - Active

	Matched conventional				ESG			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low ambiguity * Min Rank	0.004	0.001	-0.036	0.045	**0.078*****	**0.065****	**0.064****	0.028
	(0.16)	(0.03)	(-1.39)	(1.17)	(3.25)	(2.52)	(2.49)	(0.88)
Mid ambiguity * Min Rank	**-0.271*****	**-0.088****	**0.108*****	0.001	0.017	0.018	**0.043*****	-0.003
	(-5.93)	(-2.28)	(3.19)	(0.04)	(0.73)	(0.76)	(3.41)	(-0.19)
High ambiguity * Min Rank	**0.298*****	**0.123****	-0.047	-0.053	**-0.088*****	**-0.084*****	**-0.097*****	-0.019
	(5.71)	(2.56)	(-1.11)	(-1.10)	(-3.34)	(-3.34)	(-5.31)	(-0.84)
Lag return		**0.037*****		0.015		**0.026****		0.010
		(3.71)		(1.60)		(2.21)		(0.87)
Lag flow		0.026		0.100		0.126		0.138
		(0.38)		(1.13)		(1.56)		(1.48)
Lag net assets		**-0.013*****		0.000		0.004		**0.007*****
		(-4.11)		(-0.03)		(0.78)		(2.61)
Lag return volatility		**-0.123*****		-0.031		0.008		0.004
		(-4.20)		(-0.98)		(0.27)		(0.19)
Lag expense ratio		0.126		**0.522***		0.104		**-0.185****
		(0.76)		(1.88)		(0.81)		(-2.02)
Age		**-0.002*****		0.001		0.000		0.000
		(-2.59)		(0.72)		(0.62)		(-0.47)
Intercept	**0.015*****	**0.281*****	**-0.008*****	-0.070	0.001	-0.093	**-0.004****	**-0.12*****
	(12.44)	(4.28)	(-4.63)	(-0.82)	(0.88)	(-1.05)	(-2.23)	(-3.14)
R^2	0.143	0.407	0.078	0.210	0.055	0.152	0.148	0.123

Table 4.15: continued								
Panel B: ESG match - Passive								
	Matched conventional				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low ambiguity * Min Rank	-0.008	-0.022	-0.016	-0.064	0.011	-0.079	0.088	0.032
	(-0.27)	(-0.58)	(-0.39)	(-1.31)	(0.33)	(-0.57)	(1.77)	(0.72)
Mid ambiguity * Min Rank	-0.004	0.015	0.022	-0.035	0.018	**0.051*** **	**-0.063***	**0.056***
	(-0.14)	(0.32)	(0.64)	(-0.73)	(0.4)	(2.85)	(-1.77)	(1.91)
High ambiguity * Min Rank	-0.029	-0.012	0.018	**0.053***	0.023	0.078	**0.072****	-0.010
	(-0.77)	(-0.18)	(0.79)	(1.72)	(0.73)	(1.17)	(2.84)	(-0.36)
Lag return		-0.013		-0.014		0.025		-0.030
		(-0.35)		(-0.33)		(0.76)		(-0.85)
Lag flow		0.076		-0.134		0.033		-0.100
		(0.95)		(-1.13)		(0.28)		(-1.01)
Lag net assets		0.000		**-0.015***		-0.016		-0.012
		(0.01)		(-1.93)		(-1.41)		(-1.61)
Lag return volatility		-0.051		-0.076		-0.087		**-0.344****
		(-0.33)		(-0.73)		(-0.64)		(-2.39)
Lag expense ratio		0.258		**-1.066***		-0.043		**-1.372****
		(0.60)		(-1.77)		(-0.21)		(-1.96)
Age		0.000		**0.005****		0.003		-0.001
		(-0.04)		(2.34)		(0.88)		(-0.23)
Intercept	**0.011*****	-0.002	**-0.006*****	**0.275***	0.004	0.263	-0.003	**0.327****
	(3.38)	(-0.01)	(-3.24)	(1.86)	(1.20)	(1.60)	(-0.65)	(2.21)
R^2	0.01	0.016	0.01	0.103	0.018	0.061	0.072	0.177

Table 4.16: Ambiguity – family size, EU, matched

This table analyses the investors' ambiguity aversion of matched conventional and ESG, both active and passive funds during the period of January 1996 – December 2022 by examining how investors' fund flow responds to the minimum performance across different levels of funds' family size. The family size is used as a proxy measure of ambiguity. Family size is the summed total net assets of funds that belong to the same fund family. Each month, three dummy variables representing family size levels across terciles (Low, mid, and high ambiguity equals 1 if the funds' family size fall in the top, medium, and bottom terciles, respectively). Funds' performance are ranked from the worst (zero) to best (one) according to their average raw return in the past 12, 24, and 36 months relative to other funds within the same investment objective (Growth, Value, or Blend), or according to their average Carhart (1997) four-factor alphas in the past 12, 24, and 36 months. Min rank is defined as the lowest performance rank achieved across the three horizons. A panel OLS regression is estimated by regressing funds' monthly net flow on the interaction between funds' minimum performance interacted with the three dummy variables of the funds' family size tercile ranks. The control variables include one-month lagged: return, flow, log total net assets, return volatility, expense ratio, and current age. Panel B repeats the same analysis for matched active and passive, both conventional and ESG funds in the EU. Reported are the time-series averages of coefficients and *t-statistics* (in parentheses) are calculated with Newey-West robust standard errors. ∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: ESG match - Active								
	Matched conventional				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low ambiguity * Min Rank	0.003	-0.025	**-0.086****	0.042	0.011	0.036	0.031	0.035
	(0.04)	(-0.27)	(-2.06)	(0.84)	(0.45)	(0.90)	(1.97)	(1.43)
Mid ambiguity * Min Rank	-0.106	-0.013	-0.025	0.226	-0.026	-0.039	**-0.039****	0.015
	(-1.81)	(-0.27)	(-0.65)	(1.15)	(-0.87)	(-1.07)	(-2.63)	(0.58)
High ambiguity * Min Rank	0.040	0.080	**0.092****	-0.092	0.027	0.010	0.014	-0.028
	(0.96)	(1.51)	(2.04)	(-0.65)	(1.12)	(0.26)	(0.83)	(-1.32)
Lag return		**0.150*****		0.019		-0.002		**0.022****
		(2.75)		(0.38)		(-0.20)		(2.21)
Lag flow		0.076		-0.018		**0.273*****		-0.023
		(0.54)		(-0.20)		(3.50)		(-0.34)
Lag net assets		**-0.043*****		-0.041		**-0.006****		**-0.013*****
		(-3.84)		(-1.01)		(-1.98)		(-3.32)
Lag return volatility		**-0.340****		-0.280		0.021		0.031
		(-2.30)		(-0.82)		(0.65)		(0.90)
Lag expense ratio		-0.171		-0.235		-0.092		**-0.400*****
		(-0.76)		(-0.92)		(-0.98)		(-2.96)
Age		0.000		-0.001		0.001		-0.001
		(0.62)		(-0.77)		(1.41)		(-0.89)
Intercept	**0.031*****	**0.829*****	0.001	0.788	**0.002***	**0.119****	0.000	**0.297*****
	(3.38)	(3.93)	(0.28)	(1.04)	(1.69)	(2.23)	(-0.24)	(4.09)
R^2	0.155	0.424	0.092	0.113	0.018	0.167	0.025	0.186

Table 4.16: continued								
Panel B: ESG match - Passive								
	Matched conventional				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low ambiguity * Min Rank	-0.023	0.018	-0.339	**1.065****	-0.005	0.052	-0.005	0.031
	(-0.92)	(0.52)	(-1.43)	(2.22)	(-0.15)	(0.93)	(-0.20)	(0.42)
Mid ambiguity * Min Rank	0.001	**-0.073****	**0.107***	0.033	0.017	-0.015	0.006	0.022
	(0.06)	(-2.06)	(1.86)	(0.27)	(0.61)	(-0.47)	(0.16)	(0.29)
High ambiguity * Min Rank	-0.022	0.016	0.041	**0.175*****	-0.053	-0.034	-0.024	-0.015
	(-0.73)	(0.35)	(0.60)	(2.83)	(-1.42)	(-0.96)	(-0.95)	(-0.21)
Lag return		-0.007		0.054		0.020		-0.013
		(-0.18)		(0.93)		(0.79)		(-0.39)
Lag flow		-0.073		0.036		-0.070		-0.035
		(-1.03)		(0.39)		(-1.01)		(-0.34)
Lag net assets		-0.001		**-0.066*****		0.001		-0.003
		(-0.05)		(-3.08)		(0.19)		(-0.26)
Lag return volatility		**-0.298***		**-0.679***		-0.022		-0.172
		(-1.95)		(-1.80)		(-0.27)		(-1.45)
Lag expense ratio		1.204*		**1.932****		0.061		**-0.844****
		(1.88)		(2.02)		(0.27)		(-2.37)
Age		0.002		**0.014*****		-0.001		**-0.008****
		(0.42)		(2.89)		(-0.51)		(-2.25)
Intercept	**0.015*****	-0.036	-0.018	**0.851*****	**0.009*****	-0.008	0.004	0.273
	(3.44)	(-0.16)	(-1.03)	(2.74)	(3.94)	(-0.06)	(0.47)	(1.24)
R^2	0.015	0.100	0.065	0.168	0.029	0.027	0.008	0.138

Table 4.17: Ambiguity – strategy change (R-squared), US, matched

This table analyses the investors' ambiguity aversion of matched conventional and ESG, both active and passive funds during the period of January 1996 – December 2022 by examining how investors' fund flow responds to the minimum performance across different levels of funds' strategy change. The strategy change is used as a proxy measure of ambiguity. Strategy change is measured by the funds' Carhart (1997) four-factor model's R-squared. Each month, three dummy variables representing strategy change levels across terciles (low, mid, and high ambiguity equals 1 if the funds' strategy change fall in the bottom, medium, and top terciles, respectively). Funds' performance are ranked from the worst (zero) to best (one) according to their average raw return in the past 12, 24, and 36 months relative to other funds within the same investment objective (Growth, Value, or Blend), or according to their average Carhart (1997) four-factor alphas in the past 12, 24, and 36 months. Min rank is defined as the lowest performance rank achieved across the three horizons. A panel OLS regression is estimated by regressing funds' monthly net flow on the interaction between funds' minimum performance interacted with the three dummy variables of the funds' strategy change tercile ranks. The control variables include one-month lagged: return, flow, log total net assets, return volatility, expense ratio, and current age. Panel B repeats the same analysis for matched active and passive, both conventional and ESG funds in the US. Reported are the time-series averages of coefficients and *t-statistics* (in parentheses) are calculated with Newey-West robust standard errors. ∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: ESG match - Active	**Matched conventional**				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low ambiguity * Min Rank	**-0.084*****	-0.002	0.023	0.004	-0.028	-0.023	-0.072	**-0.041****
	(-3.44)	(-0.06)	(1.26)	(0.14)	(-1.22)	(-0.66)	(-4.52)	(-1.97)
Mid ambiguity * Min Rank	**0.075****	0.045	**-0.076****	**-0.105****	0.03	**0.120*****	0.020	0.032
	(2.12)	(1.10)	(-2.35)	(-2.38)	(0.95)	(3.23)	(0.99)	(1.51)
High ambiguity * Min Rank	**0.029****	-0.003	**0.059****	**0.072****	0.004	**-0.108*****	0.014	0.002
	(2.43)	(-0.20)	(3.40)	(2.50)	(0.33)	(-4.01)	(1.93)	(0.20)
Lag return		**0.027*****		0.016		0.015		0.010
		(3.05)		(1.64)		(1.47)		(0.91)
Lag flow		0.016		0.081		-0.134		0.135
		(0.23)		(0.97)		(-1.11)		(1.50)
Lag net assets		**-0.008****		-0.004		**0.017*****		**0.006****
		(-2.26)		(-0.87)		(2.84)		(2.11)
Lag return volatility		**-0.07****		**-0.052***		**0.081****		0.009
		(-2.03)		(-1.77)		(2.03)		(0.37)
Lag expense ratio		**0.878*****		0.274		-0.003		-0.238**
		(4.61)		(1.07)		(-0.02)		(-2.29)
Age		**0.001***		0.000		**-0.002***		0.000
		(1.70)		(-0.02)		(-1.71)		(-0.15)
Intercept	**-0.005*****	0.041	**-0.006*****	0.043	**-0.003*****	**-0.310*****	0.000	**-0.093****
	(-5.58)	(0.54)	(-3.24)	(0.39)	(-2.68)	(-3.21)	(-0.05)	(-2.39)
R^2	0.114	0.303	0.088	0.235	0.012	0.199	0.090	0.133

Table 4.17: continued

Panel B: ESG match - Passive	**Matched conventional**				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low ambiguity * Min Rank	0.002	0.034	-0.053	-0.039	0.127	-0.094	**-0.108****	-0.002
	(0.05)	(0.47)	(-1.33)	(-0.99)	(2.79)	(-1.06)	(-2.35)	(-0.04)
Mid ambiguity * Min Rank	-0.037	-0.021	**0.078***	0.026	**-0.103****	0.125	0.033	0.034
	(-0.77)	(-0.4)	(1.71)	(0.46)	(-2.07)	(1.44)	(1.11)	(0.8)
High ambiguity * Min Rank	0.037	-0.046	0.026	0.007	0.026	0.034	**0.074*****	0.037
	(1.12)	(-0.72)	(0.69)	(0.13)	(1.14)	(0.65)	(3.39)	(1.18)
Lag return		-0.009		-0.015		-0.043		-0.039
		(-0.25)		(-0.35)		(-1.21)		(-1.11)
Lag flow		-0.020		-0.111		-0.028		-0.092
		(-0.19)		(-0.97)		(-0.34)		(-0.97)
Lag net assets		-0.009		**-0.020****		-0.006		**-0.012***
		(-0.98)		(-2.46)		(-0.59)		(-1.78)
Lag return volatility		-0.123		-0.089		**-0.262***		-0.236
		(-1.08)		(-0.87)		(-1.93)		(-1.49)
Lag expense ratio		-1.089		-0.952		**-0.579***		**-0.931***
		(-1.35)		(-1.61)		(-1.95)		(-1.66)
Age		0.001		**0.005****		0.001		0.000
		(0.31)		(2.12)		(0.39)		(0.18)
Intercept	-0.001	0.207	**-0.007*****	**0.363****	0.001	0.133	0.007	**0.282****
	(-0.65)	(1.26)	(-3.70)	(2.51)	(0.25)	(0.94)	(1.58)	(2.36)
R^2	0.009	0.058	0.024	0.095	0.101	0.215	0.110	0.171

Table 4.18: Ambiguity – strategy change (R-squared), EU, matched

This table analyses the investors' ambiguity aversion of matched conventional and ESG, both active and passive funds during the period of January 1996 – December 2022 by examining how investors' fund flow responds to the minimum performance across different levels of funds' strategy change. The strategy change is used as a proxy measure of ambiguity. Strategy change is measured by the funds' Carhart (1997) four-factor model's R-squared. Each month, three dummy variables representing strategy change levels across terciles (low, mid, and high ambiguity equals 1 if the funds' strategy change fall in the bottom, medium, and top terciles, respectively). Funds' performance are ranked from the worst (zero) to best (one) according to their average raw return in the past 12, 24, and 36 months relative to other funds within the same investment objective (Growth, Value, or Blend), or according to their average Carhart (1997) four-factor alphas in the past 12, 24, and 36 months. Min rank is defined as the lowest performance rank achieved across the three horizons. A panel OLS regression is estimated by regressing funds' monthly net flow on the interaction between funds' minimum performance interacted with the three dummy variables of the funds' strategy change tercile ranks. The control variables include one-month lagged: return, flow, log total net assets, return volatility, expense ratio, and current age. Panel B repeats the same analysis for matched active and passive, both conventional and ESG funds in the EU. Reported are the time-series averages of coefficients and *t-statistics* (in parentheses) are calculated with Newey-West robust standard errors. ∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: ESG match - Active	**Matched conventional**				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low ambiguity * Min Rank	0.080	-0.071	-0.039	0.059	0.029	0.022	0.007	**0.074****
	(1.05)	(-0.83)	(-1.10)	(1.08)	(1.57)	(0.83)	(0.31)	(2.47)
Mid ambiguity * Min Rank	0.016	-0.018	0.054	-0.035	-0.026	-0.023	0.017	0.024
	(0.31)	(-0.23)	(1.29)	(-0.71)	(-0.75)	(-0.54)	(0.64)	(0.72)
High ambiguity * Min Rank	-0.036	-0.004	-0.016	-0.014	-0.034	-0.020	-0.024	-0.030
	(-1.32)	(-0.04)	(-0.29)	(-0.16)	(-1.37)	(-0.77)	(-1.27)	(-1.08)
Lag return		0.082		0.030		0.006		**0.021****
		(1.21)		(0.65)		(0.54)		(2.18)
Lag flow		-0.136		-0.004		**0.200****		-0.038
		(-0.44)		(-0.06)		(2.36)		(-0.56)
Lag net assets		0.016		-0.014		-0.003		**-0.012*****
		(0.81)		(-0.35)		(-0.59)		(-2.72)
Lag return volatility		-0.187		-0.090		0.034		0.038
		(-0.71)		(-0.24)		(1.08)		(1.07)
Lag expense ratio		0.328		-0.187		-0.099		**-0.415*****
		(0.90)		(-0.94)		(-1.37)		(-3.83)
Age		-0.001		0.002		0.000		-0.001
		(-1.47)		(0.96)		(0.15)		(-1.33)
Intercept	-0.003	-0.301	0.000	0.247	**0.004*****	0.060	0.000	**0.296*****
	(-0.44)	(-0.82)	(0.01)	(0.34)	(3.00)	(0.81)	(0.21)	(3.69)
R^2	0.034	0.087	0.048	0.048	0.054	0.163	0.009	0.199

