Do Responsible Investment Funds (RIFs) *really* Invest Responsibly? Evidence from US RIFs

Huiqiong Tang

A thesis submitted to Auckland University of Technology in fulfilment of the requirements for the degree of Doctor of Philosophy

2023

Faculty of Business, Economics and Law

Finance Department

Abstract

Responsible Investment Funds (RIFs) are managed funds that consider Environmental, Social and Governance (ESG) objectives in their investment process. In 2022, it was estimated that approximately 12.6% of total US assets under professional management were classified as responsible (Forum for Sustainable and Responsible Investment [US SIF], 2022). With the growing popularity of RIFs, investors are increasingly seeking greater transparency regarding how responsibly their money is being invested (Amel-Zadeh & Serafeim, 2018). Academic scholars document a wide variety of responsible investing strategies that result in varying levels of responsible investing intensity and by extension, non-financial outcomes, which raise concerns about the authenticity of the RIF (Revelli, 2017). Furthermore, the US government oversight agency, the Securities and Exchange Commission (SEC) has noted potentially misleading marketing practices, known as greenwashing, within US funds and issued an alert to address these concerns (Chin, 2021). These lines of inquiry, in origin, are all related to a fundamental question, "Do RIFs invest in a responsible way?" My thesis aims to contribute to the literature in this field and examine the ESG performance of US domestic equity RIFs from various angles in three empirical studies.

In the first manuscript, I examine the existence of window dressing, a deceptive practice where managers manipulate portfolio holdings prior to a reporting date to mislead investors and the market. Using fund holdings information, I find that some RIFs alter their holdings towards higher ESG-score firms close to reporting dates. Such clustered end-of-quarter rebalancing is more likely to be window dressing than routine holding adjustments. Additionally, I also find that RIFs with poor past performance, higher tracking errors, or those managed by companies with less assets committed to sustainable investment are more likely to engage in ESG window dressing behaviours.

The second manuscript investigates the potential impact of Fund Management Companies (FMCs, also referred to as 'fund families') on funds' ESG performance based on their ESG commitment level. I proxy the FMCs' commitment level using their proportion of Assets Under Management (AUM) engaged in responsible investment, with the assumption that it represents the importance of responsible investment to an FMC's overall benefit. The findings suggest that improvement of the fund's ESG score is more like the 'icing on the cake' and will be sacrificed quickly if the fund suffers outflows. Furthermore, I find that funds managed by

FMCs with either the lowest (≤20%) or the highest (>80%) ESG commitment levels are more likely to put extra effort into enhancing funds' ESG scores. Additionally, I observe that investors who choose FMCs with the highest ESG commitment level tend to exhibit lower sensitivity to financial returns when controlling for ESG performance.

The final manuscript focuses on how a responsible investment fund manager's past career path impacts their funds' ESG performance. My results suggest that when solely considering ESG performance, RIFs tend to exhibit better ESG performance when managed by a team containing all members with conventional fund management work experience. When considering *joint* ESG and financial performance, the proportion of managers with exclusive RIF work experience positively impacts funds' joint efficiency. Additionally, I also find insignificant differences in financial performance between funds with pure RIF managers and those where all the managers have conventional experience.

This thesis aims to bring greater transparency to an important and rapidly developing segment of the finance industry, which currently requires investors to simply trust that managers are fulfilling their statements on responsible investment. By providing additional insight into fund ESG performance, my findings may benefit "true believer" responsible investors when making asset allocation decisions. It may also be helpful for regulators (e.g., the SEC) in their efforts to monitor and promote transparency within capital markets.

Table of Contents

List of Figures

List of Tables

Attestation of Authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor used artificial intelligence tools or generative artificial intelligence tools (unless it is clearly stated, and referenced, along with the purpose of use), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

Huiqiong Tang

December 2nd, 2023

Declaration of Co-Authored Works

I declare that I am the principal author of the jointly authored manuscripts listed below. I have taken primary responsibility for the major tasks in this thesis, including collecting data, conducting analyses, writing the thesis, journal submission, and journal revise and resubmit requests (where applicable). All data analyses and results were overseen by my supervision team. The co-authors, who are my supervisors, have assisted in the development of research ideas, research design, clarification of analyses, editing, commenting on drafts, and assisting with the review process. The agreed percentage contribution of each manuscript is listed below:

	Manuscript Details
Manuscript 1	***Title:*** Window Dressing among Responsible Investment Funds ***Status:*** under review
Manuscript 2	***Title:*** Responsible investment funds and their management companies' emphasis on ESG performance: First priority or icing on the cake? ***Status:*** under review
Manuscript 3	***Title:*** Do responsible investment fund (RIF) managers' career paths impact their fund's ESG performance? ***Status:*** under review

Huiqiong Tang
(PhD Candidate)

Dr Ayesha Scott
(First supervisor)

Professor Aaron Gilbert
(Second supervisor)

Professor Bart Frijns
(Third supervisor)

Acknowledgements

When I began writing this section, it also signified that I am nearing to the end of my doctoral studies. This journey started in the autumn of 2019 and concluded in spring 2023.

First and foremost, I would like to express my special appreciation and gratitude to my supervisors, Dr Ayesha Scott, Professor Aaron Gilbert and Professor Bart Frijns. Ayesha, you have been everything I could have wished for in a primary supervisor with your insightful guidance, swift responses, continuous encouragement, and profound knowledge. Aaron, your encouragement was what nudged me to start this PhD. I am grateful for everything you taught me as a Master's student. Your unwavering support and exceptional expertise have expanded my passion for the research. Bart, it has been a pleasure to have your expertise, support, and advice throughout this process. Your constructive feedback, encouragement, and mentorship have enabled me to overcome obstacles. A huge thanks to all three of you. I could not finish this thesis without your patience, encouragement, guidance and supervision.

I am grateful for the feedback and comments from the New Zealand Finance Meeting and the New Zealand Finance Colloquium PhD Symposium. Likewise, I would like to thank everyone from the Finance Department at Auckland University of Technology, for kindly sharing their experiences on the research and feedback on my manuscripts through the department seminars. I would also like to thank reviewers and the audiences for feedback and comments on my research overview which was presented at the 2023 AFAANZ Doctoral Symposium.

A special thanks is reserved for my husband, Xing Wang, for his wonderful support and loving consideration throughout this extensive path of learning. Your patience, encouragement, and belief in me have been my pillars of strength, which allowed me to pursue my doctoral degree dream. I also want to thank my adorable dogs, Dobby and Freddy, whose enthusiasm for daily walks motivated me to stay active and maintain my health. Likewise, my cat, Timothy, with his fluffy and soft cuddle, has been a constant emotional support during this journey.

Lastly, I am thankful for my perseverance, positive attitude to every challenge, and diligent efforts that have led me to this point.

Chapter 1: Introduction

1.1 Background

Responsible investment, also known as socially responsible investment, ethical investment, or sustainable investment[1], seeks to include non-financial objectives in the investment process, specifically investing with Environmental, Social and Governance (ESG) objectives in mind (Mallin et al., 1995). In recent decades, global financial markets have witnessed significant growth in responsible investment, with a 33% increase between 2016 and 2022 across five major markets (Europe, the US, Canada, Australasia, and Japan), reaching US$30.3 trillion at the beginning of 2022 (Global Sustainable Investment Alliance [GSIA], 2023). Between them, the US and Europe account for over 80% of global responsible investment assets, and Canada, Japan, and Australasia represented 7%, 8%, and 3%, respectively.

As the largest sustainable investment market,[2] US responsible investment has shown remarkable development. In 2022, it was estimated that the total US-domiciled assets under management (AUM) invested sustainably grew from $639 billion in 1995 to $8.4 trillion[3] at the start of 2022, representing approximately 12.6% of total US assets under professional management (Forum for Sustainable and Responsible Investment [US SIF], 2022). The almost explosive AUM growth can be primarily attributed to rising interest from investors. Morgan Stanley (2019) reports 85% of US individual investors expressed interest in responsible investment; younger investors appear to be leading the charge, with 95% of millennial respondents interested in responsible investment.

One of the essential investment vehicles for responsible investment is Responsible Investment Funds (RIFs), defined as managed mutual funds that apply ESG strategies when making investment decisions. The concept of responsible investment originated in religious traditions. According to Renneboog et al. (2008), Islamic

---

[1] According to Global Sustainable Investment Alliance (2021), responsible investment, socially responsible investment and sustainable investment are “related or interchangeable terms”, although there are some variations in meaning and use. In addition, the CFA Institute treats responsible investment as an umbrella term for the investment approaches, including Socially Responsible Investment, Thematic Investment, Social Investment, Impact Investment, Ethical (or Value-Driven) and Faith-Based Investment.
[2] Over the 2018 to 2020 period, the US represented 48% of global sustainable investing assets (GSIA, 2021).
[3] The material drop between 2020 ($17.1 trillion) and 2022 ($8.4 trillion) is due to a revised methodology.

investors' finance and investment principles are deeply rooted in the teachings of the Koran, which prohibit participation in pork production, pornography, gambling, and interest-based financial institutions. The first US mutual fund that screened for religious prohibitions (banned investment in alcohol or tobacco) was the Pioneer Fund, founded in 1928. In 1971, the first modern mutual fund implementing negative screens in weapons was established, the Pax World Fund, to target investors who were against war and militarism (Renneboog et al., 2008). Another early mutual fund concerned with socially responsible issues is the Dreyfus Third Century Fund, established in 1972, and is still in existence today. It emphasizes the importance of environmental protection and improvement of employment equality and workplace safety (Sparks, 2002).