Table 4.18: continued								
Panel B: ESG match - Passive								
	Matched conventional				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low ambiguity * Min Rank	-0.088	-0.018	-0.001	-0.074	**-0.087****	-0.07	-0.016	-0.032
	(-1.25)	(-0.22)	(-0.0)	(-0.43)	(-2.43)	(-1.44)	(-0.66)	(-0.38)
Mid ambiguity * Min Rank	0.155	-0.162	0.156	0.128	0.020	0.044	-0.029	-0.059
	(1.41)	(-1.64)	(1.93)	(1.37)	(0.73)	(0.93)	(-0.90)	(-0.55)
High ambiguity * Min Rank	0.004	0.004	0.102	0.108	0.057	0.038	0.002	-0.011
	(0.05)	(0.06)	(1.42)	(1.27)	(1.47)	(0.87)	(0.08)	(-0.34)
Lag return		0.035		0.025		0.025		0.056
		(0.72)		(0.42)		(1.08)		(1.43)
Lag flow		-0.050		0.053		0.027		0.041
		(-0.38)		(0.42)		(0.40)		(0.66)
Lag net assets		**-0.036*****		**-0.027***		**-0.012****		-0.004
		(-2.94)		(-1.96)		(-2.45)		(-0.41)
Lag return volatility		**-0.577****		-0.306		0.100		-0.182
		(-2.20)		(-0.84)		(1.09)		(-1.52)
Lag expense ratio		**-0.782***		-0.329		0.021		-0.075
		(-1.75)		(-0.53)		(0.19)		(-0.36)
Age		**0.010*****		**0.006***		**0.004****		0.002
		(2.87)		(1.83)		(2.25)		(0.69)
Intercept	-0.007	**0.583*****	-0.023	**0.386***	0.003	**0.153***	0.006	0.062
	(-1.18)	(3.18)	(-1.27)	(1.84)	(0.99)	(1.89)	(1.42)	(0.36)
R^2	0.024	0.091	0.036	0.121	0.058	0.098	0.008	0.045

Table 4.19: Ambiguity – strategy change (change in factor loadings), US, matched

This table analyses the investors' ambiguity aversion of matched conventional and ESG, both active and passive funds during the period of January 1996 – December 2022 by examining how investors' fund flow responds to the minimum performance across different levels of funds' strategy change. The strategy change is used as a proxy measure of ambiguity. Strategy change is measured by the funds' average absolute change in the funds' Carhart (1997) factor loadings between the previous 1-30 and 31-60 months. Each month, three dummy variables representing strategy change levels across terciles (low, mid, and high ambiguity equals 1 if the funds' strategy change fall in the bottom, medium, and top terciles, respectively). Funds' performance are ranked from the worst (zero) to best (one) according to their average raw return in the past 12, 24, and 36 months relative to other funds within the same investment objective (Growth, Value, or Blend), or according to their average Carhart (1997) four-factor alphas in the past 12, 24, and 36 months. Min rank is defined as the lowest performance rank achieved across the three horizons. A panel OLS regression is estimated by regressing funds' monthly net flow on the interaction between funds' minimum performance interacted with the three dummy variables of the funds' strategy change tercile ranks. The control variables include one-month lagged: return, flow, log total net assets, return volatility, expense ratio, and current age. Panel B repeats the same analysis for matched active and passive, both conventional and ESG funds in the US. Reported are the time-series averages of coefficients and *t-statistics* (in parentheses) are calculated with Newey-West robust standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: ESG match - Active

	Matched conventional				ESG			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low ambiguity * Min Rank	0.064	0.050	0.003	-0.048	**-0.026***	0.004	**-0.061*****	-0.008
	(1.20)	(1.59)	(0.12)	(-1.55)	(-1.81)	(0.19)	(-2.82)	(-0.39)
Mid ambiguity * Min Rank	-0.046	-0.024	0.027	0.025	0.005	-0.018	**0.082*****	0.021
	(-1.20)	(-0.77)	(0.79)	(0.63)	(0.22)	(-0.53)	(2.83)	(0.87)
High ambiguity * Min Rank	-0.044	-0.015	-0.004	**0.045***	0.031	0.021	0.029	0.025
	(-1.11)	(-0.42)	(-0.13)	(1.70)	(1.65)	(0.75)	(1.49)	(1.42)
Lag return		-0.013		0.006		0.003		0.003
		(-0.65)		(0.38)		(0.26)		(0.23)
Lag flow		0.498		-0.037		**0.182***		**0.206****
		(1.51)		(-0.25)		(1.90)		(2.24)
Lag net assets		-0.005		-0.001		0.003		**0.007****
		(-0.66)		(-0.09)		(1.04)		(2.07)
Lag return volatility		0.111		**-0.138****		0.006		-0.046
		(1.40)		(-2.17)		(0.12)		(-1.18)
Lag expense ratio		-0.016		**0.430*****		0.055		**-0.639*****
		(-0.16)		(2.92)		(0.55)		(-2.61)
Age		**-0.001***		0.000		**-0.001*****		0.000
		(-1.72)		(-0.65)		(-3.37)		(0.97)
Intercept	-0.002	0.113	**-0.006****	-0.023	**-0.002***	-0.041	**-0.011*****	**-0.092***
	(-1.22)	(0.72)	(-2.05)	(-0.25)	(-1.81)	(-0.82)	(-4.10)	(-1.85)
R^2	0.060	0.256	0.007	0.146	0.022	0.180	0.174	0.237

Table 4.19: continued

Panel B: ESG match - Passive

	Matched conventional				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low ambiguity * Min Rank	0.007	0.028	0.011	0.033	0.048	**0.086*****	**0.068*****	-0.009
	(0.20)	(0.48)	(0.50)	(1.48)	(1.85)	(3.33)	(2.93)	(-0.25)
Mid ambiguity * Min Rank	-0.002	0.008	-0.041	-0.074	0.014	-0.031	**0.088*****	**0.149***
	(-0.06)	(0.12)	(-0.71)	(-1.35)	(0.27)	(-0.88)	(2.27)	(1.76)
High ambiguity * Min Rank	-0.026	-0.084	0.016	0.007	0.011	-0.003	-0.061	0.126
	(-0.63)	(-1.26)	(0.63)	(0.16)	(0.18)	(-0.07)	(-1.36)	(1.22)
Lag return		0.031		-0.014		-0.017		-0.014
		(1.27)		(-0.30)		(-0.38)		(-0.28)
Lag flow		-0.145		-0.004		0.102		**-0.199***
		(-1.22)		(-0.01)		(1.08)		(-1.83)
Lag net assets		-0.010		0.000		0.004		**-0.031****
		(-1.19)		(0.01)		(0.90)		(-2.47)
Lag return volatility		-0.134		-0.185**		0.085		0.047
		(-1.64)		(-2.28)		(0.71)		(0.22)
Lag expense ratio		**-1.711****		0.474		-0.060		**-1.717****
		(-2.56)		(0.41)		(-0.17)		(-2.53)
Age		**-0.003*****		0.000		-0.001		**0.010***
		(-2.75)		(0.13)		(-0.74)		(1.78)
Intercept	0.001	**0.326***	-0.003	-0.019	-0.002	-0.052	-0.003	**0.505*****
	(0.41)	(1.75)	(-1.22)	(-0.08)	(-0.66)	(-0.84)	(-0.69)	(2.71)
R^2	0.007	0.214	0.009	0.113	0.094	0.117	0.178	0.196

Table 4.20: Ambiguity – strategy change (change in factor loadings), EU, matched

This table analyses the investors' ambiguity aversion of matched conventional and ESG, both active and passive funds during the period of January 1996 – December 2022 by examining how investors' fund flow responds to the minimum performance across different levels of funds' strategy change. The strategy change is used as a proxy measure of ambiguity. Strategy change is measured by the funds' average absolute change in the funds' Carhart (1997) factor loadings between the previous 1-30 and 31-60 months. Each month, three dummy variables representing strategy change levels across terciles (low, mid, and high ambiguity equals 1 if the funds' strategy change fall in the bottom, medium, and top terciles, respectively). Funds' performance are ranked from the worst (zero) to best (one) according to their average raw return in the past 12, 24, and 36 months relative to other funds within the same investment objective (Growth, Value, or Blend), or according to their average Carhart (1997) four-factor alphas in the past 12, 24, and 36 months. Min rank is defined as the lowest performance rank achieved across the three horizons. A panel OLS regression is estimated by regressing funds' monthly net flow on the interaction between funds' minimum performance interacted with the three dummy variables of the funds' strategy change tercile ranks. The control variables include one-month lagged: return, flow, log total net assets, return volatility, expense ratio, and current age. Panel B repeats the same analysis for matched active and passive, both conventional and ESG funds in the EU. Reported are the time-series averages of coefficients and *t-statistics* (in parentheses) are calculated with Newey-West robust standard errors. ∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: ESG match - Active	**Matched conventional**				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low ambiguity * Min Rank	0.069	-0.054	-0.009	0.016	-0.003	-0.017	0.074	**0.096***
	(0.98)	(-1.59)	(-0.38)	(0.57)	(-0.13)	(-0.61)	(1.42)	(1.80)
Mid ambiguity * Min Rank	0.046	-0.019	0.037	0.037	0.027	0.067	0.005	-0.052
	(0.96)	(-0.48)	(1.46)	(0.26)	(0.84)	(1.15)	(0.08)	(-1.04)
High ambiguity * Min Rank	-0.100	0.024	0.007	-0.060	-0.024	-0.043	**-0.115****	**-0.173****
	(-0.93)	(0.39)	(0.18)	(-1.29)	(-0.60)	(-0.84)	(-2.58)	(-2.42)
Lag return		0.050		-0.016		0.023		0.012
		(1.26)		(-0.21)		(1.64)		(0.60)
Lag flow		-0.045		-0.104		0.031		-0.166
		(-0.33)		(-0.58)		(0.31)		(-0.98)
Lag net assets		-0.001		-0.016		-0.011		**-0.021****
		(-0.12)		(-0.59)		(-0.52)		(-2.13)
Lag return volatility		0.018		-0.292		-0.100		0.050
		(0.16)		(-0.50)		(-1.00)		(0.44)
Lag expense ratio		0.134		-0.026		-0.379		**-0.881****
		(1.12)		(-0.11)		(-0.39)		(-1.96)
Age		-0.001		-0.001		-0.001		**0.003****
		(-1.43)		(-0.19)		(-0.32)		(2.41)
Intercept	-0.001	0.019	-0.004	0.301	0.000	0.272	0.004	**0.452****
	(-0.35)	(0.11)	(-0.95)	(0.58)	(0.21)	(0.51)	(1.63)	(1.98)
R^2	0.067	0.191	0.021	0.085	0.008	0.264	0.128	0.454

Table 4.20: continued

Panel B: ESG match - Passive	**Matched conventional**				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low ambiguity * Min Rank	0.039	0.293	0.126	0.507	-0.068	0.036	-0.010	-0.140
	(0.25)	(1.48)	(0.54)	(0.95)	(-1.22)	(0.51)	(-0.20)	(-1.52)
Mid ambiguity * Min Rank	0.164	0.036	0.469	-0.140	0.019	0.082	0.106	-0.010
	(1.74)	(0.25)	(0.94)	(-0.08)	(0.56)	(1.35)	(1.25)	(-0.07)
High ambiguity * Min Rank	-0.150	-0.197	0.087	0.182	-0.006	-0.014	-0.042	0.138
	(-1.01)	(-1.44)	(0.81)	(0.64)	(-0.15)	(-0.34)	(-0.51)	(0.90)
Lag return		0.128		-0.082		0.121		**0.144***
		(1.08)		(-0.23)		(1.14)		(1.79)
Lag flow		-0.172		-0.402		-0.005		-0.090
		(-0.74)		(-0.58)		(-0.05)		(-1.13)
Lag net assets		-0.089		0.052		-0.028		-0.004
		(-1.38)		(0.08)		(-1.21)		(-0.12)
Lag return volatility		-0.054		0.285		0.140		**-0.735***
		(-0.09)		(0.07)		(0.37)		(-1.85)
Lag expense ratio		6.320		3.428		0.049		0.360
		(1.45)		(0.06)		(0.33)		(0.80)
Age		-0.004		0.024		0.004		0.003
		(-0.32)		(0.47)		(1.37)		(1.41)
Intercept	-0.003	1.356	-0.061	-1.601	0.007	0.431	-0.001	0.028
	(-0.18)	(1.50)	(-0.90)	(-0.11)	(1.16)	(1.16)	(-0.10)	(0.05)
R^2	0.068	0.365	0.045	0.383	0.019	0.078	0.026	0.167

4.7 Conclusion

This chapter empirically examines the behaviour of ESG investors as compared to that of conventional investors assuming both are ambiguity averse. The theoretical models of decision-making under ambiguity, including those by Epstein and Schneider (2008) and Ju and Miao (2012), suggest a higher tendency of ambiguity-averse investors to put greater weight on the worst signals when they encounter news with uncertain quality. Following Li et al. (2017), the chapter uses past performance over multiple horizons to measure the ambiguity of fund performance. The study compares the behaviour of ESG and conventional investors, whether active or passive and across regions (US and EU), in regard to how they respond to ambiguity.

The findings contribute to three strands of literature (e.g. Anderson et al. 2009; Antoniou et al. 2015; Anantanasuwong et al. 2024). First, the literature which studies the effect of ambiguity on asset prices in an empirical setting. The only empirical evidence from the mutual fund industry is provided by Li et al. (2017) who examined ambiguity aversion using a sample of US active mutual funds. Their findings suggest that US active investors are ambiguity averse. Second, the fund flow-performance sensitivity by providing evidence of how ESG and conventional investors respond to past performance by investigating the role of ambiguity aversion in their investment decisions across management styles and across regions (US and EU). Third, the literature examining the divergence of ESG rating and its impact on stock prices (Gibson-Brandon et al. 2021; Avramov et al. 2022; Luo et al. 2023).

While Li et al. (2017) suggest that US conventional active investors are sensitive to poor performance, this study reveals mixed results across ambiguity proxies and performance measures. This implies a more complicated response function by investors across the US and the EU. Specifically, the findings indicate that ESG active investors show no significant response to ambiguity, while US matched conventional active investors display evidence of ambiguity aversion. In Europe, neither ESG nor matched conventional active investors exhibit sensitivity to the minimum rank measure, consistent with the unmatched sample. For passive investors, the evidence suggests that US ESG investors have become more sensitive to poor past performance, measured by four-factor alpha, though only at a weak level of significance. By contrast, US matched conventional passive funds show no sensitivity to minimum performance, consistent with results from the unmatched sample. In Europe, ESG passive funds also display no reaction to the worst performance, whereas their matched conventional counterparts are averse to ambiguity when measured by risk-adjusted alpha. This is inconsistent with the unmatched sample, where EU conventional passive investors show no sensitivity to the worst performance.

The chapter also examines alternative proxies for ambiguity, including fund flow volatility, family size, and strategy changes. Using flow volatility, the results show that both US ESG and matched conventional active investors are ambiguity neutral, consistent with the unmatched sample. In contrast, European ESG active investors are not sensitive to the worst performance. On the other hand, their matched conventional peers display ambiguity aversion toward poorly performing funds with low flow volatility but are less averse when such funds exhibit high and mid flow volatility. This finding contradicts the unmatched EU conventional active sample, where investors appear ambiguity neutral, suggesting that characteristics such as fund age, loads, and portfolio composition shape investors' responses to ambiguity.

Turning to passive investors, US ESG funds exhibit ambiguity aversion toward poorly performing funds with low flow volatility but ambiguity-seeking behaviour when volatility is high. Their matched conventional peers, however, remain ambiguity neutral—similar to evidence from the unmatched sample, on a risk-adjusted basis. In Europe, ESG passive investors seek ambiguity in high-volatility funds, while their matched conventional counterparts display aversion when volatility is low. This pattern contrasts with the unmatched conventional sample, which shows that EU conventional passive investors exhibit flow sensitivity to the worst performance of high volatility funds.

Using family size as a proxy for ambiguity, the findings reveal that both US ESG and their matched conventional peers are neutral to ambiguity of funds at all family sizes, as measured by risk-adjusted alpha. This contradicts the unmatched conventional sample, where US conventional active investors appear to seek ambiguity in small family size funds but avoid it in large family funds. For Europe, active funds, both EU ESG and conventional active funds are not averse to ambiguity, as measured by C-4 alpha. This is inconsistent with the unmatched sample. Among passive investors, US ESG passive investors are averse to ambiguity (worst performance of mid-family size) funds, while their matched conventional counterparts are averse to small family funds. This finding differs from the unmatched sample, which indicates ambiguity seeking behaviour only in large family funds. In the EU, ESG passive investors are neutral across all family sizes funds, whereas matched conventional passive investors are averse to large and small family size funds. By contrast, the unmatched conventional sample reports ambiguity-neutral behaviour across all family sizes funds.

Finally, using strategy change as a proxy for ambiguity, conventional and ESG investors do not respond to ambiguity in a linear way. Using R-squared to measure strategy change. On a risk-adjusted basis, US ESG active investors only flow into poor performing funds with less frequent strategy change (low ambiguity) when their performance improves. Using the factor loading to measure strategy change, this result becomes insignificant. For matched conventional active investors, inflow increases towards medium levels of strategy change but decreases for funds with more frequent strategy change. By contrast, the unmatched US conventional active sample shows flow sensitivity to the worst performance of funds with less strategy change, on a risk-adjusted basis. Based on the factor loadings, US ESG active investors are averse to the worst performance of funds with less aggressive strategy change, while matched conventional active investors are averse to funds with more aggressive strategy change. The unmatched sample, however, report no flow sensitivity to the worst performance. Regarding EU conventional and ESG active funds, EU ESG active funds are averse to funds with less frequent strategy change (R^2) and seek ambiguity in funds with more aggressive strategy change (factor loadings). The matched conventional funds, however, show no sensitivity to the worst performance (R^2 and factor loadings), consistent with the unmatched sample.

For passive investors, US ESG passive investors do not show sensitivity to the worst performance across all levels of strategy change (R^2) but display aversion at medium level of strategy change (factor loading), on risk-adjusted return. Their matched conventional peers do not show sensitivity to the worst performance under either proxy. In contrast, the unmatched US conventional passive investors are averse to the worst performance at a medium level of strategy change, while remain indifferent to those with less frequent changes. For Europe, both EU ESG conventional passive investors- whether matched or unmatched – show no added sensitivity to the worst performance under either measure of strategy change.

Taken together, the findings suggest that neutrality to ambiguity exists among US and EU ESG active investors. This implies that they might derive utility from the non-financial as well as the financial aspect of their investment. Inconsistent with the prediction of ambiguity theory (Ellsberg 1961; Einhorn and Hogarth 1985), this finding may suggest that US and EU ESG active investors treat ESG information as sufficiently reliable. This could be due to the increasing standardisation, transparency, and availability of ESG data, which reduces uncertainty and allow investors to incorporate ESG factors without penalising their portfolios.

On the other hand, US ESG passive investors are more concerned about the financial aspect of their investment. This is evidenced by their demonstrated aversion to ambiguity, which likely stems from their belief that ESG factors are financially material (Edmans et al. 2024) and that it should generate additional returns, despite expectations to the contrary (Hartzmark and Sussman 2019). This finding aligns with Epstein and Schneider (2008) and Easley and O'Hara (2009) who show that investors exhibit aversion to information of uncertain quality. In the context of ESG investing, this suggests that the inconsistent and subjective nature of ESG data may lead investors to treat ESG funds cautiously, reflecting sensitivity to the ambiguity in ESG investing. This might also indicate that US ESG passive investors are not ready to sacrifice financial return, or they might perceive non-ESG passive funds as a less risky investment. However, these results should be interpreted with caution as the limited sample size of US ESG index funds may lead to a biased estimate, limited generalisability, and challenge the validity of the findings (Faber and Fonseca 2014).

Moreover, the use of other ambiguity proxies, such as funds flow volatility, family size, and strategy change, indicate that conventional and ESG investors rely on different characteristics of the funds when evaluating ambiguity and while some investors use raw return to evaluate performance, others prefer risk-adjusted return. Finally, the heterogeneity in ambiguity aversion among ESG and conventional, active and passive investors would affect asset prices as a result of only ambiguity-seekers and ambiguity-neutral investors rather than ambiguity-averse investors determine asset prices (Anantanasuwong et al. 2024).

Chapter 5: Conclusion

5.1 Summary of findings and implications

This thesis examines the behaviour of ESG investors. Chapter 2 examines the investors and managers' response to the application and announcement of the EU SFDR regulation, respectively. Chapter 3 compares conventional and ESG funds' performance and flow-performance sensitivity across the US and EU. Chapter 4 examines the behaviour of ESG investors when faced with ambiguity and compare this to investors who focus on conventional funds across the US and EU.

Chapter 2 contributes to the literature on the effect of external sustainability rating and policy intervention on investor and fund manager behaviour on two fronts (Del Guercio and Tkac 2008; Ammann et al. 2019; Hartzmark and Sussman 2019; Huang et al. 2020; El Ghoul and Karoui 2021; Ben-David et al. 2022). First, the study addresses the research question: did investors respond to the application of the SFDR in March 2021? This is investigated by using different methodologies such as panel regression, event study of flows, PSM, and DiD panel regression. Second, providing the first evidence on fund managers' responses to the disclosure requirements of the EU SFDR regulation in November 2019, this Chapter uses fund holdings to answer the research question: did fund managers respond to the announcement of the SFDR in November 2019? The investigation is conducted by evaluating SFDR-labelled funds' change of their holdings given their ESG score and identification to either Article 9, Article 8 or Article 6 funds.

The chapter provides empirical evidence on the effect of the EU SFDR on portfolio management and investment practices. The study finds evidence that the SFDR effect on fund flow varies depending on the methodological approach. The evidence in this chapter indicates that that there are significant inflows into Article 6 funds, weak but significant inflows into Article 8 funds relative to their size, and insignificant inflows into Article 9 funds. Consistent with this finding, the event study of flows suggests a significant inflow into Article 6 and Article 8 funds but not Article 9 funds. Moreover, the DiD panel regression shows no evidence of a difference between the mean flows into Article 8 and Article 6 funds. However, after controlling for fund attributes using PSM, the results show higher mean flows into Article 9 funds than their matched peers of Article 8 and Article 6. Overall, although panel, DiD, and event study of flows analyses show limited or no increased inflows to Article 9 funds, PSM results indicate that these funds remained the most attractive to investors. Furthermore, the findings suggest that, after controlling for other fund and firm's characteristics, only Article 8 fund managers increased their exposure into firms with medium and high Refinitiv ESG score, while Article 9 and 6 managers did not change their positions.

Chapter 3 contributes to the literature on the financial implications of ESG investing. The findings show US ESG active performance is not statistically different from their matched US conventional peers which is consistent with Renneboog et al. (2008a). Conversely, in the EU market, EU ESG active funds outperform their matched conventional peers. Additionally, US ESG passive funds underperform their matched conventional peers while there is no evidence of a difference between EU conventional and ESG passive funds. Furthermore, Chapter 3 complements the literature on understanding the preferences underlying ESG investments. Several studies find that investors have high sensitivity to past performance, particularly the best performing funds. However, this sensitivity is less than the flow-performance sensitivity for conventional funds (Bollen 2007; Benson and Humphrey 2008; Renneboog et al. 2011; Białkowski and Starks 2016; Ridel and Smeets 2017; El Ghoul and Karoui 2021; Humphrey et al. 2021), documented for a sample of monthly observations, as opposed to prior literature which focuses on annual (Bollen 2007) and quarterly observations (Benson and Humphrey 2008). Moreover, this chapter extends the literature by examining the flow sensitivity to the past 36-month of monthly raw returns and Carhart (1997) four-factor alpha for both ESG and conventional funds. Finally, this study extends existing literature by providing additional evidence on fund performance and flow-performance sensitivity across two dimensions (a) management styles (active vs. passive) and (b) regions (US and EU). Therefore, this Chapter addresses three main research questions. (1) Did ESG investing command a premium. (2) Did this premium vary across regions? (3) Did ESG investors' investment behaviour differ from those of conventional investors, across investment styles and regions?

The findings suggest that during the sample period (January 1996 to December 2022) the US ESG active funds' performance is not statistically different from that of their matched conventional peers, in line with prior literature (Statman 2000; Bauer et al. 2005; Geczy et al. 2005; Renneboog et al. 2008a; Renneboog et al. 2008b), whereas the

EU ESG active funds outperform their conventional peers. The performance difference is traced to the different portfolio compositions across the two regions. Specifically, US ESG active funds are skewed towards growth stocks, less risky assets, and follow momentum reversal more strongly, as compared to the US conventional funds. On the contrary, EU ESG active funds are skewed towards smaller capitalisation, growth stocks, with weaker operating profitability and follow momentum more strongly than their conventional peers. Additionally, the variations of the findings between the unmatched and matched samples confirm that age, load fees, and portfolio composition affect fund performance. On the other hand, US ESG passive funds underperformed their conventional peers in both the matched and the unmatched samples. In contrast to the above evidence, European ESG active funds outperform their conventional active peers in both the matched and unmatched samples. Yet, there is no difference in risk-adjusted returns between ESG and conventional passive funds. These findings suggest that the outperformance of ESG active funds in the EU might be attributable to a superiority of ESG active management or may be driven by regulatory and tax reasons.

The findings suggest a difference in the flow-performance sensitivity of ESG and conventional funds, both active and passive, across the US and EU markets, consistent with Renneboog et al. (2011). For example, over the short- term, matched conventional active funds are negatively sensitive to the lowest 20% performers and positively sensitive to the mid performers based on risk-adjusted alpha. In the EU, both matched conventional and ESG active funds show no flow sensitivity to the past 12-month risk-adjusted alpha. Over the long- horizon, US matched conventional active investors penalise funds that underperform the benchmark, US ESG active funds exhibit no flow-performance sensitivity. In the EU, matched conventional funds are positively sensitive to underperformers, whereas ESG active funds are negatively sensitive to underperformers.

In the passive fund space, over the short-term, US matched conventional passive investors show no sensitivity to past risk-adjusted alpha, while ESG passive investors reward penalise low-ranked funds based on C-4 alpha. In the EU, matched conventional passive investors penalise outperformers (C-4) alpha, whereas ESG passive investors show no sensitivity to past C-4 alpha. Over the long-term, both ESG and matched conventional funds show no sensitivity to the 36- months past performance. One exception is that US ESG passive investors are positively sensitive to mid-performers based on C-4 alpha. Over the long term, matched conventional passive investors reward low-ranked funds and penalise the mid-ranked funds based on raw return, while ESG passive investors reward mid performers based on C-4 alpha. However, these results should be interpreted with caution as they may lead to a biased estimate, limited generalisability, and challenge the validity of the findings (Faber and Fonseca 2014).

In addition to the matched sample analysis, the results from the unmatched conventional funds, both active and passive, highlight some important distinctions. The observed variations can largely be attributed to differences in fund age, load fees, and portfolio composition. Furthermore, the evidence suggests that EU ESG investors, whether active or passive, place greater emphasis on the non-financial attributes of ESG investments compared to their US counterparts, while US conventional active investors appear to exhibit a higher degree of investment sophistication than their EU peers.

Chapter 4 contributes to three strands of literature. First, it extends the empirical literature on the impact of ambiguity on asset prices (e.g. Anderson et al. 2009; Antoniou et al. 2015; Anantanasuwong et al. 2024) by examining this relationship in the context of ESG investing. Second, it adds to the fund flow–performance sensitivity literature by providing new evidence on how ESG and conventional investors respond to past performance, highlighting the role of ambiguity aversion across management styles and across regions (US and EU). Finally, it contributes to the growing body of work on ESG rating divergence and its implications for asset pricing (Gibson-Brandon et al. 2021; Avramov et al. 2022; Luo et al. 2023). Hence, this Chapteranswers the following research question: did ESG investors respond differently than conventional investors to ambiguity signalled by the worst performance?

For passive investors, the evidence suggests that US ESG investors have become more sensitive to poor past performance, measured by four-factor alpha, though only at a weak level of significance. By contrast, US matched conventional passive funds show no sensitivity to minimum performance, consistent with results from the unmatched sample. In Europe, ESG passive funds also display no reaction to the worst performance, whereas their matched conventional counterparts are averse to ambiguity when measured by risk-adjusted alpha. This is inconsistent with the unmatched sample, where EU conventional passive investors show no sensitivity to the worst performance. However, this finding should be interpreted with cautious due to the limited sample size of US ESG index funds.

Overall, the evidence suggests that US and EU ESG active investors derive more utility from the non-financial rather than the financial aspect of investment, as indicated by their neutral response to ambiguity (minimum performance). Conversely, US ESG passive investors behave as if ESG is financially material. Specifically, they are averse to the worst performance measure and hence, they are, evidently, concerned about the financial aspect of their investment. This heterogeneity in ambiguity aversion among ESG active and passive investors could theoretically affect the pricing of ESG assets given that ambiguity seekers and neutral investors determine the asset prices, as opposed to ambiguity averse investors (Anantanasuwong et al. 2024).

5.2 Research implications and limitations

This thesis provides implications for academics, asset pricing, asset managers, and regulators. About academic research, this research contributes to the expanding body of literature on socially responsible investment or ESG investing, particularly the preference of investors to allocate their capital into ESG mutual, and the effect of external sustainability rating and policy intervention on investor and fund manager behaviour. In essence, the overall findings from the thesis imply that investors behaviour is not fostering the rise in ESG investment as it should be. Politicians and different cultures play a crucial role in ESG investment.

Chapter 2 speaks to asset managers to change their funds' positions in firms to better reflect their ESG funds' objectives and meet the regulatory requirement. Chapters 3 and 4 provide implications for asset managers to form ESG portfolios with long-term goals while emphasizing ESG goals over short-term financial return, especially in the US. In the EU, asset managers may create portfolios that differentiate investors preference over the short-term. Additionally, asset managers would better differentiate between conventional and ESG funds through marketing.

However, the thesis presents some limitations. For example, the limited access to other firms' ESG score than Refinitiv limited chapter 2 to examine fund managers response based on different ESG rating from different providers. Also, the chapter could employ qualitative methodology like survey and interviews as a robust to better understand fund managers' response to the announcement of the SFDR regulation. The chapter could also investigate whether SFDR has affected other funds domiciled in non-European countries. As the regulation is still progressing, further research would investigate the implications of SFDR level II and the PAI for allocating capital for the transition towards a green economy through regulated investment management and ESG portfolio investing. Chapter 3 compares the performance and flow-performance of conventional and ESG funds, whether active or passive. The sample excludes Exchange-traded funds (ETFs) because of their different trading structure. Another limitation is evaluating ESG funds based on general market benchmarks (CAPM and Fama-French factor models) rather than ESG-focused benchmarks. This limitation is due to the limited access to such data. Finally, Chapter 4 is focused on the minimum rank to examine the ambiguity aversion. Further research could examine it using different measure such as measure developed by Brenner and Izhakian (2018). This research did not use this measure because of limited availability of intraday data. A further limitation of chapters 3 and 4 is that the small sample of 19 US ESG index funds may produce biased estimates, constrain generalizability, and undermine the robustness of the results (Faber and Fonseca, 2014).