In 1981, the Social Investment Forum (now the US SIF) was founded to report and promote responsible investment in the US. Since the early 1990s, an increasing number of funds have committed to incorporate ESG attributes in their investment analysis and asset decisions (Renneboog et al., 2008). With the growth in responsible investment funds, various companies, like Calvert Investments and KLD Research and Analytics, started to provide services evaluating company Corporate Social Responsibility (CSR) behaviour via rating systems and responsible investment indices (Berry & Junkus, 2013). Additionally, since 1995, the US SIF has provided extensive information on ESG-related issues, including quantitative analysis on RIFs in the US. More recently, several legislative and regulatory mechanisms have been developed to promote and manage the industry. For instance, the United Nations Principles for Responsible Investment (UNPRI) was launched in April 2006, which outlines six principles for signatories to implement, thereby aligning their fiduciary responsibilities with responsible investment.[4] With the increased investor interest and an overall shift toward incorporating ESG factors into investment decisions, the RIF market has exhibited considerable growth in the past three decades.

[4] According to UNPRI (2023), the six Principles are:

> Principle 1: We will incorporate ESG issues into investment analysis and decision-making processes.
> Principle 2: We will be active owners and incorporate ESG issues into our ownership policies and practices.
> Principle 3: We will seek appropriate disclosure on ESG issues by the entities in which we invest.
> Principle 4: We will promote acceptance and implementation of the Principles within the investment industry.
> Principle 5: We will work together to enhance our effectiveness in implementing the Principles.
> Principle 6: We will each report on our activities and progress towards implementing the Principles. (Signatories' commitment section, para. 3)

1.2 Financial and ESG Performance of RIFs

The growth of responsible investment funds is increasingly drawing the attention of practitioners and scholars. Following Moskowitz's (1972) work, which shed light on socially responsible stocks, non-financial performance related topics have gathered momentum, and the number of empirical studies has grown significantly. Approximately 74% of RIF-studies between 1990 and 2014 investigate financial performance (van Dijk-de Groot & Nijhof, 2015). These articles assess whether RIFs can competitively yield financial returns relative to conventional (non-RI) funds. However, the findings are mixed. The majority of these studies demonstrate that the risk-adjusted performance of ethical funds does not differ significantly compared to conventional funds, either before or after fees (Friede et al., 2015; Thompson et al., 2011). In contrast, a few studies highlight that RIFs outperform non-RIFs (Gil-Bazo et al., 2010; Lean et al., 2015; Alda, 2020) or RIFs underperform non-RIFs (El Ghoul & Karoui, 2017; Ibikunle & Steffen, 2017, Azmi et al., 2020). In a recent meta-study, Whelan et al. (2021) find that among investment studies focused on financial performance published between 2015 and 2020, 59% showed similar or better, or at least no worse, performance compared to conventional investment.

Irrespective of their findings, however, most financial performance evaluations implicitly assume that RIFs comply with their stated ESG principles and, therefore, do not assess RIFs' adherence to their investment objectives (Capelle-Blancard & Monjon, 2012; Nitsche & Schröder, 2018). In response, another strand of literature has emerged to consider the non-financial performance of RIFs, including portfolio composition and to assess whether RIFs are, in fact, "responsible". Again, the extant literature documents a range of findings. For instance, Utz and Wimmer (2014) rank all US mutual funds based on their annual ESG scores and find that approximately one-third (36.7%) of RIFs lie below the average level of ESG performance of all funds. This finding indicates that RIFs may not be achieving their non-financial performance goals, in line with investor and market expectations. Conversely, several studies demonstrated that RIFs tend to exhibit better ESG performance than conventional funds (Kempf & Osthoff, 2008; Bialkowski & Starks, 2016; Joliet & Titova, 2018). The appearance of these arguments, in origin, is all related to the simple question, "Do RIFs really invest in a responsible way?". My thesis attempts to address this question.

The debate has gained increasing attention in recent years for four reasons:

First, the ESG strategies that a fund may implement differ between RIFs. Funds can employ one or more different ESG strategies. These include “negative/exclusionary screening, positive/best-in-class screening, norms-based screening, ESG integration, sustainability-themed investing, impact/community investing, and corporate engagement and/or shareholder activism” (Global Sustainable Investment Alliance, 2021). There are differences in the intensity of these strategies. For example, ESG integration, a strategy that is defined as taking a few key ESG criteria into consideration when making decisions, is less restrictive and can be somewhat vague compared to negative screening, potentially raising concerns about the authenticity of the RIF (Revelli, 2017).

Second, the intensity of ESG strategy implementation varies. There is considerable variation in the application of a particular ESG strategy between funds. For instance, funds engaged in negative screening have differing numbers and compositions of excluded industries. The most commonly applied screens are alcohol, gambling, defence weapons, and tobacco, while there are also other so-called controversial industries refused by investors based on their personal beliefs and values, such as animal testing, fur, and genetic engineering (Trinks & Scholtens, 2017). The different combinations of screens also generate varying results. In the literature, there are different classifications for a “sin portfolio”. For instance, Ahrens (2004) defined the 4Bs portfolio, representing booze, bets, bombs, and butts, identifying sin stocks as alcohol, gambling, controversial weapons, and adult entertainment; the “Triumvirate of Sin”, commonly seen in the literature, e.g. Hong and Kacperczyk (2009) and Salaber (2009), comprises alcohol, tobacco, and gambling; Lobe and Walkshäusl (2011) expand the list to the “Sextet of Sin” by adding controversial weapons, adult entertainment, and nuclear power to the “Triumvirate of Sin”. Additionally, the Medical Sin portfolio includes controversial medical stocks, such as abortion, animal testing, contraceptives, genetic engineering, and embryonic stem cells (Trinks & Scholtens, 2017). My focus in this introduction, and thesis, is not to debate which screen combination is more “responsible”. Rather, I aim to highlight that the exclusion of different industry and company combinations requires different efforts, resource inputs, and managerial skills in both the research and management process. These exclusions may result in various costs (screening costs, opportunity costs and a limited asset universe) and consequently generate different impacts on a fund’s ESG performance.

Third, the increasing convergence of RIFs and conventional funds. On one hand, investors' growing demand for funds that consider ESG impacts, and world-wide acceptance of integrating ESG principles as a part of fiduciary duty,[5] means conventional funds have integrated ESG dimension practices into their asset management process (Arjaliès, 2010; Armstrong & Green, 2013; Van Duuren et al., 2016; Crifo & Mottis, 2016; Hasford & Farmer, 2016). On the other hand, Revelli (2017) argues that RIFs are increasingly financialized, meaning that instead of prioritizing ESG objectives, fund managers treat the financial objective as their main goal. The consequence of convergence is that real ESG impacts may be diluted (Revelli & Viviani, 2015). Such dilution raises questions about the ESG performance of RIFs. If RIFs fail to show superior ESG performance relative to conventional funds, it may also raise concerns about RIFs' distinctiveness in ESG consideration proposition and may generate questions about their ability to be treated as a unique market presence.

Last, increasing regulatory focus on responsible investment. For example, in April 2021, the US Securities and Exchange Commission (SEC) (2021) issued an alert that several asset managers may be engaging in misleading behaviour. This practice, referred to as greenwashing, involves funds that are marketed as environmentally friendly but, in practice, are not fully aligned with their advertised investment focus. Douglas and Michelle (2021) also report that SEC staff identified cases of some firms not establishing formal ESG procedures for ESG investment, despite being required to. Such misleading or overstated disclosures may generate obstacles for investors to "reasonably track" or screen portfolio firms' ESG performance (SEC, 2021; Chin, 2021) and consequently, lead to investor uncertainty about the true ESG performance of RIFs.

1.3 Manuscript Summary and Key Research Questions

To address the overarching aims of my thesis, I build a comprehensive, hand-collected dataset of US domestic equity RIFs to connect fund holdings, ESG scores of individual firms, fund management companies' characteristics, and fund managers' characteristics (including career path). I employ fund holdings information and ESG performance (company-level ESG scores) for companies held by funds to proxy fund-level ESG

[5] For example, the signatories of UNPRI adherence to incorporate ESG criteria into investment analysis and decision-making process, including use the standardised report for ESG, disclose how ESG integrated within the process and promote acceptance and implementation within industry.

performance, and then employ several established models, including the rank gap, backward holding return gap (Agarwal et al., 2014), three- and four-factor models (Fama & French, 1993; Carhart, 1997), a Kalman filter (Swinkels & Van Der Sluis, 2006), data envelopment analysis (DEA) method (Charnes et al., 1978) and the Fama–MacBeth regression method (Fama & MacBeth,1973) to analyse RIFs' ESG (non-financial) performance from different angles in three manuscripts.

Manuscript 1: Window Dressing in Responsible Investment Funds

This manuscript focuses on how fund managers may manipulate holdings around portfolio disclosure dates and seeks to answer the question: "Do RIFs exhibit window dressing?" Window dressing is a deceptive practice where managers change the companies they invest in prior to a reporting date to mislead investors and the market. In this manuscript, I argue that RIF managers may not only window dress for financial returns but also window dress for ESG performance. Using fund holdings information, I find that some RIFs alter their holdings towards higher ESG-score firms close to reporting dates. Such clustered end-of-quarter rebalancing is more likely to be window dressing than routine holding adjustments. Additionally, RIFs with poor past performance, higher tracking errors, or those managed by companies with lower sustainable investment levels are more likely to engage in ESG window dressing behaviours.

Manuscript 2: Responsible investment funds and their management companies' emphasis on ESG performance: First priority or icing on the cake?

The second manuscript investigates "How do RIFs' Fund Management Companies impact fund-level ESG performance?". I address this question by looking at the impact of Fund Management Companies (FMCs, also referred to as 'fund families') on their RIFs by proxying FMC's overall ESG commitment level using the proportion of AUM engaged in responsible investment by the entire fund family. I argue that this proportion represents the importance of responsible investment to an FMC and thus reflects the emphasis FMCs place on ESG. In this manuscript, I employ fund flows to measure the overall impact for an FMC of pursuing their strategy, since fund inflows represent increases in AUM and as a result fee income, which are the fundamental benefits for FMCs. My results show an improvement in fund-level ESG score is more like the "icing on the cake" and will be sacrificed quickly if the fund suffers fund outflows. I also find that RIFs managed by FMCs with either the lowest (≤20%) or the highest (>80%) ESG commitment levels are more likely to put extra effort into enhancing funds' ESG scores, by investing more heavily in higher ESG score companies and/or reducing holdings in lower ESG score companies. Additionally, I observe that investors who choose FMCs with the highest ESG commitment level are less sensitive to financial returns when controlling for ESG performance.

Manuscript 3: Do responsible investment fund (RIF) managers' career paths impact their fund's ESG performance?

In this manuscript, I focus on the potential impact of RIF managers on ESG performance. The specific research question addressed is: "Does a fund manager's career path impact their fund's ESG performance?" I argue that RIF managers with conventional fund management experience before managing a RIF may make different investment decisions than those with solely RIF management experience. My results indicate that when considering ESG performance alone, RIFs managed by teams with conventional work experience are more likely to exhibit better ESG performance. When considering financial returns and ESG performance together, an increase in the proportion of managers with exclusive RIF work experience leads to better overall efficiency (joint financial return and ESG performance), on average.

My research aims to bring greater transparency to an important and rapidly developing market segment that currently requires investors to simply trust that managers are doing what they say. By providing additional insight into fund ESG performance, my findings may provide insight for "true believers" in responsible investment when making asset allocation decisions. It may also be helpful for regulators (i.e., the SEC) in their efforts to monitor and promote transparency within capital markets.

1.4 Thesis Structure

Following this introductory chapter, my thesis is organized into four chapters. Within my work, there are three distinct manuscripts. The thesis is structured as follows: Chapter 1 has provided an introduction of the entire thesis, including the background, research questions, and summaries of all three manuscripts. Chapter 2 presents my first manuscript, discussing RIF window dressing at the fund level. Chapter 3 contains my second manuscript, an empirical research paper focusing on fund management at the fund family level. In Chapter 4, I present my final manuscript, investigating the impact of fund managers' past work experience on fund ESG performance. Chapters 2 to 4 are the distinct manuscripts summarized in the previous section, and are written to be ‘standalone’, each with an introduction, literature review, data, methodology and results, and conclusion. Chapter 5 concludes the thesis by providing a summary of key findings, the theoretical and practical implications of my research, and avenues for future research.

Chapter 2 (Manuscript 1): Window Dressing in Responsible Investment Funds

Abstract

Window dressing is a strategy fund managers use to manipulate portfolio holdings for the purposes of reporting more favourable information to investors about the funds' risk level, financial performance, and/or investment style. This paper examines the presence of financial performance and ESG window dressing in US domestic equity responsible investment funds (RIFs). Our results support the existence of financial return and ESG window dressing in RIFs. We also identify that RIFs with poor past performance, higher tracking errors, or those managed by companies with a lower commitment to sustainable investment are more likely to exhibit ESG window dressing.

JEL classifications: G10, G11, G12

Keywords: Responsible investment funds, window dressing, ESG performance

2.1. Introduction

Responsible investing seeks to promote Environmental, Social, and Governance (ESG) factors in its investment objectives (Mallin et al., 1995). Sustainable investment has shown considerable growth in recent years with global assets under management reaching US$30.3 trillion at the beginning of 2022 (Global Sustainable Investment Alliance, 2023). A considerable fraction of this capital is managed through Responsible Investment Funds (RIFs) – managed funds that consider the ESG attributes of investments when making investment allocations.[6]

As sustainable investment continues to develop, academic interest in RIFs correspondingly increases. Extant literature predominantly focuses on the financial performance of RIFs versus conventional funds (van Dijk-de Groot & Nijhof, 2015). Much of this literature finds that RIF investors do not sacrifice returns to achieve their non-financial goals (Friede et al., 2015; Whelan et al., 2021), despite RIFs having fewer diversification opportunities. Currently, only a few regulations exist to govern the ESG strategies of RIFs in the US.[7] Given the assumption that RIF investors are more likely to consider ESG attributes and the evidence that a smaller investment universe does not harm financial performance, it is reasonable – arguably essential – to ask whether RIFs make investment allocations that are different from conventional funds. That is, do RIFs live up to their ESG-incorporation strategies or do they only state they are "RIFs"? The most direct method to verify our question is to consider fund holdings information, as in Dorfleitner et al. (2012), Utz and Wimmer (2014) and Joliet and Titova (2018). These studies assess disclosed companies held by RIFs to determine their ESG performance. However, there are two potential problems with such analysis. First, holdings are only available on a quarterly basis,[8] which means portfolios held between two reporting dates are unknown. Second, most studies rely on funds' self-reported information, but relatively little is known about the veracity of the disclosed information. Managers may be less willing to show investors a portfolio that held poorly performing stocks as

[6] ESG factors are typically addressed using one or more of several possible strategies, including negative/exclusionary screening, positive/best-in-class screening, norms-based screening, ESG integration, sustainability themed investing, impact/community investing, and corporate engagement and/or shareholder action (Global Sustainable Investment Alliance, 2021).

[7] The SEC is developing regulations related to Climate Disclosures for Public Companies. The US Federal Insurance Office (FIO) is working on regulations concerning Climate-related Financial Risks and Insurers. Both are still in development.

[8] Since 2004, mutual funds in the US are required to disclose their complete portfolio holdings quarterly, with a 60-day delay (Securities and Exchange Commission, 2004).

investors are (at least partially) evaluating fund managers based on their disclosed portfolio holdings (Solomon et al., 2014). The interest of investors in fund holdings gives fund managers an incentive to manipulate their holdings close to a reporting date to provide a more favourable impression, a behaviour commonly known as 'window dressing' (Agarwal et al., 2014).

Extant literature has shown some mutual fund managers window-dress their holdings with respect to risk level (Morey & O'Neal, 2006), financial performance (Agarwal et al., 2014), and investment style (Meier & Schaumburg, 2006) to show a more favourable portfolio to investors, attract new investors and cash inflows, and avoid losing investors to other funds. We argue that RIF managers may adopt the same practice as RIFs are affected by the same pressures as traditional mutual funds. In addition to altering holdings to better performing, less risky firms, RIFs may also adjust holdings with regard to ESG aspects. Specifically, they may strategically sell (buy) companies with low (high) ESG performance prior to a reporting date, suggesting a greater sustainability focus to investors who care about responsible investment. We refer to this as *ESG window dressing*. ESG window dressing misleads investors, competitors, and rating agencies, and can negatively impact funds' value due to unnecessary rebalancing costs. However, relatively little research has addressed this issue. This paper attempts to fill this gap.

Our study examines whether US domestic equity RIFs window-dress along the ESG dimension. We employ fund holdings information and ESG scores of companies held by funds to proxy for funds' ESG performance. We test for two types of window dressing: financial return and ESG window dressing. We compute the "rank gap" and "backward holding return gap" (BHRG) as in Agarwal et al. (2014) to detect financial return window dressing. The first measure detects the gap between performance-based and average rankings based on disclosed holding proportions of winner and loser stocks. The second method captures the difference between a fund's actual return and the hypothetical returns imputed from a fund's reported holdings. Both methods demonstrate that RIFs engage in financial performance-based window dressing.