Appendices

Appendix 2A

Table 2A.1: Investor reaction to the EU SFDR Level 1 regulation - Propensity score matching – Normalised flow

The table reports the difference in net normalised flows between the treatment and control groups from the nearest-neighbour matching across three different settings that compare a treatment vs. a control group: Article 9 vs. Article 6, Article 8 vs. Article 6; and Article 9 vs. Article 8. Funds are matched within their SFDR-labelled group based on flow, return, age, four-factor alpha, and log of total net assets as of December 2022. The difference in SFDR-labelled fund flow is calculated over six-time intervals relative to March 2021 (the application of SFDR Level 1): six months and three months before March 2021(columns 1 and 2) and for the three, six, nine, and 12 months starting from March 2021 (columns 3 to 6). *t*-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Normalised flow					
	Months					
	-6 - 0	**-3 - 0**	**0 - 3**	**0 - 6**	**0 - 9**	**0 - 12**
Article 9 vs. Article 6	**0.289*** **	**0.338*** **	0.157	**0.128*** **	**0.168*** **	**0.127*** **
	(5.21)	(4.24)	(1.75)	(2.34)	(4.21)	(3.72)
Article 8 vs. Article 6	0.021	0.008	0.05	0.046	0.03	0.018
	(0.87)	(0.23)	(1.22)	(1.80)	(1.64)	(1.09)
Article 9 vs. Article 8	**0.277*** **	**0.301*** **	0.148	0.058	**0.094*** **	0.056
	(5.20)	(4.04)	(1.73)	(1.12)	(2.51)	(1.73)

Table 2A.2: Investor reaction to the EU SFDR Level 1 regulation - Event study of flows – Normalised flow

This table reports the average standardised abnormal flow $\widehat{ASAF_t}$ (Panel A), averaged across EU funds within the same SFDR-label group (Articles 9, 8, or 6) for the 6 months after the application of the SFDR Level 1 (t=[0;6]). Standardised abnormal flow in month t is calculated as the difference between the fund actual flow and the expected flow, standardised by the estimated predicted error (RMSE) (Dodd and Warner 1983). Expected flow is estimated for each fund i in each SFDR-label category based on a time-series benchmark regression where the fund flow at month t is regressed on average flow at time t to funds in the same style group (blended, value, and growth), one-month lagged return, flow, percentage change in the Carhart (1997) four-factor alpha, percentage change in the Carhart (1997) four-factor alpha squared. Panel B reports the same tests for the average cumulative standardised abnormal flow $\widehat{ACSAF_t}$. The cumulative standardised abnormal flow for each fund is calculated by summing the standardised abnormal flow from event time 0 to t and then dividing it by the square root of the number of event times used in the cumulation. Then, the average of $\widehat{ASAF_t}$ and $\widehat{ACSAF_t}$ across N funds is calculated within each event window and for each fund category (Articles 9, 8, and 6). The table report the *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Average standardised Abnormal Normalised Flow for the SFDR labelled funds									
	Article 9			Article 8			Article 6		
Event month	$\widehat{ASAF_t}$	**t-stat**	**%> 0**	$\widehat{ASAF_t}$	**t-stat**	**%> 0**	$\widehat{ASAF_t}$	**t-stat**	**%> 0**
0	0.217	(2.38)	60.34	**0.180*****	(6.37)	62.22	**0.134*****	(3.80)	61.34
1	-0.028	(-0.30)	58.47	0.075	(2.62)	61.91	0.059	(1.67)	58.13
2	-0.004	(-0.04)	55.93	0.037	(1.28)	57.96	0.035	(0.99)	58.47
3	0.072	(0.78)	64.41	**0.095*****	(3.32)	61.44	0.055	(1.57)	59.75
4	-0.030	(-0.32)	54.31	-0.046	(-1.60)	52.77	-0.027	(-0.76)	56.39
5	0.155	(1.72)	60.83	0.055	(1.94)	57.20	0.040	(1.14)	56.76
6	-0.078	(-0.86)	53.72	0.026	(0.93)	54.68	0.082	(2.34)	60.29

Panel B: Average cumulative standardised Abnormal Normalised Flow for the SFDR labelled funds									
	Article 9			Article 8			Article 6		
Event month	$\widehat{ACSAF_t}$	**t-stat**	**%> 0**	$\widehat{ACSAF_t}$	**t-stat**	**%> 0**	$\widehat{ACSAF_{t\,t}}$	**t-stat**	**%> 0**
0	0.080	(2.40)	60.34	**0.066*****	(6.34)	62.22	**3.797*****	(3.82)	61.34
1	0.070	(1.58)	65.25	**0.093*****	(8.27)	65.54	**1.672*****	(5.19)	61.29
2	0.056	(1.22)	57.63	**0.109*****	(8.88)	65.85	**0.994*****	(5.84)	62.74
3	0.101	(2.19)	58.47	**0.146*****	(11.23)	67.76	**1.565*****	(6.83)	65.00
4	0.070	(1.61)	56.90	**0.126*****	(9.29)	63.78	**-0.756*****	(6.02)	63.28
5	**0.141*****	(3.25)	61.67	**0.146*****	(10.19)	65.78	**1.141*****	(6.76)	63.88
6	0.112	(2.96)	63.64	**0.159*****	(10.67)	64.11	**2.342*****	(7.90)	64.22

Appendix 3A

Table 3A.1: Fund performance and risk exposure – Active vs. passive

This table reports the estimation from three risk models (CAPM, C-4, and FF6) from January 1996 to December 2022. Reported are the OLS estimates for conventional and ESG funds, both active and passive and within two different regions (US and EU). Difference is calculated by subtracting the mean of passive from active fund estimated alphas and risk factors. Panel A shows the results for the Capital Asset Pricing Model (CAPM). Panel B shows the results for the four-factor model which incorporates the size (*SMB*), value (*HML*), and momentum (*MOM*) factors to the CAPM model. Panel C shows the results for the six-factor model which augment the operating profitability (*RMW)* and the investment (*CMA)* factors to the four-factor model. For each fund, regression is estimated with Newey-West robust standard errors. *T-statistics (in parentheses)* calculated with two-tailed student t-test. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Conventional						ESG					
	US			EU			US			EU		
	Active	Passive	Difference	Active	Passive	Difference	Active	Passive	Difference	Active	Passive	Difference
Panel A: CAPM												
α_1	-0.010	-0.005	**-0.005*****	-0.016	-0.005	**-0.011*****	-0.012	-0.008	**-0.004*****	-0.014	-0.005	**-0.009*****
			(-11.96)			(-17.98)			(-3.32)			(-14.82)
β_M	0.818	0.957	**-0.139*****	0.768	0.909	**-0.142*****	0.886	0.966	-0.081	0.822	0.910	**-0.089*****
			(-5.80)			(-6.98)			(-1.40)			(-3.73)
Panel B: Four-Factor Model												
α_4	-0.010	-0.005	**-0.005*****	-0.017	-0.005	-0.012***	-0.012	-0.008	-0.004***	-0.015	-0.005	**-0.010*****
			(-12.38)			(-18.66)			(-3.42)			(-15.53)
β_M	0.794	0.934	**-0.139*****	0.780	0.917	-0.137***	0.866	0.949	-0.083	0.837	0.916	**-0.078*****
			(-6.20)			(-7.06)			(-1.50)			(-3.35)
β_{SMB}	0.085	0.036	**0.049****	0.233	0.118	0.115***	0.068	-0.035	0.102*	0.255	0.138	**0.117*****
			(2.35)			(5.21)			(1.84)			(4.39)
β_{HML}	0.061	0.067	-0.007	-0.038	-0.143	0.105***	0.008	0.029	-0.021	-0.094	-0.146	**0.052****
			(-0.35)			(6.18)			(-0.46)			(2.54)
β_{MOM}	-0.027	-0.045	**0.018****	0.051	-0.016	0.067***	-0.023	-0.061	0.038*	0.033	-0.020	**0.053*****
			(2.50)			(8.09)			(1.86)			(5.53)
Panel C: Six-Factor Model												
α_6	-0.010	-0.005	**-0.005*****	-0.017	-0.005	**-0.012*****	-0.012	-0.008	**-0.004*****	-0.015	-0.005	**-0.010*****
			(-12.10)			(-18.51)			(-3.28)			(-15.47)
β_M	0.792	0.934	**-0.141*****	0.781	0.903	**-0.122*****	0.861	0.945	-0.084	0.828	0.901	**-0.073*****
			(-6.40)			(-6.74)			(-1.55)			(-3.38)
β_{SMB}	0.105	0.062	**0.043****	0.217	0.088	**0.129*****	0.091	0.001	0.090	0.229	0.107	**0.122*****
			(2.12)			(6.02)			(1.65)			(4.72)
β_{HML}	0.041	0.039	0.002	-0.102	-0.116	0.014	0.002	0.012	-0.010	-0.106	-0.122	0.016
			(0.13)			(0.61)			(-0.28)			(0.63)
β_{MOM}	-0.025	-0.045	**0.019*****	0.053	0.000	**0.053*****	-0.018	-0.057	**0.039***	0.045	-0.003	**0.047*****
			(2.60)			(6.55)			(1.82)			(5.18)
β_{RMW}	0.021	0.031	-0.010	-0.150	-0.093	**-0.058****	0.039	0.051	-0.012	-0.116	-0.101	-0.015
			(-0.68)			(-2.25)			(-0.30)			(-0.50)
β_{CMA}	-0.009	0.028	**-0.037*****	-0.043	-0.158	**0.115*****	-0.039	0.029	**-0.068***	-0.125	-0.159	0.034
			(-2.99)			(4.63)			(-1.92)			(1.09)

Table 3A.2: Flow persistence – 24 months

This table reports funds' flow statistics for conventional and ESG funds, both active and passive and within two different re gions (US and EU). First, each month, the funds were ranked and divided into five quintile portfolios based on their last month raw return or their past 60-month four-factor model alphas. The low quintile contains the funds with the lowest 20% and the high contains the highest 20% performed funds. Then, the funds raw return or four-factor alphas are averaged over 24-month. The High minus Low portfolio is formed by subtracting the average monthly flow of the low from the high portfolio, according to return or four-factor alpha. Two-tailed t-stat is calculated on the time series flow of the high-minus low portfolio. ∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% level, respectively.

	Mean flow											
	Raw return						**Four-factor alpha**					
	Low quintile		High quintile		High minus Low		Low quintile		High quintile		High minus Low	
	Mean	t-stat	Mean	t-stat	Mean	t-stat	Mean	t-stat	Mean	t-stat	Mean	t-stat
Panel A: US												
Conventional active	**-0.005*****	(-3.68)	**0.025*** **	(8.76)	**0.030*****	(9.51)	**-0.011*****	(-26.66)	**0.009*****	(17.85)	**0.021*****	(30.65)
ESG active	**-0.010*****	(-2.80)	**0.022*****	(7.97)	**0.033*****	(7.06)	**-0.010*****	(-10.64)	**0.008*****	(6.16)	**0.018*****	(11.09)
Conventional passive	-0.002	(-0.24)	0.003	(0.58)	0.005	(0.52)	0.000	(0.10)	0.001	(0.55)	0.001	(0.39)
ESG passive	0.002	(1.150)	**0.016*****	(6.93)	**0.014*****	(4.27)	**0.005****	(2.26)	**0.012*****	(4.50)	**0.007****	(2.12)
Panel B: EU												
Conventional active	-0.004	(-1.46)	**0.006*****	(3.29)	**0.01*****	(2.97)	**-0.004*****	(-3.62)	**0.003*****	(2.83)	**0.008*****	(4.56)
ESG active	0.003	(1.63)	**0.007*****	(3.66)	**0.004***	(1.71)	**-0.004*****	(-4.07)	**0.004*****	(4.42)	**0.008*****	(6.00)
Conventional passive	**0.005****	(2.14)	**0.007*****	(4.51)	0.002	(0.61)	0.001	(0.40)	0.001	(0.42)	0.000	(0.06)
ESG passive	**0.005***	(1.66)	**0.006*****	(3.42)	0.001	(0.16)	0.001	(0.55)	-0.001	(-0.43)	-0.002	(-0.69)

Table 3A.3: Difference in fund flows – 24 months

This table compares the mean flows of the lowest 20% and the highest 20% performed funds' portfolios of conventional and ESG funds across the US and EU. First, each month, the funds are ranked and divided into five quintile portfolios based on their last month raw return or their past 60-month four-factor model alpha. Each month, the funds' raw return or four-factor alpha are averaged over 24-month. Two portfolios were formed for each region. One is a portfolio of the lowest 20% performed conventional and ESG funds and the other is a portfolio of the highest 20% performed conventional and ESG funds, according to their average monthly return or past 36-month four-factor alpha. Difference is a portfolio constructed by subtracting the average monthly flow of low (high) ESG fund from low (high) conventional fund, within both regions. Two-tailed t-stat is calculated on the time series flow low or high portfolio. ∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% level, respectively.

	Active				**Passive**			
	Mean flow							
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
	Difference	t-stat	Difference	t-stat	Difference	t-stat	Difference	t-stat
Panel A: US								
Low: Conv - ESG	0.005	(1.40)	**-0.002***	(-1.68)	-0.004	(-0.40)	-0.005	(-1.79)
High: Conv - ESG	0.002	(0.59)	0.001	(0.82)	-0.013	(-1.43)	**-0.011****	(-2.70)
Panel B: EU								
Low: Conv - ESG	**-0.007****	(-2.04)	-0.0004	(-0.28)	0.000	(0.04)	-0.001	(-0.18)
High: Conv - ESG	-0.001	(-0.39)	-0.001	(-0.67)	0.001	(0.58)	0.002	(0.60)

Table 3A.4: Fund flow comparisons – 12 months, active vs. passive

This table compares the mean flows of the lowest 20% and the highest 20% performed funds' portfolios of active and passive funds across the US and EU. First, each month, the funds are ranked and divided into five quintile portfolios based on their last month raw return or their past 60-month four-factor model alpha. Each month, the funds' raw return or four-factor alpha are averaged over 12-month. Two portfolios were formed for each region. One is a portfolio of the lowest 20% performed conventional and ESG funds and the other is a portfolio of the highest 20% performed active and passive funds according to their average monthly return or past 36-month four-factor alpha. Difference is a portfolio constructed by subtracting the average monthly flow of low (high) passive fund from low (high) active fund, within both regions. Two-tailed t-stat is calculated on the time series flow low or high portfolio. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Conventional				**ESG**			
	Mean flow							
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
	Difference	t-stat	Difference	t-stat	Difference	t-stat	Difference	t-stat
Panel A: US								
Low: Active - Passive	0.004	(0.62)	**-0.011*** **	(-4.30)	**-0.012*** **	(-3.10)	**-0.012*** **	(-5.52)
High: Active - Passive	**0.016*** **	(3.58)	**0.009** **	(2.24)	**0.009* **	(1.72)	**-0.007* **	(-1.88)
Panel B: EU								
Low: Active - Passive	**-0.014*** **	(-2.98)	-0.002	(-0.77)	**-0.010** **	(-2.52)	-0.002	(-0.95)
High: Active - Passive	0.004	(1.13)	0.004	(1.27)	0.005	(1.26)	0.005	(1.61)

Table 3A.5: Fund flow comparisons – 24 months, active vs. passive

This table compares the mean flows of the lowest 20% and the highest 20% performed funds' portfolios of active and passive funds across the US and EU. First, each month, the funds are ranked and divided into five quintile portfolios based on their last month raw return or their past 60-month four-factor model alpha. Each month, the funds' raw return or four-factor alpha are averaged over 24-month. Two portfolios were formed for each region. One is a portfolio of the lowest 20% performed conventional and ESG funds and the other is a portfolio of the highest 20% performed active and passive funds according to their average monthly return or past 36-month four-factor alpha. Difference is a portfolio constructed by subtracting the average monthly flow of low (high) passive fund from low (high) active fund, within both regions. Two-tailed t-stat is calculated on the time series flow low or high portfolio. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Conventional				ESG			
	Mean flow							
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
	Difference	t-stat	Difference	t-stat	Difference	t-stat	Difference	t-stat
Panel A: US								
Low: Active - Passive	-0.003	(-0.48)	**-0.011*****	(-7.20)	**-0.013****	(-2.34)	**-0.015*****	(-7.22)
High: Active - Passive	**0.022*****	(3.74)	**0.008*****	(3.64)	0.007	(1.34)	-0.004	(-1.47)
Panel B: EU								
Low: Active - Passive	**-0.010****	(-2.26)	**-0.005****	(-2.28)	-0.002	(-0.79)	**-0.005****	(-2.04)
High: Active - Passive	-0.001	(-0.47)	0.002	(0.91)	0.001	(0.42)	**0.005****	(2.05)

Table 3A.6: Fund flow comparisons – 36 months, active vs. passive

This table compares the mean flows of the lowest 20% and the highest 20% performed funds' portfolios of active and passive funds across the US and EU. First, each month, the funds are ranked and divided into five quintile portfolios based on their last month raw return or their past 60-month four-factor model alpha. Each month, the funds' raw return or four-factor alpha are averaged over 36-month. Two portfolios were formed for each region. One is a portfolio of the lowest 20% performed conventional and ESG funds and the other is a portfolio of the highest 20% performed active and passive funds according to their average monthly return or past 36-month four-factor alpha. Difference is a portfolio constructed by subtracting the average monthly flow of low (high) passive fund from low (high) active fund, within both regions. Two-tailed t-stat is calculated on the time series flow low or high portfolio. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Conventional				**ESG**			
	Mean flow							
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
	Difference	t-stat	Difference	t-stat	Difference	t-stat	Difference	t-stat
Panel A: US								
Low: Active - Passive	-0.006	(-0.71)	**-0.010*****	(-4.45)	**-0.007***	(-1.73)	**-0.013*****	(-5.67)
High: Active - Passive	0.005	(1.42)	**0.004****	(2.48)	**0.014*****	(3.00)	0.004	(1.17)
Panel B: EU								
Low: Active - Passive	**-0.006****	(-2.20)	**-0.005***	(-1.79)	-0.004	(-1.36)	**-0.006****	(-1.97)
High: Active - Passive	0.001	(0.26)	-0.001	(-0.43)	0.003	(1.18)	0.001	(0.46)

Table 3A.7: Flow-performance sensitivity – 24 months, US

This table examines the flow-performance sensitivity of conventional and ESG active funds, in the US (Panel A), for a sample period ranges from January 1996 to December 2022. Performance is measured by raw return or past 60-month four-factor alpha. Funds' performance is ranked from zero to one according to their 24-month raw return within the same investment objective (Growth, Value, or Blend), or Carhart (1997) four-factor alpha. Then, the performance rank is classified into ranked into three-performance ranked portfolios. Low quintile portfolio representing the bottom 20% performed funds (Low). Mid quantile portfolio composes of the three middle 20% performed funds. The high quintile portfolio includes the top 20% performed funds. The control variables include one-month lagged: raw return, flow, log total net assets, return volatility, expense ratio, and current age. Panel B repeats the same analysis for conventional and ESG passive funds in the US. Reported are the time-series coefficients for main variables (Low, Mid, and High) and average time-series coefficients for control variables. *t-statistics* (in parentheses) are calculated with Newey-West robust standard errors. ∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% level, respectively. Reported are the time-series average coefficients and *t-statistics* (in parentheses) are calculated with Newey-West robust standard errors. ∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Active – US

	Conventional				**ESG**			
	raw return		Four-factor alpha		raw return		Four-factor alpha	
Low	**-0.049*****	-0.015	**-0.371*****	-0.160	-0.024	0.007	0.186	**0.267***
	(-2.62)	(-0.95)	(-4.17)	(-1.61)	(-1.00)	(0.31)	(1.28)	(1.70)
Mid	**0.043****	0.002	**0.321*****	0.072	0.008	-0.003	**-0.318****	-0.273
	(2.20)	(0.13)	(3.69)	(0.70)	(0.33)	(-0.14)	(-2.22)	(-1.37)
High	**0.027*****	0.005	**0.147****	0.100	**0.027*****	**0.018****	**0.399*****	**0.347****
	(4.97)	(0.97)	(2.14)	(1.38)	(3.76)	(2.36)	(4.93)	(2.00)
Lag return		**0.023*****		**0.023*****		**0.041*****		0.016
		(2.78)		(3.07)		(3.35)		(1.25)
Lag flow		**0.308*****		**0.222*****		**0.224*****		0.040
		(4.78)		(3.23)		(3.28)		(0.38)
Lag net assets		-0.003		**-0.003***		-0.006		-0.004
		(-0.82)		(-1.74)		(-1.54)		(-0.94)
Lag return volatility		**-0.075*****		**-0.038***		-0.013		-0.015
		(-2.62)		(-1.77)		(-0.41)		(-0.35)
Lag expense ratio		0.225		**0.277****		0.104		0.194
		(1.54)		(2.25)		(0.69)		(1.60)
Age		**-0.001***		0.000		0.000		0.000
		(-1.67)		(-0.51)		(-0.66)		(0.15)
Intercept	-0.001	0.050	**-0.008*****	0.047	0.001	**0.112***	**-0.006*****	0.049
	(-0.77)	(0.63)	(-5.49)	(1.14)	(0.61)	(1.78)	(-3.07)	(0.70)
R^2	0.062	0.567	0.293	0.463	0.048	0.229	0.081	0.122

Table 3A.7: continued								
Panel B: Passive – US								
	Conventional				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low	-0.025	0.008	-0.004	-0.142	0.034	0.006	**-0.314***	**-0.699***
	(-0.91)	(0.26)	(-0.02)	(-0.68)	(0.90)	(0.12)	(-1.67)	(-1.65)
Mid	0.024	0.016	**0.611*****	-0.024	0.068	0.026	0.031	0.748
	(0.86)	(0.62)	(3.65)	(-0.12)	(1.62)	(0.53)	(0.09)	(0.94)
High	**0.031*****	**0.029*****	**-0.382***	**-0.466****	**0.040***	0.003	-0.116	-0.287
	(2.64)	(2.60)	(-1.79)	(-2.57)	(1.81)	(0.12)	(-0.40)	(-0.17)
Lag return		-0.009		0.012		0.021		**0.075***
		(-0.52)		(0.74)		(0.72)		(1.76)
Lag flow		**0.161*****		0.025		0.192		0.146
		(2.72)		(0.43)		(1.27)		(1.50)
Lag net assets		**-0.015*****		-0.004		-0.007		-0.006
		(-3.2)		(-1.48)		(-0.69)		(-0.62)
Lag return volatility		-0.053		-0.055		-0.120		-0.233
		(-0.97)		(-0.91)		(-0.74)		(-1.57)
Lag expense ratio		**-1.200*****		0.258		-0.084		-0.097
		(-4.50)		(0.65)		(-0.91)		(-1.10)
Age		**-0.001***		**-0.002*****		0.002		0.002
		(-1.77)		(-2.97)		(0.63)		(1.23)
Intercept	0.001	**0.35*****	0.004	0.099	**0.008***	0.130	0.002	0.100
	(0.20)	(3.71)	(1.10)	(1.52)	(1.65)	(0.85)	(1.06)	(0.65)
R^2	0.032	0.286	0.037	0.106	0.030	0.065	0.014	0.099

Table 3A.8: Flow-performance sensitivity – 24 months, EU

This table examines the flow-performance sensitivity of conventional and ESG active funds, in the EU (Panel A), for a sample period ranges from January 1996 to December 2022. Performance is measured by raw return or past 60-month four-factor alpha. Funds' performance is ranked from zero to one according to their 24-month raw return within the same investment objective (Growth, Value, or Blend), or Carhart (1997) four-factor alpha. Then, the performance rank is classified into ranked into three-performance ranked portfolios. Low quintile portfolio representing the bottom 20% performed funds (Low). Mid quantile portfolio composes of the three middle 20% performed funds. The high quintile portfolio includes the top 20% performed funds. The control variables include one-month lagged: raw return, flow, log total net assets, return volatility, expense ratio, and current age. Panel B repeats the same analysis for conventional and ESG passive funds in the EU. Reported are the time-series average coefficients and *t-statistics* (in parentheses) are calculated with Newey-West robust standard errors. ∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Active - EU	**Conventional**				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low	-0.009	0.011	-0.299	-0.087	0.002	0.021	-0.300	-0.047
	(-0.44)	(0.34)	(-1.21)	(-0.29)	(0.12)	(0.87)	(-1.55)	(-0.13)
Mid	**0.085***	0.021	-0.024	-0.119	0.014	-0.033	0.066	-0.016
	(1.91)	(0.48)	(-0.18)	(-0.88)	(0.54)	(-1.33)	(0.74)	(-0.10)
High	0.010	-0.011	0.079	0.283	0.009	0.001	0.036	0.068
	(1.12)	(-1.18)	(0.53)	(1.40)	(1.51)	(0.11)	(0.47)	(0.42)
Lag return		**0.038***		0.027		0.008		0.011
		(1.74)		(1.22)		(0.61)		(1.04)
Lag flow		0.145		-0.121		**0.346*****		0.106
		(0.92)		(-0.94)		(5.21)		(0.97)
Lag net assets		0.001		-0.007		-0.002		-0.004
		(0.25)		(-1.11)		(-0.64)		(-0.99)
Lag return volatility		-0.080		0.049		-0.029		0.057
		(-1.12)		(0.73)		(-0.72)		(1.56)
Lag expense ratio		**-0.269****		0.037		**-0.329*****		-0.029
		(-2.45)		(0.28)		(-2.90)		(-0.34)
Age		0.000		0.000		0.000		0.001
		(-0.38)		(0.29)		(-0.14)		(1.51)
Intercept	0.000	0.025	**-0.006*****	0.121	**0.003****	**0.079***	**-0.005****	0.061
	(-0.03)	(0.39)	(-2.71)	(0.91)	(2.12)	(1.66)	(-2.33)	(0.80)
R^2	0.022	0.141	0.043	0.066	0.010	0.243	0.056	0.073

Table 3A.8: continued								
Panel B: Passive - EU								
	Conventional				**ESG**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low	0.039	0.021	0.214	-0.006	0.029	0.053	0.192	-0.083
	(0.91)	(0.34)	(1.09)	(-0.02)	(0.65)	(0.92)	(0.98)	(-0.27)
Mid	**-0.084****	**-0.096*****	-0.082	-0.095	**-0.087*****	**-0.093*****	-0.078	0.028
	(-2.49)	(-3.12)	(-0.59)	(-0.47)	(-2.66)	(-2.91)	(-0.59)	(0.14)
High	0.012	0.004	0.087	-0.086	0.008	0.004	0.080	-0.070
	(0.91)	(0.32)	(1.25)	(-0.78)	(0.63)	(0.28)	(1.12)	(-0.65)
Lag return		0.010		**0.034***		0.032		0.032
		(0.5)		(1.67)		(1.36)		(1.46)
Lag flow		0.048		0.003		0.030		0.001
		(0.31)		(0.05)		(0.49)		(0.02)
Lag net assets		0.000		**-0.010****		0.001		**-0.009****
		(0.01)		(-2.32)		(0.20)		(-2.01)
Lag return volatility		-0.007		0.022		0.048		0.080
		(-0.08)		(0.31)		(0.61)		(1.08)
Lag expense ratio		0.016		0.130		0.059		0.116
		(0.08)		(0.88)		(0.48)		(0.87)
Age		-0.001		**0.004****		-0.001		**0.004****
		(-0.53)		(2.29)		(-0.37)		(2.22)
Intercept	**0.009*****	0.018	0.003	**0.112***	**0.009*****	-0.004	0.003	0.088
	(3.25)	(0.30)	(0.72)	(1.66)	(2.86)	(-0.07)	(0.79)	(1.26)
R^2	0.027	0.056	0.013	0.064	0.024	0.048	0.010	0.055

Table 3A.9: Fund performance and risk exposure – matched active vs. passive

This table reports the estimation from three risk models (CAPM, C-4, and FF6) from January 1996 to December 2022. Reported are the OLS estimates for conventional and ESG funds, both active and passive and within two different regions (US and EU). Difference is calculated by subtracting the mean of passive from matched active fund estimated alphas and risk factors. Panel A shows the results for the Capital Asset Pricing Model (CAPM) when each monthly observation of ESG fund is matched to monthly observation of three conventional funds where the match is based on age size and CAPM market risk factor. Panel B shows the results for the four-factor model which incorporates the size (*SMB*), value (*HML*), and momentum (*MOM*) factors to the CAPM model when each monthly observation of ESG fund is matched to monthly observation of three conventional funds where the match is based on age size and four-factor model's risk factors. Panel C shows the results for the six-factor model which augment the operating profitability (*RMW*) and the investment (*CMA*) factors to the four-factor model when each monthly observation of ESG fund is matched to monthly observation of three conventional funds where the match is based on age size and six-factor model's risk factors. For each fund, regression is estimated with Newey-West robust standard errors. *T-statistics (in parentheses)* calculated with two-tailed student t-test. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% level, respectively.

	Conventional						ESG					
	US			EU			US			EU		
	Active	Passive	Difference	Active	Passive	Difference	Active	Passive	Difference	Active	Passive	Difference
Panel A: CAPM												
α_1	-0.010	-0.005	**-0.005*****	-0.015	-0.005	**-0.010*****	-0.012	-0.008	**-0.004*****	-0.013	-0.005	**-0.008*****
			(-10.22)			(-11.38)			(-2.78)			(-10.48)
β_M	0.958	0.957	0.001	0.871	0.909	**-0.038***	0.961	0.966	-0.006	0.883	0.910	-0.028
			(0.04)			(-1.94)			(-0.19)			(-1.35)
Panel B: Four-Factor Model												
α_4	-0.010	-0.005	**-0.005*****	-0.015	-0.005	**-0.010*****	-0.010	-0.008	**-0.003***	-0.014	-0.005	**-0.0086*****
			(-11.28)			(-11.35)			(-1.99)			(-11.6)
β_M	0.908	0.934	-0.025	0.855	0.917	**-0.062*****	0.894	0.949	-0.054	0.899	0.916	-0.017
			(-1.52)			(-3.17)			(-1.4)			(-0.85)
β_{SMB}	0.092	0.036	**0.056****	0.243	0.118	**0.125*****	0.000	-0.035	0.035	0.250	0.138	**0.113*****
			(2.06)			(4.29)			(0.62)			(3.68)
β_{HML}	0.080	0.067	0.012	-0.077	-0.143	**0.066*****	-0.004	0.029	-0.033	-0.115	-0.146	0.032
			(0.66)			(2.95)			(-0.78)			(1.41)
β_{MOM}	-0.039	-0.045	0.006	0.028	-0.016	**0.044*****	-0.052	-0.061	0.009	0.020	-0.020	**0.040*****
			(0.72)			(5.0)			(0.43)			(3.82)
Panel C: Six-Factor Model												
α_6	-0.010	-0.005	**-0.005*****	-0.014	-0.005	**-0.009*****	-0.011	-0.008	**-0.003****	-0.013	-0.005	**-0.0078*****
			(-11.07)			(-10.5)			(-2.32)			(-11.18)
β_M	0.891	0.934	**-0.043*****	0.844	0.903	**-0.059*****	0.887	0.945	**-0.058***	0.877	0.901	-0.025
			(-2.87)			(-3.15)			(-1.74)			(-1.29)
β_{SMB}	0.117	0.062	**0.055****	0.209	0.088	**0.122*****	0.031	0.001	0.030	0.181	0.107	**0.074****
			(2.08)			(4.34)			(0.5)			(2.51)
β_{HML}	0.048	0.039	0.009	-0.087	-0.116	0.028	-0.008	0.012	-0.020	-0.120	-0.122	0.002
			(0.69)			(1.19)			(-0.67)			(0.07)
β_{MOM}	-0.037	-0.045	0.008	0.040	0.000	**0.040*****	-0.044	-0.057	0.013	0.020	-0.003	**0.022****
			(0.96)			(4.53)			(0.59)			(2.51)
β_{RMW}	0.041	0.031	0.010	-0.104	-0.093	-0.011	0.091	0.051	0.040	-0.099	-0.101	0.003
			(0.81)			(-0.35)			(1.26)			(0.08)
β_{CMA}	0.013	0.028	-0.015	-0.052	-0.158	**0.106*****	0.008	0.029	-0.021	-0.128	-0.159	0.032
			(-1.32)			(3.68)			(-0.62)			(1.03)