To assess ESG window dressing, we follow Fama and French (1993) and construct an ESG factor to capture the return premium on a strategy that is long in high ESG stocks and short in low ESG stocks. By regressing the BHRG on the ESG factor, we find that 68 out of 196, or 34.6%, of RIFs alter their holdings to companies with a higher ESG score close to reporting dates. We also use daily returns data and conduct an event study considering windows of 5, 10, 15, and 20 days before the reporting date. Depending on the window, we find between 11.76% and 24.26% of RIFs have a significantly higher loading on the ESG factor just prior to the reporting date, and these percentages sharply drop after the portfolio disclosure date. Such clustered end-of-quarter rebalancing is more likely to be window dressing than routine holding adjustments, which should be uniformly distributed throughout the entire period. To further support our findings, we compute daily coefficients of return on the ethical index based on a Kalman filter. The result from a subsample of funds with significant positive coefficients on the ESG factor indicates the sensitivity of returns to sustainable funds persistently increases 12 days before the disclosure date. This finding also suggests that some RIFs adjust their holdings in accordance with ESG window dressing immediately prior to the reporting date. We further identify that RIFs with poor past performance, higher tracking errors, or those managed by companies with lower sustainable investment levels overall are more likely to engage in ESG window dressing behaviours.

Our paper offers two contributions to the RIF and window dressing literature. First, we supplement the RIF literature by assessing ESG performance. RIFs are marketing themselves as investments with higher ESG values. They attract investors who, at least in part, are concerned about the social impact of their investments and want to improve the world they live in. However, extant studies often assume that RIF investments comply with their ESG principles and therefore do not assess RIFs' consistency with their investment objectives (Capelle-Blancard & Monjon, 2012; Nitsche & Schröder, 2018). This paper evaluates the sensitivity of RIF returns to an ethical index and thus provides investors with a broader picture of these funds' ESG performance. Second, unlike extant papers that investigate window dressing in the context of risk level or performance-based window dressing, this paper provides unique insights into ESG-based window dressing. Such "deceptive" behaviour may mislead investors about their actual investment and the social impact they are generating. In addition, widespread window dressing may render RIFs ineffective in promoting social change. Therefore, it is essential to know whether RIFs engage in ESG window dressing.

This paper may also have practical contributions. The SEC has noted potential misleading ESG-related marketing practices within the US mutual funds market and issued an alert to address these concerns (Chin, 2021). Our findings provide evidence to support the existence of ESG window dressing and suggest the importance of addressing this issue. Furthermore, due to concerns about whether RIFs invest in companies that meet certain ESG objectives, the SEC proposed amendments to the Investment Company Act ("Names Rule") in 2023. These changes require funds with an ESG-related term in their name to have at least 80% of their holdings aligned with the ESG objectives described in their name (Fisch & Robertson, 2023). Given the ESG window dressing behaviors we have found, this paper may suggest that the Names Rule may need further amendments to achieve the expected objective of monitoring funds' ESG performance.

2.2. Literature Review

2.2.1 Financial and Non-financial Returns of RIFs

The literature on RIFs has grown rapidly over the past two decades. One strand of literature assesses the financial performance of RIFs compared to either all or characteristics-matched conventional funds, aiming to detect a potential performance penalty caused by ESG considerations. However, the comparison results are mixed. The majority of these studies demonstrate that the risk-adjusted performance of responsible funds do not differ significantly when compared to conventional funds, either before or after fees (Friede et al., 2015; Thompson et al., 2011; Whelan et al., 2021). In contrast, a few studies find that RIFs outperform non-RIFs (Gil-Bazo et al., 2010; Lean et al., 2015; Alda, 2020) and RIFs underperform non-RIFs (El Ghoul & Karoui, 2017; Ibikunle & Steffen, 2017, Azmi et al., 2020) in specific settings.

Another strand of literature studies the non-financial performance of RIFs. These studies focus on portfolio composition and assessing whether RIFs deserve the label "Responsible". For example, Bello (2005) compares assets held by RIFs and randomly selected conventional funds, finding no significant difference between these two groups. Similar results have also been reported by Chieffe and Lahey (2009). More recently, Utz and Wimmer (2014) ranked all US mutual funds from the Asset4 database into quintiles based on their annual ESG scores. They find that only 11.58% of RIFs have average ESG scores high enough to be in the highest quintile, compared with 20.13% of conventional funds. In addition, approximately 36.7% of RIFs lie below the average level of ESG performance for all funds. These figures suggest that some RIFs may not be meeting reasonable expectations of ESG performance. However, contrasting results are obtained by other researchers. For example, Kempf and Osthoff (2008) rank US equity funds based on their holding stocks' KLD rating and find that RIFs have a significantly higher ESG ranking than conventional funds. Bialkowski and Starks (2016) examine the ESG scores of US RIFs and conventional funds holdings between 2002 and 2011 and state that RIFs have higher ESG profiles for five of seven categories.[9] More recently, Nitsche and Schröder (2018) employ ESG information provided by three rating agencies (Oekom research AG, Sustainalytics and ASSET4) and find that RIFs have, on average, higher ESG rankings based on the top 10 fund holdings in the European and Global fund universe. Joliet and Titova (2018) find a similar result in the US based on a sample of 47 US domestic equity funds between September 2009 and November 2015.

Both financial and ESG performance-based analyses have resulted in studies that compare RIFs with conventional funds in terms of general fund characteristics, such as size, age, turnover ratio, and investment style (Alda, 2020; Ivanisevic Hernaus, 2019); fund manager characteristics, such as age, gender, skill, and whether they are group managers or not (Agarwal et al., 2014; Muñoz et al., 2015); investor behaviour (Amel-Zadeh & Serafeim, 2018; Riedl & Smeets, 2017); and performance in crisis and non-crisis periods (Muñoz et al., 2015; Nofsinger & Varma, 2014). For RIFs, researchers have also examined the intensity of ESG screens they apply, such as positive screens, negative screens and best in class (Nofsinger & Varma, 2014; Trinks & Scholtens, 2017). However, although these studies have addressed both the financial and non-financial performance of RIFs, they tend to use funds' announced information and assume reported holdings accurately represent the entire investment period, which may not be the case in practice. This paper aims to discuss this point and expand existing knowledge of RIFs.

2.2.2 Window Dressing

Window dressing has occupied the attention of many researchers over the years. One of the pioneering works is Haugen and Lakonishok (1987), who argue window dressing may be an alternative explanation for the January effect. Since then, considerable empirical research has been conducted to test whether fund managers are "dressing up" their portfolios. According to Agarwal et al. (2014), window dressing behaviour may be caused by potential agency problems between mutual fund companies and their investors. Investors would like the fund company to maximize risk-adjusted fund returns within the constraints of the company's stated investment style and objective. The fund manager, in contrast, is seeking to maximize their fees by maximizing

[9] The MSCI ESG research rating covers seven categories of social responsibility: community, corporate governance, diversity, employee relations, environment, human rights and products. Bialkowski and Starks (2016) find that RIFs offer higher positive exposures to these categories, except for community and diversity.

the fund's assets under management (AUM). Ideally, a fund manager can satisfy both objectives by earning high returns, satisfying existing shareholders, attracting new investors, and thereby increasing the assets under management and their management fees. Attracting new inflows is the quickest way to increase the size of the fund but requires a fund to (at least appear to) outperform its peers. At the very least, managers want to retain their existing AUM, which means they need to avoid looking worse than their peers. According to Morey and O'Neal (2006), in the case of poor past performance, investors are more likely to stay if the fund is holding recent top-performing securities. For attracting new fund flows, Elton et al. (2011) state that by changing holdings to better-performing securities, investors may get the impression that the fund is holding winners and infer that this fund held winner stocks that have superior performance. Therefore, window dressing may help managers to retain existing or attract new fund flows and thus generate additional fee income and even increase their standing and job security (Cici et al., 2021). Window dressing, therefore, can allow managers with either poor performance or deficient managerial skills to appear better than they are, giving them a strong incentive to engage in window dressing (Hung et al., 2020; Agarwal et al., 2014).

The existing literature discusses two types of window dressing. The first type occurs due to performance-chasing behaviour. Managers try to sell poorly performing companies and/or buy winner stocks before the holding disclosure date to "make up" their portfolio. For example, O'Neal (2001) investigates 195 US equity mutual funds' 6-month rolling window return and states that December (just before the required disclosure date) exhibits the strongest evidence of window dressing. Similar tests have been done by Meier and Schaumberg (2006). They investigate 4,025 US domestic equity mutual funds between 1997 and 2002 and examine the difference between the actual fund return and a hypothetical buy-and-hold portfolio based on disclosed holdings. They find strong evidence of window dressing during the last days of the quarter. More recently, Ortiz et al. (2015) and Hung et al. (2020) extend the literature by studying Spain and Taiwan, respectively. They both find that equity funds attempt to increase the weights of return-winner stocks and decrease the return-loser stocks in disclosure months. Ortiz et al. (2015) also find that non-disclosure months show the opposite trend, which supports the existence of window dressing. Another interesting finding discussed by Solomon et al. (2014) is that investors respond positively to funds which include media-covered past winner stocks, although the premium return of winner stocks may not be captured by these funds.

The second type of window dressing happens when managers try to change the risk characteristics of a fund. Before the disclosure date, managers may purchase less risky stocks and/or decrease high-risk assets to show a less-risky portfolio to attract investors who prefer a safer investment. For instance, Chevalier and Ellison (1997) find that growth and income funds modify their holdings in the last quarter of the year to alter the riskiness of their investment portfolio. Similar results have been found in bond funds. Morey and O'Neal (2006) assess portfolio credit quality holdings and daily returns of US corporate bond funds between 1998 and 2001. They point out that bond funds invest in significantly more government bonds during reporting periods compared with non-reporting periods, presumably to disclose a less risky portfolio to investors. More recently, Patton and Ramadorai (2013) investigate 14,194 hedge funds and funds of funds between 1994 and 2009, finding that hedge funds exhibit significant day-of-month seasonality changes on risk exposure, which may be caused by intra-month window dressing.

Both types of window dressing may have negative consequences for fund investors. If fund managers window-dress their holding portfolio, the investors are not only misled about their investment but are also bearing unnecessary transaction costs. O'Neal (2001) estimates that within the American equity funds market, the annual costs attributable to window-dressing portfolio rebalancing may exceed $1 billion,[10] an economically meaningful sum. Agarwal et al. (2014) also state that due to unnecessary transactions, window dressing may potentially impact fund value adversely.

2.2.3 Window Dressing in RIFs

Although literature documents evidence of window dressing behaviour in mutual funds, limited attention has been given to RIFs, which typically have constraints on their investment universe. In addition to performance and risk exposure-based window dressing, RIFs may exhibit another type of window dressing, *ESG* window dressing. RIF managers may change their holdings from socially conscious investments to some high financial performance but low-ESG performance industries between reporting dates. A few papers mention window dressing in RIFs. For example, Elaut et al. (2015) state that because of potential window dressing, the use of

[10] Funds incur costs with every buy and sell trade conducted as a result of the bid-ask spread.

responsible funds' current holdings to assess RIFs' performance may lead to upward biased results.[11] However, to date, limited work has been done in this field.

Kempf and Osthoff (2008) mention that ESG rankings of RIFs are higher than those of conventional funds,, and they state that this superior ESG ranking is not caused by window dressing. In their paper, they conduct two tests to rule out the impacts of window dressing. The first measure compares the ranking of mid-year reported holdings and end-year reported holdings. They find the difference is not statistically significant and argue there is no evidence for window dressing. The main drawback of this measure is that it assumes the mid-year reporting is not affected by window-dressing, which may not be the case. Their second test detects window dressing by analysing fund performance against conventional and ethical indices. They assume that if window dressing exists, the sensitivity of fund returns is expected to be higher shortly before the reporting date than at other time periods. However, this method is impacted by data availability. They only test this method on 66 RIFs between 2001 and 2004 (the original sample is between 1998 and 2004) based on semi-annual holding data and find no significant outcomes. Additionally, it is worth noting that the sample period of Kempf and Osthoff (2008) represents the early days of responsible investing, resulting in a small number of funds that were likely highly committed to the goals of responsible investing. Since 2004 there has been a significant increase in providers, including more traditional fund families offering responsible products as a portion of their total offered funds. This raises the possibility that window dressing, which has been extensively documented in conventional funds, may have become more prevalent in RIFs as the segment has become a larger and more important part of the market. Therefore, this paper re-examines Kempf and Osthoff's (2008) method by employing a more frequent,[12] representative,[13] and recent RIF sample.

Relatively less work has been done in ESG window dressing (altering fund holdings for a better ESG score before the reporting date) compared to financial return window dressing. However, several papers examine a

[11] This is because the current holdings introduce a look-ahead bias. At the same time, window dressing may reveal a portfolio that performed well historically, potentially leading to overestimated performance.
[12] The SEC required US mutual funds to disclose their complete portfolio holdings to shareholders on a quarterly basis (with a 60-day delay period) after 2004. The SEC states that this change aims to ask funds to provide more information for investors to assess the fund strategies and managers' skills, as well as to better monitor some market manipulations, such as window dressing and portfolio pumping. While the opinion on the value of this change is still mixed (see Parida & Teo, 2018; Parida, 2017; Schwarz & Potter, 2016; Gormley et al. 2019; Frank et al. 2004), we take advantage of this change, employing quarterly holding data to analyse window dressing in RIFs.
[13] Kempt and Osthoff (2008) identify RIFs based on Morningstar's classification, while our research identifies RIFs based on the USSIF report, a comprehensive report specialised in the responsible investment industry in the US.

related concept: greenwashing,[14] commonly defined as manipulating and disseminating environmental information to mislead the public (Lyon & Maxwell, 2011). According to Delmas and Burbano (2011), greenwashing is derived from consumer and investor demand, incentive structures, the 'ethical climate', and an optimistic bias. The existence of greenwashing may reduce consumer confidence and undermine the green investment market. Several papers have detected the existence of greenwashing in sustainable investment. For example, Findlay and Moran (2018)[15] find evidence some funds are presented as impact investments, but which do not fulfil their announced definition. More recently, Brandon et al. (2021) state US institutions that publicly commit to responsible investing reveal at best similar, if not significantly worse, portfolio ESG scores than other non-committed institutions, and they classify such behaviour as greenwashing. Examining window dressing and greenwashing reflects researchers' growing interest in assessing the integrity of sustainable investment funds. This paper further explores this criticism faced by RIFs and assesses if they are living up to their stated ESG goals.

2.3. Hypotheses

The extant literature suggests that window dressing is a strategy fund managers implement to attract investors via more favourable holdings information. Responsible investors seek two sorts of benefits: financial benefits and benefits related to non-financial considerations (Levitt & List, 2007). Both benefits impact investors' choice of fund decision (Døskeland & Pedersen, 2016). To accomplish investors' dual objectives and show favourable holdings to investors, RIF managers may engage in two types of window dressing. First, for investors who are primarily driven by financial performance, and for whom ESG is a secondary but important consideration, RIFs managers may engage in financial performance window dressing. Specifically, they might attempt to increase (decrease) the proportion of winner (loser) stocks in reported holdings. Second, for pure

[14] The definition of greenwashing in the Oxford English Dictionary is: "The creation or propagation of an unfounded or misleading environmentalist image". Compared with ESG window dressing, greenwashing is more related to the environmental practices of a company or the climate-friendly benefits of a product or service.
[15] Findlay and Moran (2018) refine the definition of greenwashing to purpose-washing by emphasising intentionality. They argue purpose-washing occurs when investors are misled about a manager's impact intentions (including measurement) or an investment's potential impact. Their definition is similar to ESG window dressing in our paper. Under this circumstance, ESG window dressing could be considered a specific type of greenwashing.

responsible investors, who prioritize ESG performance over financial returns, fund managers have incentives to distort holdings to companies that have a better ESG score. That is, *ESG* window dressing.

To test the existence of the two possibilities above, we propose the following two hypotheses:

Hypothesis 1: RIFs exhibit financial return window dressing

Hypothesis 2: RIFs exhibit ESG window dressing

2.4. Data

To investigate window dressing by RIFs, we obtain data from three sources. The Forum for Sustainable and Responsible Investment (US SIF) reports provide lists of RIFs. US SIF is a non-profit membership association that focuses on sustainable investment practices in America and is one of the most widely used providers of RIF information in the literature (Benson & Humphrey, 2008; Humphrey et al., 2016; In et al., 2014). Morningstar Direct is used to retrieve information about fund holdings, fund returns, and other characteristics, such as the fund management company, share classes, net assets, and expense ratio. Information on stock prices and ESG scores of the companies held by RIFs is obtained from Thomson Reuters Eikon.[16] In line with the existing literature, we identify RIFs based on the fund list provided in the US SIF trend reports between 2007-2020.[17] To avoid survivorship bias, RIFs are kept in the sample once they appear in one of these report lists. From the reports, we initially identify 1,193 different share classes.[18]

As this paper focuses on US equity RIFs, we exclude balanced, bond, and global money market funds (Agarwal et al., 2014; In et al., 2014; Kempf & Osthoff, 2008). Based on the Morningstar Global Category, funds belonging to US Equity Large Cap Blend, US Equity Large Cap Growth, US Equity Large Cap Value, US Equity Mid Cap and US Equity Small Cap remain in the sample. After filtering for fund category, the sample

[16] The scores are currently published by Refinitiv.
[17] As the 2020 report was not published when we began data collection, the 2020 list was derived from the US SIF website.
[18] Morningstar provides fund information at the share classes level, which means different classes of the same funds are treated as separate observations. To avoid double-counting, the share class level information has been aggregated to fund level in the later part of the analysis.

size decreases to 747 different share classes. This list includes not only active classes but also liquidated and merged classes to avoid survivorship bias (Kempf & Osthoff, 2008).[19]

Some funds in our sample have multiple share classes. The main differences between the share classes are their loads and expense ratios, while portfolio holdings remain the same (Alda et al., 2020; Doshi et al., 2015; Humphrey et al., 2016; Ibikunle & Steffen, 2017; Kurniawan et al., 2016; O'Neal, 2001). Following the existing literature, we aggregate each share class at the fund level based on share-class total net assets to obtain value-weighted monthly return and annual expense ratio. The 747 different share classes are therefore aggregated into 216 funds.

Then, consistent with Agarwal et al. (2014), funds with less than 24 monthly returns within the sample period are excluded. We also exclude funds where less than 75% of their holdings can be successfully matched with stock information from TR Eikon (Borgers et al., 2015).[20] This cleaning process results in a final sample of 196 RIFs between January 2005 and December 2019. Fund level descriptive statistics are presented in Table 2-1. The average fund is about 18 years (215 months) old, has US$3672 million of assets under management, and has a turnover ratio of 53%.