Table 3A.10: Difference in fund flows – 12 months, matched conventional vs. ESG

This table compares the mean flows of the lowest 20% and the highest 20% performed funds' portfolios of matched conventional to ESG funds across the US and EU. . Each monthly observation of ESG fund is matched to monthly observation of three conventional funds where the match is based on age size and four-factor model's risk factors. First, each month, the funds are ranked and divided into five quintile portfolios based on their last month raw return or their past 60-month four-factor model alpha. Each month, the funds' raw return or four-factor alpha are averaged over 12-month. Two portfolios were formed for each region. One is a portfolio of the lowest 20% performed conventional and ESG funds and the other is a portfolio of the highest 20% performed conventional and ESG funds, according to their average monthly return or past 36-month four-factor alpha. Difference is a portfolio constructed by subtracting the average monthly flow of low (high) ESG fund from low (high) conventional fund, within both regions. Two-tailed t-stat is calculated on the time series flow low or high portfolio. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Active				**Passive**			
	Mean flow							
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
	Difference	t-stat	Difference	t-stat	Difference	t-stat	Difference	t-stat
Panel A: US								
Low: Conv - ESG	**0.022*** **	(6.90)	-0.001	(-0.73)	0.017	(1.41)	-0.003	(-0.84)
High: Conv - ESG	**0.010*** **	(2.95)	0.002	(1.18)	0.005	(0.62)	**-0.011***	(-1.81)
Panel B: EU								
Low: Conv - ESG	**0.033*** **	(7.07)	**0.004** **	(1.98)	**0.015*** **	(3.47)	-0.006	(-1.63)
High: Conv - ESG	**0.015*** **	(3.33)	0.003	(1.36)	**0.016*** **	(4.13)	0.002	(0.35)

Table 3A.11: Difference in fund flows – 24-month -matched conventional vs. ESG

This table compares the mean flows of the lowest 20% and the highest 20% performed funds' portfolios of matched conventional to ESG funds across the US and EU. Each monthly observation of ESG fund is matched to monthly observation of three conventional funds where the match is based on age size and four-factor model's risk factors. First, each month, the funds are ranked and divided into five quintile portfolios based on their last month raw return or their past 60-month four-factor model alpha. Each month, the funds' raw return or four-factor alpha are averaged over 24-month. Two portfolios were formed for each region. One is a portfolio of the lowest 20% performed conventional and ESG funds and the other is a portfolio of the highest 20% performed conventional and ESG funds, according to their average monthly return or past 36-month four-factor alpha. Difference is a portfolio constructed by subtracting the average monthly flow of low (high) ESG fund from low (high) conventional fund, within both regions. Two-tailed t-stat is calculated on the time series flow low or high portfolio. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Active				Passive			
	Mean flow							
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
	Difference	t-stat	Difference	t-stat	Difference	t-stat	Difference	t-stat
Panel A: US								
Low: Conv - ESG	**0.030*****	(7.59)	-0.002	(-1.59)	0.010	(1.03)	**-0.009*****	(-2.69)
High: Conv - ESG	0.003	(0.82)	-0.001	(-0.42)	**-0.005***	(-1.74)	-0.006	(-1.16)
Panel B: EU								
Low: Conv - ESG	**0.029*****	(11.53)	**0.006***	(1.76)	**0.012*****	(3.28)	**-0.008***	(-1.77)
High: Conv - ESG	**0.018*****	(5.39)	-0.002	(-1.19)	**0.014*****	(4.22)	**0.007***	(1.78)

Table 3A.12: Difference in fund flows – 36 months, matched conventional vs. ESG

This table compares the mean flows of the lowest 20% and the highest 20% performed funds' portfolios of matched conventional to ESG funds across the US and EU. Each monthly observation of ESG fund is matched to monthly observation of three conventional funds where the match is based on age size and four-factor model's risk factors. First, each month, the funds are ranked and divided into five quintile portfolios based on their last month raw return or their past 60-month four-factor model alpha. Each month, the funds' raw return or four-factor alpha are averaged over 36-month. Two portfolios were formed for each region. One is a portfolio of the lowest 20% performed conventional and ESG funds and the other is a portfolio of the highest 20% performed conventional and ESG funds, according to their average monthly return or past 36-month four-factor alpha. Difference is a portfolio constructed by subtracting the average monthly flow of low (high) ESG fund from low (high) conventional fund, within both regions. Two-tailed t-stat is calculated on the time series flow low or high portfolio. ∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% level, respectively.

	Active				**Passive**			
	Mean flow							
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
	Difference	t-stat	Difference	t-stat	Difference	t-stat	Difference	t-stat
Panel A: US								
Low: Conv - ESG	**0.024*****	(8.55)	-0.001	(-0.62)	0.008	(0.87)	**-0.007****	(-2.03)
High: Conv - ESG	-0.004	(-1.51)	**-0.003****	(-2.10)	-0.002	(-0.37)	0.0004	(0.09)
Panel B: EU								
Low: Conv - ESG	**0.030*****	(13.01)	0.002	(0.58)	**0.011*****	(2.89)	-0.007	(-1.53)
High: Conv - ESG	**0.009****	(2.31)	0.001	(0.42)	**0.016*****	(2.98)	0.007	(1.41)

Table 3A.13: Difference in fund flows – 12 months, matched active vs. passive

This table compares the mean flows of the lowest 20% and the highest 20% performed funds' portfolios of matched active to passive funds across the US and EU. Each monthly observation of ESG fund is matched to monthly observation of three conventional funds where the match is based on age size and four-factor model's risk factors. First, each month, the funds are ranked and divided into five quintile portfolios based on their last month raw return or their past 60-month four-factor model alpha. Each month, the funds' raw return or four-factor alpha are averaged over 12-month. Two portfolios were formed for each region. One is a portfolio of the lowest 20% performed conventional and ESG funds and the other is a portfolio of the highest 20% performed active and passive funds, according to their average monthly return or past 36-month four-factor alpha. Difference is a portfolio constructed by subtracting the average monthly flow of low (high) passive fund from low (high) active fund, within both regions. Two-tailed t-stat is calculated on the time series flow low or high portfolio. ∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% level, respectively.

	Conventional				**ESG**			
	Mean flow							
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
	Difference	t-stat	Difference	t-stat	Difference	t-stat	Difference	t-stat
Panel A: US								
Low: Active - Passive	**0.023*****	(3.13)	**-0.008*****	(-3.10)	**0.010*****	(3.17)	**-0.013*****	(-3.87)
High: Active - Passive	**0.011****	(2.04)	**0.009****	(2.21)	**0.024*****	(3.30)	-0.005	(-1.21)
Panel B: EU								
Low: Active - Passive	**0.039*****	(8.38)	**0.010*****	(3.09)	**0.026*****	(7.03)	-0.0001	(-0.03)
High: Active - Passive	**0.007***	(1.72)	0.003	(0.65)	**0.011*****	(3.19)	**0.008***	(1.79)

Table 3A.14: Difference in fund flows – 24-month -matched active vs. passive

This table compares the mean flows of the lowest 20% and the highest 20% performed funds' portfolios of matched active to passive funds across the US and EU. Each monthly observation of ESG fund is matched to monthly observation of three conventional funds where the match is based on age size and four-factor model's risk factors. First, each month, the funds are ranked and divided into five quintile portfolios based on their last month raw return or their past 60-month four-factor model alpha. Each month, the funds' raw return or four-factor alpha are averaged over 24-month. Two portfolios were formed for each region. One is a portfolio of the lowest 20% performed conventional and ESG funds and the other is a portfolio of the highest 20% performed active and passive funds, according to their average monthly return or past 36-month four-factor alpha. Difference is a portfolio constructed by subtracting the average monthly flow of low (high) passive fund from low (high) active fund, within both regions. Two-tailed t-stat is calculated on the time series flow low or high portfolio. ∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% level, respectively.

	Conventional				**ESG**			
	Mean flow							
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
	Difference	t-stat	Difference	t-stat	Difference	t-stat	Difference	t-stat
Panel A : US								
Low: Active – Passive	**0.014***	(1.72)	**-0.008*****	(-4.44)	**0.007****	(2.51)	**-0.017*****	(-5.43)
High: Active – Passive	**0.017*****	(3.16)	**0.009*****	(3.65)	**0.008****	(2.33)	0.001	(0.13)
Panel B: EU								
Low: Active – Passive	**0.024*****	(7.42)	0.005	(1.37)	**0.018*****	(4.40)	-0.003	(-0.89)
High: Active – Passive	**0.006****	(2.36)	-0.001	(-0.27)	**0.012*****	(5.84)	0.005	(1.49)

Table 3A.15: Difference in fund flows – 36 months, matched active vs. passive

This table compares the mean flows of the lowest 20% and the highest 20% performed funds' portfolios of matched active to pas sivefunds across the US and EU. Each monthly observation of ESG fund is matched to monthly observation of three conventional funds where the match is based on age size and four-factor model's risk factors. First, each month, the funds are ranked and divided into five quintile portfolios based on their last month raw return or their past 60 -month four-factor model alpha. Each month, the funds' raw return or four-factor alpha are averaged over 36-month. Two portfolios were formed for each region. One is a portfolio of the lowest 20% performed conventional and ESG funds and the other is a portfolio of the highest 20% performed active and passive funds, according to their average monthly return or past 36-month four-factor alpha. Difference is a portfolio constructed by subtracting the average monthly flow of low (high) passive fund from low (high) active fund, within both regions. Two -tailed t-stat is calculated on the time series flow low or high portfolio. ∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% level, respectively.

	Conventional				**ESG**			
	Mean flow							
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
	Difference	t-stat	Difference	t-stat	Difference	t-stat	Difference	t-stat
Panel A : US								
Low: Active - Passive	0.010	(1.10)	**-0.008*****	(-3.33)	**0.009*****	(2.71)	**-0.013*****	(-3.77)
High: Active - Passive	0.004	(1.16)	**0.005****	(2.47)	**0.012****	(2.43)	**0.011****	(2.25)
Panel B: EU								
Low: Active - Passive	**0.026*****	(9.72)	0.001	(0.28)	**0.013*****	(5.00)	-0.003	(-1.04)
High: Active - Passive	0.006	(1.41)	-0.003	(-0.60)	**0.013*****	(3.82)	0.001	(0.18)

Table 3A.16: Flow-performance sensitivity – 24 months, US, matched

This table examines the flow-performance sensitivity of matched conventional and ESG, both active and passive funds, in the US (Panel A), for a sample period ranges from January 1996 to December 2022). Each monthly observation of ESG (passive) fund is matched to monthly observation of three conventional (active) funds where the match is based on age size and four-factor model's risk factors. Performance is measured by raw return or past 60-month four-factor alpha. Funds' performance is ranked from zero to one according to their 24-month raw return within the same investment objective (Growth, Value, or Blend), or Carhart (1997) four-factor alpha. Then, the performance rank is classified into ranked into three-performance ranked portfolios. Low quintile portfolio representing the bottom 20% performed funds (Low). Mid quantile portfolio composes of the three middle 20% performed funds. The high quintile portfolio includes the top 20% performed funds. The control variables include one-month lagged: raw return, flow, log total net assets, return volatility, expense ratio, and current age. Panel B repeats the same analysis for matched active and passive, both conventional and ESG funds in the US. Reported are the time-series average coefficients and *t-statistics* (in parentheses) are calculated with Newey-West robust standard errors. ∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: ESG match -US

	Conventional active				**Conventional passive**			
	Raw Return		Four-factor alpha		Raw Return		Four-factor alpha	
Low	-0.013	0.007	**-0.284****	**-0.252***	-0.019	0.003	-0.146	0.015
	(-1.33)	(0.54)	(-2.24)	(-1.79)	(-0.58)	(0.07)	(-0.75)	(0.06)
Mid	0.016	0.037	**0.227****	**0.232***	-0.057	-0.049	-0.234	-0.319
	(0.32)	(1.03)	(2.08)	(1.74)	(-0.62)	(-0.67)	(-0.76)	(-0.68)
High	0.021	0.004	**0.177****	0.039	0.007	0.023	0.926	0.487
	(1.04)	(0.26)	(2.28)	(0.47)	(0.24)	(0.72)	(1.42)	(0.80)
Lag return		**0.027****		**0.025****		0.024		-0.013
		(2.46)		(2.39)		(0.79)		(-0.48)
Lag flow		**0.128***		0.112		**0.096***		-0.002
		(1.83)		(1.60)		(1.72)		(-0.02)
Lag net assets		**-0.007***		**-0.006****		**-0.017****		-0.005
		(-1.83)		(-2.26)		(-2.36)		(-1.03)
Lag return volatility		**-0.100****		**-0.118*****		-0.032		-0.014
		(-2.66)		(-4.00)		(-0.32)		(-0.12)
Lag expense ratio		0.098		**0.549*****		-0.028		**-0.910****
		(0.62)		(3.28)		(-0.10)		(-2.34)
Age		**-0.001*****		**0.001***		0.001		0.000
		(-2.90)		(1.82)		(0.93)		(0.09)
Intercept	**0.013*****	**0.154***	**-0.008*****	0.049	**0.013*****	**0.349****	**-0.004****	0.137
	(7.79)	(1.90)	(-5.15)	(0.72)	(3.12)	(2.56)	(-2.23)	(1.45)
R^2	0.011	0.465	0.185	0.292	0.010	0.111	0.023	0.051

Table 3.A16: continued

Panel B: Passive match – US

	Conventional active				ESG active			
	Raw Return		Four-factor alpha		Raw Return		Four-factor alpha	
Low	-0.004	0.008	-0.138	-0.125	-0.027	**-0.070*** **	0.136	0.205
	(-0.46)	(0.72)	(-1.30)	(-1.04)	(-0.83)	(-2.69)	(1.31)	(0.90)
Mid	-0.046	-0.054	**0.466*** **	0.217	0.151	-0.060	0.118	-0.052
	(-0.91)	(-1.23)	(4.27)	(1.47)	(0.83)	(-1.13)	(0.48)	(-0.13)
High	**0.042** **	**0.042*** **	-0.055	0.013	-0.014	**0.115*** **	**0.401** **	0.291
	(2.57)	(2.99)	(-0.51)	(0.11)	(-0.19)	(3.40)	(2.09)	(0.90)
Lag return		**0.034*** **		**0.029** **		**0.057** **		-0.021
		(3.18)		(2.47)		(2.27)		(-0.86)
Lag flow		**0.185*** **		0.075		0.077		0.234
		(2.86)		(0.83)		(0.88)		(0.85)
Lag net assets		**-0.010*** **		0.003		-0.005		-0.006
		(-2.99)		(0.60)		(-0.99)		(-0.82)
Lag return volatility		**-0.112*** **		-0.022		**-0.116** **		**-0.128* **
		(-2.85)		(-0.45)		(-2.14)		(-1.67)
Lag expense ratio		**0.493*** **		0.129		**0.807*** **		-0.263
		(3.13)		(0.50)		(3.19)		(-0.65)
Age		0.001		**-0.001** **		0.002		-0.001
		(1.17)		(-2.13)		(1.60)		(-0.46)
Intercept	**0.012*** **	**0.174*** **	0.001	-0.059	**0.024*** **	0.025	-0.001	0.161
	(12.06)	(2.71)	(0.42)	(-0.52)	(5.04)	(0.27)	(-0.31)	(1.00)
R^2	0.022	0.459	0.143	0.198	0.013	0.268	0.050	0.122

Table 3A.17: Flow-performance sensitivity – 24 months, EU, matched

This table examines the flow-performance sensitivity of matched conventional and ESG, both active and passive funds, in the EU (Panel A), for a sample period ranges from January 1996 to December 2022). Each monthly observation of ESG (passive) fund is matched to monthly observation of three conventional (active) funds where the match is based on age size and four-factor model's risk factors. Performance is measured by raw return or past 60-month four-factor alpha. Funds' performance is ranked from zero to one according to their 24-month raw return within the same investment objective (Growth, Value, or Blend), or Carhart (1997) four-factor alpha. Then, the performance rank is classified into ranked into three-performance ranked portfolios. Low quintile portfolio representing the bottom 20% performed funds (Low). Mid quantile portfolio composes of the three middle 20% performed funds. The high quintile portfolio includes the top 20% performed funds. The control variables include one-month lagged: raw return, flow, log total net assets, return volatility, expense ratio, and current age. Panel B repeats the same analysis for matched active and passive, both conventional and ESG funds in the EU. Reported are the time-series average coefficients and *t-statistics* (in parentheses) are calculated with Newey-West robust standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: ESG match – EU