Table 2-1 Fund level descriptive statistics

	Size (Million)	Turnover Ratio % (annual)	Age (month)
Mean	3,671.69	53.25	214.87
Standard Error	1,029.85	2.33	12.53
Median	232.13	45.47	187.00
Standard Deviation	14,417.93	32.34	175.41
Kurtosis	61.16	2.46	7.34
Skewness	7.14	0.70	2.34
Minimum	1.94	10.67	28.00

[19] Following the work of Alda et al., (2020), we use information provided by Morningstar under the labels "Obsolete type", "Obsolete date", "Merged into Security", and "Merged into Security ID". The first item indicates if the share class has been liquidated or merged with others. The second item indicates the date of liquidation or merger. The remaining two indicate the acquiring fund name and ID, which advise if the mergers happened within-family or across families. There are 119 share classes liquidated between 2005-2020. 126 share classes merged with another fund. Within these merged share classes, 55 share classes merged into other share classes of the same type. 57 share classes merged into different funds, but the target funds remain in the RIF list. 14 share classes merged into different funds, but the target funds are not included in the RIF list. For liquidated and merged classes, we keep them in the sample until their obsolete date.

[20] The portfolio holdings downloaded using the Morningstar Excel Add-in only include company name, SECID and proportion held by funds. The identifier SECID is only used in Morningstar. We begin by downloading all the listed US companies' price information and identifiers (such as ISIN and Ticker) from Eikon. We then match firms with Morningstar Direct and use the SECID and companies' names provided by Morningstar Direct to match downloaded portfolio holdings.

Maximum	150,220.29	120.75	1,101.00
Number of Funds	196	192	196

Note: Table 2-1 reports the summary statistics of 196 US domestic equity RIFs from January 2005 to March 2010. *Size* is the average fund size for the studied period, reported in millions of dollars. *Age* is the number of months since the fund's inception date to the end of the study period or the last month that the fund has return information. *Turnover ratio %* is computed by taking the lesser of purchases or sales (excluding all securities with maturities of less than one year) and dividing by average monthly net assets.

2.5. Methodology and Results

We first use the two window dressing measures, Rank Gap and Backward Holding Return Gap (BHRG), of Agarwal et al. (2014) and Solomon et al. (2014) to detect the existence of return window dressing in RIFs. Then, we construct the ESG factor by employing a similar method to Fama and French (1993) and regress the BHRG on the ESG factor to test whether it is tilted towards high ESG score companies and infer if ESG window dressing exists. For robustness, we then employ the performance comparison test (Kempf & Osthoff, 2008) and a Kalman filter (Swinkels & Van Der Sluis, 2006), finding that RIFs shift holdings from high to low ESG companies between reporting dates. Lastly, we perform a logistic regression and test the potential determinants of ESG window dressing.

2.5.1 Financial Return Window Dressing

Agarwal et al. (2014) develop the "rank gap" method to measure performance inconsistency and use this as a relative measure of window dressing. This method has been widely used in recent papers (Hung et al., 2020; Marques et al., 2020; Cici, et al., 2021). The rank gap is calculated as follows. First, company returns are ranked at the end of each month. Second, we allocate all companies to quintile portfolios. The first (fifth) portfolio includes companies with the highest (lowest) return. Third, based on the quarterly reported holdings[21] of each fund, we calculate the proportion of each fund's assets invested in the first and fifth quintile stocks. The two proportions are defined as the winner and loser proportions. Fourth, for each month and each fund that reported holdings, we compute three alternative rankings:

1. We rank all funds based on their past return (the highest return is given the highest rank);

[21] Most funds in sample report their holdings quarterly. We use current quarterly end reported holdings and assume that the holdings stay consistent from the beginning of the current quarter.

2. We rank all funds based on their winner proportion (the highest proportion is given the highest rank);

3. We rank all funds based on their loser proportion (the lowest proportion is given the highest rank).

A higher rank means that a fund has a higher return, a larger proportion of its investments in higher return companies, and a smaller proportion in lower return companies. In the spirit of Agarwal et al. (2014), a fund with a low-performance ranking but a high ranking in the winner and loser proportions is more likely to engage in window dressing. The last step is to calculate the *rank gap,* the difference between performance ranking and average proportion ranking. Agarwal et al. (2014) scales the difference by dividing by 200 to produce a theoretical bound around the *rank gap* between -0.495 and +0.495 (as shown in Equation 2.1). A larger *rank gap* indicates greater performance inconsistency and thus a higher likelihood window dressing is occurring.

$$rank\ gap_{i,t} = \left(performance\ rank_{i,t} - \frac{winner\ rank_{i,t} + loser\ rank_{i,t}}{2}\right) \div 200 \qquad (2.1)$$

Table 2-2 reports summary statistics for the rank gap and the percentage of loser and winner holdings. The average monthly *rank gap* is 0.0021, and the median is about 0.0025.[22] These figures provide evidence for financial performance window dressing in our sample. Although the average is near zero, the high standard deviation of 0.1077[23] and the large range (-0.46, 0.48) indicate that the level of window dressing across RIFs varies. The mean percentage of loser stocks is 4.9%, and the corresponding standard deviation is 4.87. The mean percentage of winner stocks is 15.28%, and the corresponding standard deviation is 9.16. On average, RIFs hold a higher proportion of winner stocks than loser stocks.

Table 2-2 Descriptive statistics of rank gap and the proportions of winner and loser stocks

	Rank Gap	**Percentage of loser stocks**	**Percentage of winner stocks**
Mean	0.0021	4.9013	15.2797
Median	0.0025	3.5249	14.0495

[22] Mean and median in our study are larger than that in Agarwal et al. (2014). Their mean and median are -0.0003 and -0.0025, respectively. In a more recent paper, Bai et al. (2019) state their mean and median rank gap are 0.00 and -0.01. Both existing papers discuss US equity funds, while our sample only includes RIFs. To the best of our knowledge, no other paper assesses the rank gap for RIFs.

[23] The standard deviation we find is much smaller than that from some other recent papers. For instance, Hung et al. (2020) find the standard deviation of the rank gap is 32.16 for Taiwan's mutual funds. This may be caused by the fact that we follow the method of Agarwal et al. (2014) to scale the rank gap within a range of (-0.495, +0.495), while Hung et al. (2020) does not.

Maximum	0.4800	48.8879	69.8622
Minimum	-0.4625	-2.5800	-0.6100
Std. Dev.	0.1077	4.8736	9.1630
Observations	25,256	25,727	25,727

Note: Table 2-2 presents the overall summary statistics of the monthly rank gap and the proportions of winner and loser holdings for 196 funds between January 2005 and December 2019. Following Agarwal et al. (2014), the *rank gap* is calculated based on Equation (2.1). *Percentage of loser (winner) stocks* is the percentage of holdings that invest in the stocks that belongs to the quintile portfolio of the lowest (highest) return.

Following Agarwal et al. (2014) and Solomon et al. (2014), we employ the "backward holding return gap" (BHRG) to measure the potential performance inconsistency of RIFs between their announced and actual returns. We first collect holding information for each RIF at their quarterly reporting date, and then combine fund holdings with stock information obtained from Thomson Reuters Eikon to calculate a hypothetical portfolio return called the backward holding return (BHR). BHR is calculated based on the buy and hold returns of disclosed holdings at the end of each quarter. Specifically, we match each fund's holdings with the return of individual companies for each quarter and then calculate the value-weighted portfolio return for those stocks with available return data, based on the holding weights. We then assess the percentage of holdings that can be matched with stock information. To remain in our sample, a fund needs to have at least 75% of its holdings successfully matched with the stock information. Finally, we scale the value-weighted portfolio return by normalizing portfolio weights to one to get the BHR for each fund. BHRG is defined as the difference between the BHR and RIFs' Actual Return (AR).[24]

$$BHRG_{i,t} = Backward\ holdings\ return\ (BHR)_{\ i,t} - Actual\ return\ (AR)_{i,t} \qquad (2.2)$$

Table 2-3 describes summary statistics of monthly *AR*, *BHR* and *BHRG* for our sample between 2005 and 2019. The average *AR*, *BHR* and *BHRG* are positive (0.0084, 0.0090, and 0.0007, respectively) and the significance tests show the average values are all significantly different from zero. According to Agarwal et al. (2014), a higher *BHRG* indicates a greater likelihood of return-based window dressing occurring. As shown in

[24] Actual Return is calculated by adding back monthly expense ratios to funds' monthly returns.

Table 2-3, monthly *BHRG*s range from -0.11 to 0.11, which may indicate the existence of return window dressing as there are differences between RIFs' announced and actual returns.

Table 2-3 Descriptive statistics of *AR*, *BHR*, *BHRG*

	AR	BHR	BHRG
Mean	0.0084***	0.0090***	0.0007***
Median	0.0129	0.0136	0.0007
Maximum	0.3141	0.2607	0.1122
Minimum	-0.3229	-0.3680	-0.1057
Std. Dev.	0.0453	0.0454	0.0085
Sum	212.7604	231.9007	17.8571
Observations	25,347	25,656	25,237

Note: Table 2-3 reports the summary statistics of *AR*, *BHR*, *BHRG* for 196 US domestic equity RIFs. *AR* is RIF's value-weighted actual return, which is aggregated from the share classes return based on the net asset values of each share class. *BHR* is the backward holding return calculated based on the disclosed holdings by applying the buy and hold strategy. *BHRG* is the difference between the *BHR* and the *AR*. *, **, *** denote significant differences from zero at 10%, 5% and 1%.

2.5.2 ESG Window Dressing

2.5.2.1 Full sample analysis

Agarwal et al. (2014) calculate the average value of the BHRG to detect the existence of financial performance-based window dressing. The higher the BHRG, the greater the likelihood of window dressing. However, the BHRG cannot explain ESG window dressing. We cannot directly check holdings information as it is unavailable during the non-reporting period. We overcome this limitation by computing an ESG factor to represent the return premium on an ESG investment strategy (long high-ESG stocks and short low-ESG stocks), in the spirit of Fama and French (1993). By regressing the BHRG on the ESG factor, we can infer whether the BHRG is tilted towards high or low ESG score companies.

To build an ESG factor, all stocks that have ESG scores[25] are ranked according to their previous year's market capitalization. They are then grouped into two portfolios, big and small, based on median market value. Within each portfolio, we rank companies based on their ESG scores and assign the highest 30% of companies to the

[25] As sustainable investment has been experiencing notable growth, various rating agencies provide an ESG rating to assess the sustainability performance of companies. We employ the Refinitiv ESG combined score (provided by Thomson Reuters Eikon) to proxy the firms' overall ESG performance. The Thomson Reuters ESG score is calculated based on reported ESG-related information and is one of the most widely used measurements of ESG performance (Dorfleitner et al.,2020; Drempetic et al., 2020). According to Refinitiv (2021), Refinitiv ESG company scores cover 9,000 companies globally and have time-series historical data from 2002. In our sample, 3988 companies have ESG scores.

high ESG portfolio and the lowest 30% of companies to the low ESG portfolio. Next, we calculate the value-weighted return for four portfolios (small high ESG, small low ESG, big high ESG and big low ESG). The *ESG* factor is the average return on the two high ESG portfolios, minus the average return on the two low ESG portfolios.[26] The ESG factor portfolios are rebalanced at the beginning of each year. Following the prior literature, the models can be expressed as follows:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{0i}(R_{m,t} - R_{f,t}) + \beta_{1i}SMB_t + \beta_{2i}HML_t + \beta_{4,i}ESG_t + \varepsilon_{it} \quad (2.3)$$

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{0i}(R_{m,t} - R_{f,t}) + \beta_{1i}SMB_t + \beta_{2i}HML_t + \beta_{3i}MOM_t + \beta_{4,i}ESG_t + \varepsilon_{it} \quad (2.4)$$

where $R_{i,t}$ - $R_{f,t}$ is the monthly excess return of the *AR*, *BHR*, and *BHRG* for RIF *i*. $R_{m,t}$ - $R_{f,t}$ is the monthly excess return of the benchmark.[27] β_{0i} is the slope of regression for RIF i and the corresponding benchmark, while β_{1i}, β_{2i}, β_{3i}, and β_{4i} are coefficients for the size factor, book-to-market ratio factor, momentum factor and ESG factor, respectively. ε_{it} is the error term in month *t*. $R_{m,t} - R_{f,t}$, *SMB*, *HML* and *MOM* factor data are from Kenneth French's website.

We run three regressions (*AR*, *BHR*, and *BHRG*, separately) for each of the 196 US equity RIFs based on Equations (2.3) and (2.4) between 2005M1 and 2019M12. Table 2-4 summarises the regression results. Panel A and panel B present the 3-factor and 4-factor models, respectively.

The ESG factor coefficients, β_{4i}, represent the estimate of window dressing, and show two interesting results. First, the average β_{4i} for both BHR and AR are negative, indicating that, on average, RIFs' returns, both recorded actual return and the backward holdings return (calculated using the disclosed holdings), are tilted towards low ESG score companies. This may not fit investors' general expectations for RIFs. A logical assumption is that RIFs tilt towards higher ESG score companies. Some investors are even willing to accept lower expected returns and/or higher management fees to invest in accordance with their social preferences (Riedl & Smeets, 2017). However, several recent works also express doubt as to whether RIFs are actually delivering their promise to focus on better ESG investment. For instance, Raghunandan and Rajgopal (2022)

---

[26] ESG factor = 1/2 * (small high ESG + big high ESG) - 1/2 * (small low ESG + big low ESG).
[27] Based on the description of Fama-French factors, $R_{m,t}$ - $R_{f,t}$ includes all firms listed on the NYSE, AMEX, and NASDAQ.

find that holding companies of self-labelled US RIFs have a significantly higher number of violations in labour and environmental laws and pay greater fines for these violations than conventional funds managed by the same financial institutions. They also find that on average, RIFs' holding companies exhibit worse performance with respect to carbon emissions, in terms of both raw emissions output and emissions intensity. Another relevant work is Kim and Yoon (2022), who analysis the signatories of United Nations Principles for Responsible Investment[28] (PRI). They find that PRI signatories (at the investment management firms' level) attract a large increase in fund flow after signing but no improvements in their ESG scores, and also find no evidence they are buying (selling) high (low) ESG performing stocks. Consistent with this argument, Liang et al. (2022) and Brandon et al. (2021) also point out (hedge) funds that signed the PRI show worse (at best similar, if not worse) ESG performance than their uncommitted peers. Therefore, it is possible that for some RIFs in our sample, AR and BHR both negatively tilt to ESG factors.

Second, the average β_{4i} when using the BHRG is positive.[29] Thus, the return differences between the reporting portfolio and the actual return for these funds are more toward high ESG companies. This may indicate that funds alter their holdings to companies with higher ESG scores, which is consistent with ESG window dressing behaviour.

Table 2-4 reports the average of the coefficients, while Figure 2-1 presents the number of funds that have a significant β_{4i} in the sample. The three- and four-factor models show similar results. The AR and BHR results show more funds with a significantly negative β_{4i}, indicating that most RIFs with significant exposure to the ESG factor are investing in lower ESG score companies. However, the BHRG results show that most funds have a significantly positive β_{4i}.

[28] The United Nations PRI is the world's leading proponent of responsible investment. The signatories of PRI are publicly committing to incorporate ESG issues into investment analysis and decision-making and be active owners. Some recent papers employ the endorsement of PRI to reflect fund management firms' commitment to ESG investment (e.g., Kim &Yoon, 2022; Liang et al., 2022; Gibson Brandon et al., 2020).

[29] In addition to the 3-factor and 4-factor models, we also run the regression using only the CAPM and ESG factors. The average β_{4i} of BHRG generated from the CAPM is also positive (0.035). Detailed results of the CAPM regression are available upon request.

As shown in Table 2-4, the average α for BHR (0.0009)[30] is larger than that for AR (0.0002), indicating that disclosed holdings could generate better performance than the actual return obtained by investors. Furthermore, the percentage of funds with a significantly positive α for the BHR (36.22%) is higher than that for the AR (14.8%), suggesting that more funds could outperform the market if RIFs were investing in what they disclose to investors. These findings may support the existence of return window dressing.

The β_{0i} in Equations (2.3) and (2.4) captures market risk exposure. In both models, the average β_{0i} generated from the AR is slightly larger than that from the BHR,[31] indicating that the actual portfolio is riskier than the disclosed portfolio. In addition, about 48.47% of funds are riskier than the market using the AR, whereas the percentage for the BHR is only 39.29%. This suggests that reported holdings may be 'safer', i.e., having a lower market exposure, than the actual portfolios held by RIFs. This idea is in line with Chevalier and Ellison (1997). They find that fund managers modify their holdings in the last quarter of the year to alter the riskiness of their investment portfolio.

[30] In Table 2-3, the difference between the two means has been tested using paired two-Sample t-tests. In the 3-factor model, the p-values for α, $\beta 0i$, $\beta 1i$, $\beta 2i$ and $\beta 4i$ are 0.0197, 0.0271, 0.0156, 0.9273 and 0.000, respectively. In the 4-factor model, the p-values for α, $\beta 0i$, $\beta 1i$, $\beta 2i$, $\beta 3i$ and $\beta 4i$ are 0.0220, 0.0822, 0.00090, 0.3695, 0.2417, and 0.0000, respectively.
[31] Coefficients for AR and BHR from the 3-factor model are not significantly different from 1.