	Conventional active				**Conventional passive**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low	-0.036	0.046	0.174	0.138	0.038	**0.089****	0.419	0.028
	(-0.8)	(0.64)	(0.54)	(0.67)	(1.36)	(2.11)	(1.10)	(0.06)
Mid	0.075	0.273	0.229	0.003	-0.104	**-0.236***	0.350	0.078
	(0.29)	(1.36)	(0.92)	(0.02)	(-0.75)	(-1.71)	(1.40)	(0.31)
High	0.130	0.060	-0.136	-0.061	0.053	0.038	-0.236	**-0.706***
	(1.54)	(0.73)	(-0.88)	(-0.63)	(0.87)	(0.69)	(-0.61)	(-1.73)
Lag return		-0.020		**0.188*****		-0.003		0.014
		(-0.23)		(3.03)		(-0.10)		(0.36)
Lag flow		0.192		**0.218***		0.026		0.030
		(0.22)		(1.88)		(0.41)		(0.29)
Lag net assets		-0.024		**-0.017****		**-0.036*****		**-0.018****
		(-1.38)		(-2.14)		(-2.59)		(-1.96)
Lag return volatility		0.052		**-0.545*****		**-0.270***		**-0.553*****
		(0.14)		(-3.77)		(-1.76)		(-2.98)
Lag expense ratio		0.071		-0.315		0.096		-0.461
		(0.32)		(-0.83)		(0.15)		(-1.15)
Age		0.003		-0.001		**0.005***		**0.005***
		(1.25)		(-1.46)		(1.95)		(1.89)
Intercept	0.025	0.438	**0.014****	0.392**	**0.017*****	**0.627****	0.005	**0.325****
	(1.59)	(1.39)	(2.02)	(2.52)	(7.12)	(2.55)	(0.71)	(2.27)
R^2	0.016	0.202	0.011	0.321	0.016	0.123	0.028	0.100

Table 3.A17: continued

Panel B: Passive match – EU

	Conventional active				**ESG active**			
	Raw return		Four-factor alpha		Raw return		Four-factor alpha	
Low	0.020	**-0.075***	0.082	-0.031	**-0.034****	0.006	**-0.372****	-0.312
	(0.65)	(-1.85)	(0.16)	(-0.06)	(-2.37)	(0.28)	(-2.05)	(-0.78)
Mid	**-0.149****	**-0.231****	0.134	-0.088	**-0.106***	-0.039	0.170	0.116
	(-2.07)	(-2.38)	(0.45)	(-0.36)	(-1.91)	(-0.90)	(1.30)	(0.63)
High	-0.150	0.282	**-0.700****	**0.451***	**0.107*****	0.044	**-0.268***	-0.148
	(-1.33)	(1.46)	(-2.20)	(1.71)	(2.65)	(1.29)	(-1.75)	(-0.77)
Lag return		0.034		0.023		**0.047****		0.019
		(1.04)		(0.50)		(2.46)		(1.04)
Lag flow		0.032		**0.156***		**0.188*****		0.063
		(0.28)		(1.72)		(3.04)		(0.57)
Lag net assets		**-0.012****		-0.003		-0.005		0.006
		(-2.28)		(-0.30)		(-1.39)		(1.00)
Lag return volatility		-0.130		0.088		0.022		0.100
		(-1.28)		(0.56)		(0.33)		(1.54)
Lag expense ratio		0.124		0.037		**0.098***		0.092
		(1.04)		(0.19)		(1.87)		(1.30)
Age		0.001		-0.003		0.001		-0.002
		(0.80)		(-1.43)		(0.68)		(-1.49)
Intercept	**0.019*****	**0.200****	**0.013*****	0.073	**0.008***	0.080	0.001	-0.096
	(2.96)	(2.13)	(3.82)	(0.42)	(1.87)	(1.51)	(0.31)	(-0.97)
R^2	0.098	0.213	0.098	0.106	0.022	0.107	0.036	0.060

Table 3A.18: Flow-performance sensitivity – 12 months, US, FF5 and FF6

This table examines the flow-performance sensitivity of conventional and ESG active funds, in the US (Panel A), for a sample period ranges from January 1996 to December 2022). Performance is measured by raw return or past 60-month four-factor alpha. Funds' performance is ranked from zero to one according to their 12-month Fama and French (2015) five-factor (FF5) alpha and six-factor (FF6) alpha. Then, the performance rank is classified into ranked into three-performance ranked portfolios. Low quintile portfolio representing the bottom 20% performed funds (Low). Mid quantile portfolio composes of the three middle 20% performed funds. The high quintile portfolio includes the top 20% performed funds. The control variables include one-month lagged: raw return, flow, log total net assets, return volatility, expense ratio, and current age. Panel B repeats the same analysis for conventional and ESG passive funds in the US. Reported are the time-series average coefficients and *t-statistics* (in parentheses) are calculated with Newey-West robust standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Active – US

	Conventional				ESG			
	Five-factor alpha		Six-factor alpha		Five-factor alpha		Six-factor alpha	
Low	-0.115	**-0.121***	-0.139	-0.121	0.113	-0.002	0.068	-0.017
	(-1.40)	(-1.68)	(-1.57)	(-1.59)	(1.13)	(-0.02)	(0.67)	(-0.14)
Mid	**0.193****	0.090	**0.207****	0.096	-0.162	-0.026	-0.115	-0.019
	(2.30)	(1.42)	(2.35)	(1.36)	(-1.62)	(-0.24)	(-1.18)	(-0.17)
High	0.045	-0.056	0.058	-0.045	**0.249*****	0.144	**0.241*****	0.145
	(0.83)	(-1.30)	(0.93)	(-0.84)	(3.98)	(1.60)	(3.95)	(1.51)
Lag return		**0.021*****		**0.022*****		0.019		0.019
		(2.77)		(2.79)		(1.52)		(1.52)
Lag flow		**0.239*****		**0.242*****		0.068		0.068
		(3.59)		(3.58)		(0.80)		(0.80)
Lag net assets		-0.002		-0.002		-0.004		-0.004
		(-1.12)		(-1.20)		(-0.98)		(-0.93)
Lag return volatility		-0.025		-0.025		-0.030		-0.031
		(-0.97)		(-0.94)		(-0.68)		(-0.71)
Lag expense ratio		**0.450*****		**0.439*****		**0.343*****		**0.333*****
		(3.09)		(3.12)		(3.16)		(3.18)
Age		0.000		0.000		0.001		0.001
		(-0.16)		(-0.11)		(1.59)		(1.56)
Intercept	**-0.003*****	0.008	**-0.004*****	0.010	**-0.004*****	0.019	**-0.004*****	0.016
	(-2.77)	(0.20)	(-2.68)	(0.25)	(-2.58)	(0.27)	(-2.88)	(0.24)
R^2	0.107	0.460	0.124	0.459	0.054	0.116	0.053	0.115

Table 3.A18: continued

Panel B: Passive – US	**Conventional**				**ESG**			
	Five-factor alpha		Six-factor alpha		Five-factor alpha		Six-factor alpha	
Low	0.067	**-0.191***	-0.028	-0.190	**-0.723*****	**-0.392****	**-0.807*****	**-0.259***
	(0.55)	(-1.69)	(-0.21)	(-1.60)	(-3.44)	(-2.10)	(-3.83)	(-1.71)
Mid	**0.383*****	0.108	**0.444*****	0.104	**0.687****	-0.025	**0.768****	-0.057
	(2.71)	(0.76)	(2.88)	(0.64)	(2.35)	(-0.10)	(2.52)	(-0.24)
High	**-0.279***	-0.200	-0.238	-0.190	**-0.551****	-0.222	**-0.668****	-0.249
	(-1.85)	(-1.33)	(-1.47)	(-1.29)	(-2.14)	(-0.84)	(-2.49)	(-0.96)
Lag return		-0.025		-0.025		0.034		0.027
		(-1.39)		(-1.33)		(1.02)		(0.83)
Lag flow		0.117		0.119		**0.136***		**0.141***
		(1.31)		(1.35)		(1.76)		(1.85)
Lag net assets		**0.006****		**0.006***		**-0.008***		-0.005
		(2.01)		(1.96)		(-1.79)		(-1.50)
Lag return volatility		**0.130***		**0.127***		0.045		-0.036
		(1.94)		(1.85)		(0.29)		(-0.25)
Lag expense ratio		**1.518*****		**1.455*****		0.028		-0.018
		(3.13)		(2.98)		(0.40)		(-0.25)
Age		**-0.001*****		**-0.001*****		**0.003***		0.002
		(-3.93)		(-3.66)		(1.82)		(1.47)
Intercept	**0.005***	**-0.172****	0.003	**-0.166****	0.002	**0.105***	0.002	0.073
	(1.72)	(-2.15)	(1.15)	(-2.09)	(0.72)	(1.68)	(0.96)	(1.38)
R^2	0.035	0.163	0.033	0.161	0.083	0.077	0.079	0.065

Table 3A.19: Flow-performance sensitivity – 24 months, US, FF5 and FF6

This table examines the flow-performance sensitivity of conventional and ESG active funds, in the US (Panel A), for a sample period ranges from January 1996 to December 2022). Performance is measured by raw return or past 60-month four-factor alpha. Funds' performance is ranked from zero to one according to their 24-month Fama and French (2015) five-factor (FF5) alpha and six-factor (FF6) alpha. Then, the performance rank is classified into ranked into three-performance ranked portfolios. Low quintile portfolio representing the bottom 20% performed funds (Low). Mid quantile portfolio composes of the three middle 20% performed funds. The high quintile portfolio includes the top 20% performed funds. The control variables include one-month lagged: raw return, flow, log total net assets, return volatility, expense ratio, and current age. Panel B repeats the same analysis for conventional and ESG passive funds in the US. Reported are the time-series average coefficients and *t-statistics* (in parentheses) are calculated with Newey-West robust standard errors. ∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Active – US

	Conventional				**ESG**			
	Five-factor alpha		Six-factor alpha		Five-factor alpha		Six-factor alpha	
Low	-0.054	0.040	**-0.262****	-0.127	0.213	0.224	0.156	0.180
	(-0.47)	(0.33)	(-2.31)	(-1.05)	(1.46)	(1.32)	(0.97)	(0.94)
Mid	0.080	-0.137	**0.191***	-0.039	**-0.338****	-0.304	**-0.273***	-0.235
	(0.80)	(-1.34)	(1.77)	(-0.34)	(-2.43)	(-1.58)	(-1.93)	(-1.22)
High	**0.241*****	**0.115****	**0.267*****	**0.167****	**0.372*****	**0.353****	**0.325*****	0.280
	(4.12)	(1.97)	(3.58)	(2.22)	(4.67)	(2.22)	(4.33)	(1.84)
Lag return		**0.025*****		**0.024*****		0.018		0.017
		(3.18)		(3.19)		(1.42)		(1.32)
Lag flow		**0.225*****		**0.220*****		0.043		0.056
		(3.28)		(3.23)		(0.41)		(0.53)
Lag net assets		**-0.004***		**-0.004****		-0.004		-0.003
		(-1.72)		(-2.05)		(-0.84)		(-0.81)
Lag return volatility		-0.027		**-0.041***		-0.008		-0.011
		(-1.16)		(-1.81)		(-0.18)		(-0.25)
Lag expense ratio		**0.240***		**0.235***		0.160		0.170
		(1.93)		(1.85)		(1.27)		(1.43)
Age		**-0.001***		-0.001		0.000		0.000
		(-1.84)		(-1.27)		(-0.34)		(-0.28)
Intercept	**-0.006*****	0.073	**-0.009*****	**0.075***	**-0.005*****	0.055	**-0.005*****	0.047
	(-4.79)	(1.63)	(-6.33)	(1.74)	(-2.94)	(0.75)	(-2.83)	(0.66)
R^2	0.195	0.459	0.263	0.466	0.072	0.116	0.068	0.107

Table 3.A19: continued

Panel B: Passive – US

	Conventional				ESG			
	Five-factor alpha		Six-factor alpha		Five-factor alpha		Six-factor alpha	
Low	0.023	-0.207	-0.041	-0.152	-0.270	-0.522	-0.228	-0.463
	(0.14)	(-1.04)	(-0.23)	(-0.72)	(-1.58)	(-1.53)	(-1.22)	(-1.22)
Mid	**0.413****	-0.084	**0.558*****	-0.150	-0.039	0.784	-0.134	0.875
	(2.31)	(-0.36)	(2.76)	(-0.56)	(-0.12)	(0.95)	(-0.37)	(0.94)
High	-0.096	**-0.326***	-0.149	**-0.441****	-0.102	-0.857	-0.121	-0.888
	(-0.50)	(-1.83)	(-0.70)	(-2.30)	(-0.34)	(-0.68)	(-0.38)	(-0.59)
Lag return		0.011		0.013		**0.073***		**0.072***
		(0.73)		(0.80)		(1.75)		(1.71)
Lag flow		0.037		0.032		0.138		0.144
		(0.63)		(0.55)		(1.40)		(1.45)
Lag net assets		-0.004		**-0.005***		-0.005		-0.002
		(-1.36)		(-1.73)		(-0.53)		(-0.24)
Lag return volatility		-0.027		-0.041		-0.168		-0.213
		(-0.46)		(-0.69)		(-1.24)		(-1.46)
Lag expense ratio		0.533		0.484		-0.068		-0.096
		(1.32)		(1.17)		(-0.62)		(-0.81)
Age		**-0.001*****		**-0.002*****		0.003		0.002
		(-3.31)		(-3.24)		(1.47)		(1.10)
Intercept	0.002	0.082	0.002	0.103	0.002	0.057	0.002	0.032
	(0.56)	(1.22)	(0.58)	(1.59)	(0.91)	(0.46)	(1.05)	(0.23)
R^2	0.016	0.099	0.022	0.102	0.018	0.104	0.014	0.096

Table 3A.20: Flow-performance sensitivity – 36 months, US, FF5 and FF6

This table examines the flow-performance sensitivity of conventional and ESG active funds, in the US (Panel A), for a sample period ranges from January 1996 to December 2022). Performance is measured by raw return or past 60-month four-factor alpha. Funds' performance is ranked from zero to one according to their 36-month Fama and French (2015) five-factor (FF5) alpha and six-factor (FF6) alpha. Then, the performance rank is classified into ranked into three-performance ranked portfolios. Low quintile portfolio representing the bottom 20% performed funds (Low). Mid quantile portfolio composes of the three middle 20% performed funds. The high quintile portfolio includes the top 20% performed funds. The control variables include one-month lagged: raw return, flow, log total net assets, return volatility, expense ratio, and current age. Panel B repeats the same analysis for conventional and ESG passive funds in the US. Reported are the time-series average coefficients and *t-statistics* (in parentheses) are calculated with Newey-West robust standard errors. ∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Active – US	Conventional				ESG			
	Five-factor alpha		Six-factor alpha		Five-factor alpha		Six-factor alpha	
Low	-0.093	0.130	**-0.368*****	-0.075	0.276	0.129	0.174	-0.004
	(-0.68)	(0.86)	(-2.88)	(-0.54)	(1.47)	(0.72)	(0.95)	(-0.02)
Mid	0.001	**-0.262****	0.108	-0.197	**-0.467*****	-0.192	**-0.325****	-0.019
	(0.01)	(-2.06)	(1.03)	(-1.51)	(-2.86)	(-1.06)	(-2.28)	(-0.10)
High	**0.327*****	**0.114***	**0.388*****	**0.217****	**0.469*****	0.227	**0.372*****	0.102
	(5.80)	(1.65)	(5.22)	(2.53)	(4.60)	(1.26)	(3.98)	(0.53)
Lag return		0.022***		**0.022*****		**0.022***		**0.021***
		(2.83)		(2.93)		(1.80)		(1.71)
Lag flow		0.213***		**0.209*****		0.051		0.057
		(2.94)		(2.89)		(0.41)		(0.45)
Lag net assets		0.000		-0.002		-0.001		0.000
		(-0.06)		(-0.82)		(-0.19)		(-0.06)
Lag return volatility		0.013		-0.009		0.019		0.016
		(0.43)		(-0.34)		(0.53)		(0.45)
Lag expense ratio		0.307**		**0.345*****		0.318**		**0.341*****
		(2.51)		(3.07)		(2.40)		(2.86)
Age		-0.001		-0.001		0.002		**0.002***
		(-1.45)		(-0.89)		(1.54)		(1.87)
Intercept	**-0.009*****	-0.002	**-0.012*****	0.019	**-0.006*****	-0.051	**-0.006*****	-0.068
	(-5.93)	(-0.03)	(-7.90)	(0.37)	(-3.05)	(-0.68)	(-2.82)	(-0.95)
***R*²**	0.225	0.472	0.298	0.475	0.083	0.152	0.067	0.145

Table 3.A20: continued

Panel B: Passive – US

	Conventional				**ESG**			
	Five-factor alpha		Six-factor alpha		Five-factor alpha		Six-factor alpha	
Low	**-0.314***	**-0.567****	**-0.514****	**-0.589****	**-0.689***	0.159	**-0.868***	0.156
	(-1.79)	(-2.24)	(-2.51)	(-2.30)	(-1.89)	(0.52)	(-1.91)	(0.48)
Mid	**1.082*****	**0.875*****	**1.275*****	**0.852****	0.816	0.671	**1.262***	**1.011***
	(4.68)	(2.88)	(4.54)	(2.27)	(1.64)	(1.53)	(1.93)	(1.81)
High	0.187	0.100	0.170	0.059	-0.476	-1.723**	0.059	-1.008
	(1.15)	(0.50)	(1.05)	(0.29)	(-0.48)	(-2.26)	(0.07)	(-1.00)
Lag return		0.022		0.022		0.056		0.054
		(1.33)		(1.33)		(1.57)		(1.46)
Lag flow		0.022		0.035		0.124		0.125
		(0.35)		(0.55)		(1.01)		(1.00)
Lag net assets		**-0.005****		**-0.006****		-0.005		-0.002
		(-2.12)		(-2.32)		(-0.91)		(-0.43)
Lag return volatility		**-0.094***		-0.097		-0.403***		**-0.410*****
		(-1.67)		(-1.64)		(-3.59)		(-3.34)
Lag expense ratio		**-0.842****		**-0.821***		-0.146		**-0.163***
		(-2.05)		(-1.93)		(-1.43)		(-1.72)
Age		-0.001		-0.001		**0.006***		0.004
		(-1.63)		(-1.18)		(1.94)		(1.59)
Intercept	-0.001	**0.149****	-0.002	**0.166*****	**0.004***	0.045	**0.004****	0.022
	(-0.46)	(2.52)	(-0.95)	(2.58)	(1.70)	(0.74)	(2.19)	(0.34)
R^2	0.074	0.136	0.090	0.127	0.033	0.111	0.041	0.113

Table 3A.21: Flow-performance sensitivity – 12 months, EU, FF5 and FF6

This table examines the flow-performance sensitivity of conventional and ESG active funds, in the EU (Panel A), for a sample period ranges from January 1996 to December 2022). Performance is measured by raw return or past 60-month four-factor alpha. Funds' performance is ranked from zero to one according to their 12-month Fama and French (2015) five-factor (FF5) alpha and six-factor (FF6) alpha. Then, the performance rank is classified into ranked into three-performance ranked portfolios. Low quintile portfolio representing the bottom 20% performed funds (Low). Mid quantile portfolio composes of the three middle 20% performed funds. The high quintile portfolio includes the top 20% performed funds. The control variables include one-month lagged: raw return, flow, log total net assets, return volatility, expense ratio, and current age. Panel B repeats the same analysis for conventional and ESG passive funds in the EU. Reported are the time-series average coefficients and *t-statistics* (in parentheses) are calculated with Newey-West robust standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Active – EU

	Conventional				**ESG**			
	Five-factor alpha		Six-factor alpha		Five-factor alpha		Six-factor alpha	
Low	**-0.266***	-0.175	**-0.299****	-0.227	**-0.270****	-0.102	**-0.264****	-0.143
	(-1.68)	(-0.97)	(-2.06)	(-1.24)	(-2.44)	(-0.92)	(-2.42)	(-1.28)
Mid	0.000	-0.114	0.035	-0.077	0.069	-0.027	0.066	-0.010
	(-0.00)	(-0.95)	(0.33)	(-0.68)	(1.00)	(-0.31)	(1.03)	(-0.14)
High	0.051	0.173	0.012	0.149	-0.009	0.029	-0.016	0.032
	(0.44)	(1.35)	(0.11)	(1.29)	(-0.16)	(0.23)	(-0.30)	(0.32)
Lag return		0.025		0.025		0.004		0.004
		(1.01)		(1.04)		(0.33)		(0.33)
Lag flow		-0.126		-0.126		0.109		0.105
		(-0.87)		(-0.87)		(1.17)		(1.12)
Lag net assets		-0.008		-0.009		0.000		0.000
		(-0.99)		(-1.09)		(0.05)		(0.08)
Lag return volatility		0.065		0.055		**0.114***		**0.112***
		(0.77)		(0.64)		(1.89)		(1.88)
Lag expense ratio		-0.019		-0.042		-0.078		-0.065
		(-0.13)		(-0.29)		(-0.49)		(-0.45)
Age		0.001		0.001		0.000		0.000
		(1.06)		(0.90)		(0.29)		(0.32)
Intercept	**-0.006*****	0.135	**-0.005****	0.158	**-0.004****	-0.007	**-0.004****	-0.013
	(-2.82)	(0.79)	(-2.43)	(0.92)	(-2.47)	(-0.09)	(-2.02)	(-0.16)
R^2	0.058	0.102	0.05	0.102	0.083	0.124	0.073	0.127

	Table 3.A21: continued							
Panel B: Passive – EU								
	Conventional				**ESG**			
	Five-factor alpha		Six-factor alpha		Five-factor alpha		Six-factor alpha	
Low	**0.326****	0.132	0.190	-0.037	**0.286***	0.063	0.201	-0.082
	(2.11)	(0.78)	(1.33)	(-0.21)	(1.94)	(0.38)	(1.46)	(-0.47)
Mid	**-0.145***	-0.156	-0.109	-0.079	**-0.153****	-0.120	**-0.135***	-0.049
	(-1.73)	(-1.26)	(-1.28)	(-0.67)	(-1.96)	(-0.98)	(-1.72)	(-0.42)
High	-0.046	-0.047	-0.028	-0.046	-0.035	-0.026	-0.021	-0.025
	(-1.31)	(-1.10)	(-0.84)	(-1.08)	(-0.98)	(-0.58)	(-0.62)	(-0.55)
Lag return		0.033*		**0.031***		0.029		0.029
		(1.75)		(1.69)		(1.45)		(1.45)
Lag flow		0.053		0.060		0.067		0.071
		(0.86)		(0.96)		(1.15)		(1.22)
Lag net assets		-0.006		-0.007		-0.004		-0.004
		(-1.28)		(-1.54)		(-0.83)		(-1.04)
Lag return volatility		-0.039		-0.038		0.047		0.044
		(-0.54)		(-0.53)		(0.62)		(0.58)
Lag expense ratio		0.038		0.059		0.050		0.069
		(0.31)		(0.42)		(0.51)		(0.63)
Age		0.002		**0.003***		0.002		0.002
		(1.53)		(1.77)		(1.22)		(1.42)
Intercept	**0.008*****	0.081	**0.006***	0.090	**0.008*****	0.038	**0.007****	0.046
	(2.74)	(1.08)	(1.92)	(1.20)	(2.64)	(0.56)	(2.15)	(0.66)
R^2	0.019	0.044	0.010	0.041	0.017	0.034	0.012	0.033

Table 3A.22: Flow-performance sensitivity – 24 months, EU, FF5 and FF6

This table examines the flow-performance sensitivity of conventional and ESG active funds, in the EU (Panel A), for a sample period ranges from January 1996 to December 2022). Performance is measured by raw return or past 60-month four-factor alpha. Funds' performance is ranked from zero to one according to their 24-month Fama and French (2015) five-factor (FF5) alpha and six-factor (FF6) alpha. Then, the performance rank is classified into ranked into three-performance ranked portfolios. Low quintile portfolio representing the bottom 20% performed funds (Low). Mid quantile portfolio composes of the three middle 20% performed funds. The high quintile portfolio includes the top 20% performed funds. The control variables include one-month lagged: raw return, flow, log total net assets, return volatility, expense ratio, and current age. Panel B repeats the same analysis for conventional and ESG passive funds in the EU. Reported are the time-series average coefficients and *t-statistics* (in parentheses) are calculated with Newey-West robust standard errors. ∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Active – EU

	Conventional				**ESG**			
	Five-factor alpha		Six-factor alpha		Five-factor alpha		Six-factor alpha	
Low	-0.253	**-0.321***	-0.223	-0.006	-0.381	-0.283	-0.312	-0.116
	(-0.94)	(-1.71)	(-0.75)	(-0.02)	(-1.79)	(-1.27)	(-1.25)	(-0.34)
Mid	-0.052	-0.012	-0.071	-0.199	0.117	0.114	0.081	0.020
	(-0.31)	(-0.09)	(-0.39)	(-1.26)	(1.08)	(0.90)	(0.65)	(0.10)
High	0.123	0.199	0.130	0.321	0.002	-0.019	0.011	0.038
	(0.66)	(1.16)	(0.63)	(1.54)	(0.02)	(-0.12)	(0.09)	(0.16)
Lag return		0.024		0.026		0.010		0.011
		(1.04)		(1.13)		(0.95)		(0.99)
Lag flow		-0.133		-0.124		0.093		0.104
		(-1.02)		(-0.97)		(0.88)		(0.98)
Lag net assets		-0.005		-0.007		-0.004		-0.004
		(-0.76)		(-1.00)		(-0.96)		(-1.01)
Lag return volatility		0.065		0.064		0.054		0.058
		(0.87)		(0.88)		(1.18)		(1.32)
Lag expense ratio		0.131		0.019		-0.006		-0.025
		(0.88)		(0.11)		(-0.05)		(-0.20)
Age		0.000		0.000		0.001*		**0.001***
		(0.73)		(0.53)		(1.74)		(1.70)
Intercept	**-0.007****	0.050	**-0.006****	0.107	**-0.006*****	0.048	**-0.005****	0.060
	(-2.49)	(0.41)	(-2.14)	(0.78)	(-3.01)	(0.67)	(-2.03)	(0.82)
R^2	0.039	0.068	0.028	0.068	0.058	0.081	0.038	0.074

Table 3.A22: continued

Panel B: Passive – EU

	Conventional				**ESG**			
	Five-factor alpha		Six-factor alpha		Five-factor alpha		Six-factor alpha	
Low	0.008	-0.164	0.047	-0.092	-0.042	-0.221	0.046	-0.169
	(0.04)	(-0.63)	(0.24)	(-0.30)	(-0.19)	(-0.78)	(0.23)	(-0.50)
Mid	-0.027	-0.054	-0.038	-0.088	-0.017	-0.009	-0.043	-0.030
	(-0.23)	(-0.28)	(-0.30)	(-0.41)	(-0.14)	(-0.05)	(-0.35)	(-0.15)
High	0.074	-0.039	0.064	-0.042	0.078	-0.027	0.065	-0.022
	(1.44)	(-0.51)	(1.30)	(-0.58)	(1.52)	(-0.34)	(1.34)	(-0.29)
Lag return		**0.033***		0.032		0.032		0.030
		(1.70)		(1.62)		(1.51)		(1.41)
Lag flow		0.002		0.002		-0.003		-0.003
		(0.04)		(0.03)		(-0.05)		(-0.06)
Lag net assets		**-0.009****		**-0.009****		**-0.008***		-0.007
		(-2.32)		(-2.12)		(-1.87)		(-1.59)
Lag return volatility		0.038		0.046		0.096		0.100
		(0.55)		(0.65)		(1.29)		(1.31)
Lag expense ratio		0.156		0.161		0.140		0.153
		(1.32)		(1.08)		(1.38)		(1.12)
Age		**0.004*****		**0.004****		**0.004*****		**0.004****
		(2.61)		(2.54)		(2.58)		(2.50)
Intercept	0.000	0.092	0.001	0.087	0.000	0.060	0.002	0.051
	(0.05)	(1.46)	(0.27)	(1.22)	(-0.01)	(0.91)	(0.39)	(0.64)
R^2	0.007	0.064	0.006	0.064	0.007	0.057	0.006	0.057

Table 3A.23: Flow-performance sensitivity – 36 months, EU, FF5 and FF6

This table examines the flow-performance sensitivity of conventional and ESG active funds, in the EU (Panel A), for a sample period ranges from January 1996 to December 2022). Performance is measured by raw return or past 60-month four-factor alpha. Funds' performance is ranked from zero to one according to their 36-month Fama and French (2015) five-factor (FF5) alpha and six-factor (FF6) alpha. Then, the performance rank is classified into ranked into three-performance ranked portfolios. Low quintile portfolio representing the bottom 20% performed funds (Low). Mid quantile portfolio composes of the three middle 20% performed funds. The high quintile portfolio includes the top 20% performed funds. The control variables include one-month lagged: raw return, flow, log total net assets, return volatility, expense ratio, and current age. Panel B repeats the same analysis for conventional and ESG passive funds in the EU. Reported are the time-series average coefficients and *t-statistics* (in parentheses) are calculated with Newey-West robust standard errors. ∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Active – EU

	Conventional				ESG			
	Five-factor alpha		Six-factor alpha		Five-factor alpha		Six-factor alpha	
Low	-0.158	**-0.495****	-0.127	**-0.476****	**-0.402***	**-0.380****	-0.357	**-0.356****
	(-0.74)	(-2.35)	(-0.52)	(-2.31)	(-1.86)	(-2.24)	(-1.56)	(-2.13)
Mid	-0.042	0.013	-0.091	-0.006	**0.206****	0.052	**0.192***	0.052
	(-0.35)	(0.10)	(-0.75)	(-0.05)	(2.06)	(0.50)	(1.91)	(0.47)
High	0.070	0.027	0.127	0.039	-0.144	-0.046	-0.144	-0.051
	(0.57)	(0.21)	(0.88)	(0.27)	(-1.58)	(-0.46)	(-1.51)	(-0.45)
Lag return		0.019		0.020		0.005		0.005
		(1.07)		(1.11)		(0.46)		(0.49)
Lag flow		-0.128		-0.125		**0.172***		**0.180****
		(-0.93)		(-0.91)		(1.95)		(2.05)
Lag net assets		-0.005		-0.006		-0.005		-0.005
		(-1.32)		(-1.54)		(-1.42)		(-1.44)
Lag return volatility		**0.151*****		**0.146*****		**0.09*****		**0.087*****
		(3.82)		(3.86)		(3.07)		(2.98)
Lag expense ratio		0.062		0.011		0.007		-0.024
		(0.69)		(0.12)		(0.09)		(-0.29)
Age		0.000		0.000		0.001		0.001
		(0.44)		(0.35)		(1.52)		(1.33)
Intercept	-0.004	0.071	-0.004	0.097	-0.003	0.064	-0.002	0.074
	(-1.29)	(0.89)	(-1.16)	(1.22)	(-1.39)	(1.04)	(-0.93)	(1.18)
R^2	0.009	0.099	0.009	0.098	0.024	0.169	0.018	0.166

Table 3.A23: continued								
Panel B: Passive – EU								
	Conventional				**ESG**			
	Five-factor alpha		Six-factor alpha		Five-factor alpha		Six-factor alpha	
Low	0.188	-0.588	0.427	-0.241	0.026	-0.698	0.314	-0.338
	(0.62)	(-1.29)	(1.59)	(-0.57)	(0.09)	(-1.50)	(1.18)	(-0.78)
Mid	0.067	**0.604****	-0.061	**0.534****	0.119	**0.603****	-0.001	**0.587****
	(0.36)	(2.52)	(-0.37)	(2.31)	(0.72)	(2.39)	(-0.01)	(2.40)
High	0.098	0.094	0.108	-0.008	0.094	0.116	0.091	-0.010
	(1.33)	(0.64)	(1.38)	(-0.06)	(1.33)	(0.78)	(1.24)	(-0.07)
Lag return		0.034		0.034		0.031		0.032
		(1.52)		(1.56)		(1.34)		(1.39)
Lag flow		0.044		0.050		0.042		0.049
		(0.71)		(0.80)		(0.72)		(0.82)
Lag net assets		**-0.012****		**-0.014*****		**-0.010***		**-0.013****
		(-2.36)		(-2.68)		(-1.91)		(-2.31)
Lag return volatility		-0.058		-0.040		-0.021		-0.009
		(-0.70)		(-0.48)		(-0.22)		(-0.10)
Lag expense ratio		0.097		0.093		0.104		0.097
		(0.68)		(0.60)		(0.83)		(0.71)
Age		**0.003****		**0.004****		**0.003***		**0.003****
		(2.02)		(2.14)		(1.91)		(2.07)
Intercept	0.001	**0.151****	0.004	**0.193****	-0.001	0.111	0.003	**0.165***
	(0.17)	(1.97)	(1.09)	(2.35)	(-0.20)	(1.36)	(0.78)	(1.84)
R^2	0.017	0.100	0.022	0.096	0.016	0.089	0.018	0.086

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