Table 2-4 Summary of coefficients from 3- and 4-factor models

	α			β_{0i}			β_{1i}(SMB)	β_{2i}(HML)	β_{3i}(MOM)	β_{4i}(ESG)
	Mean	% of funds significant positive α	% of funds significant negative α	Mean	% of funds β0i significantly >1	% of funds β_{0i} significantly <1	Mean	Mean	Mean	Mean
Panel A 3-factor model										
AR	0.0002	14.80%	6.12%	1.0013	48.47%	51.53%	0.1547***	0.0066		-0.1191***
BHR	0.0009***	36.22%	18.88%	0.9906	39.29%	60.71%	0.1671***	0.0062		-0.0767***
BHRG	-0.0004	22.45%	55.10%	-0.0073***	0.00%	55.10%	0.018***	0.0019		0.0415***
Panel B 4-factor model										
AR	0.0002*	18.88%	3.57%	0.9955	47.96%	52.04%	0.1523***	-0.0034	-0.0127*	-0.1257***
BHR	0.0009***	35.71%	18.37%	0.9868*	39.29%	60.71%	0.1663***	0.0006	-0.0088	-0.0814***
BHRG	-0.0004	22.45%	57.65%	-0.0058***	0.00%	58.16%	0.0189***	0.0047	0.0028	0.0425***

Note: This table reports the regression results of Equations (2.3) and (2.4) for 196 US domestic equity RIFs between 2005M1 and 2019M12. $R_{i,t}$ - $R_{f,t}$ is monthly excess return of RIF i. $R_{m,t}$ - $R_{f,t}$ is monthly excess return of the benchmark. β_{0i} is the slope of the regression for RIFs and the corresponding benchmark. β_{1i}, β_{2i}, β_{3i}, and β_{4i} are the coefficients for the size factor, book-to-market ratio factor, momentum factor and ESG factor, respectively. ε_{it} is error term in month t. Panel A and Panel B present the 3-factor and 4-factor models, respectively. We also report the percentage of funds that have a significant positive/negative α, and the % of funds have a significant β_{0i} greater (less) than 1. *, **, *** denote significant differences from zero (except for β_{0i}, the test is if the average is significantly different from 1) at 10%, 5% and 1%.

The results of coefficients for *SMB*, *HML* and *MOM* factors (in Table 2-4) find that: 1) The average β_{1i} for the AR is smaller than that for the BHR, which suggests that RIFs' disclosed portfolios are more small-stock-oriented than their actual holdings are. 2) The average β_{2i} for the AR and the BHR are both negative for the 3-factor model. For the 4-factor model, the average β_{2i} of the AR is negative, but β_{2i} of the BHR is positive. However, the difference in means is statistically insignificant for both models. 3) Both AR and BHR are tilted towards loser stocks, and the difference between the two means is statistically insignificant.

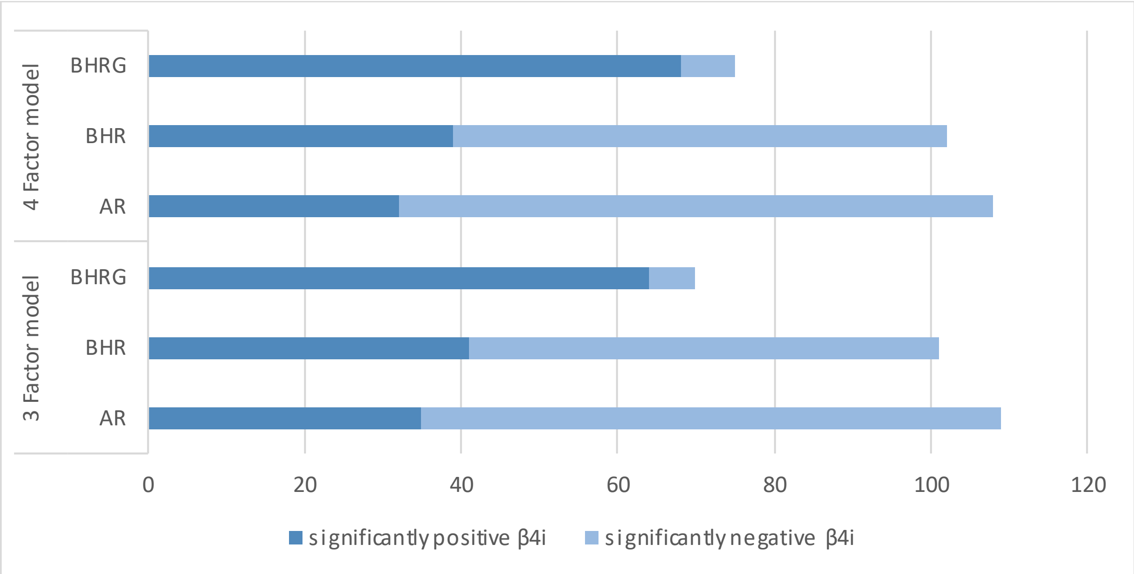


Figure 2-1 Funds with significant β_{4i}
Note: Figure 2-1 presents the number of funds that have significant β_{4i} based on Equations (2.3) and (2.4). The upper part summarises the result from Equation (2.4), and the lower part shows the result from Equation (2.3).

2.5.2.2 Subsample analysis

The above analysis indicates that a proportion of RIFs may exhibit ESG window dressing, i.e., the funds' BHRG have significant β_{4i} in the regressions (2.3) and (2.4). In this section, we identify common characteristics of these funds.

Based on the value of the funds' coefficient on the ESG factor, we split the sample into three subsamples. Funds with 1) significantly positive, 2) significantly negative, and 3) insignificant β_{4i} (the ESG factor coefficient). Table 2-5 presents the mean value of fund characteristics for the subsamples.

Table 2-5 Characteristics of the subsamples

	Size (million)	Age (month)	Turnover % (annually)	BHRG	Rank gap	N
Funds with significant positive β_{4i}(ESG)	8,417.13	283.13	45.83	0.0004	0.0015	68
Funds with significant negative β_{4i}(ESG)	750.66	231.29	48.89	-0.0025	0.0053	7
Funds with insignificant β_{4i}(ESG)	1,173.81	175.55	57.83	0.0013	0.0064	121

Note: This table presents the mean value of characteristics on three subsamples: funds with 1) significant positive, 2) significant negative, and 3) insignificant ESG factor coefficients, i.e., β_{4i}. Significance of differences are tested using the Welch's t-test, and the results are reported in Appendix 2-1. *Size* is the average of fund size for the studied period, reported in millions of dollars. *Age* is the number of months since the fund's inception date to the end of the study period or the last month the fund has return information. *Turnover ratio %* is computed by taking the lesser of purchases or sales (excluding all securities with maturities of less than one year) and dividing by average monthly net assets. *Rank gap* and *BHRG* are the average of rank gap and BHRG for the studied period, defined in Equations (2.1) and (2.2).

Funds that exhibit ESG window dressing are larger (average sizes are 8,417, 751 and 1151 million, respectively), older (average ages are 283, 231 and 176 months, respectively), and have a lower turnover ratio (46%, 49%, and 58%, respectively) than funds with significant negative and insignificant β_{4i} (ESG). This may indicate that the established players are more likely to strategically obfuscate their ESG performance. In addition, we observe that the average BHRG and rank gap, the indicators of financial performance window dressing, is smaller in magnitude for subsample 1 than in the other subsamples. This suggests that these RIFs show less performance inconsistency and smaller differences between announced holding returns and actual returns. Therefore, RIFs which exhibit ESG window dressing are less likely to engage in return window dressing compared to other RIFs. One possible explanation for such a finding is that some RIFs may be primarily focused on ESG performance rather than on returns when disclosing their holding portfolios. As we noted earlier, it is possible that RIF investors are not homogenous: some may value returns more highly within the context of investing responsibly, while other investors prioritise ESG performance over returns. Different funds may target different investor segments, hence focus on different types of window dressing.

2.5.3 Performance Comparison Testing

The results generated from the ESG factor models may be interpreted as the effects of fund managers' general trading activity. However, normal portfolio adjustment should be uniformly distributed throughout the entire period, whereas window dressing is more likely to happen just prior to the reporting date. To rule out the possibility of mistaking ordinary portfolio adjustments for window dressing, we follow Kempf and Osthoff (2008) and use performance comparison to detect if RIFs shift holdings from high ESG to low ESG companies between two reporting dates. If RIFs window dress, i.e., buy (sell) companies with higher (lower) ESG scores before the disclosure dates, a higher exposure is expected to the ethical index just before the reporting dates. Therefore, the daily return of each RIF is used to run the regression:

$$R_{it} - R_{ft} = \alpha_i + \beta_{1i}(R_{St} - R_{ft}) + \beta_{2i}(R_{Et} - R_{ft}) + \beta_{3i}D_{it}(R_{St} - R_{ft}) + \beta_{4i}D_{it}(R_{Et} - R_{ft}) + \varepsilon_{it}, \qquad (2.5)$$

Where $R_{it} - R_{ft}$ is the daily excess return of RIF i, and $R_{St} - R_{ft}$ is the daily excess return of the conventional index. R_{Et} is the excess return of the ethical index that has been made orthogonal to the standard index (i.e., following the method of Kempf and Osthoff (2008), the ethical index, MSCI KLD 400 Social Index, is regressed against the conventional index, then the sum of the residual and the intercept forms R_{Et}). D_{it} is a dummy variable that equals one if day t is within the event period (5, 10, 15, or 20 days before the reporting date[32]), and equals 0 for other days. If RIFs apply window dressing in low-ESG stocks, we should find a significantly positive β_{4i}.

We obtain daily fund prices and net assets at the share class level from Morningstar. Then, we aggregate the share classes' daily return to the fund level based on each class's daily net asset value. Daily data availability limits our sample size to 136 funds.[33] Following Joliet and Titova (2018), the period starts from the fourth quarter of 2009 to avoid the effects of the financial crisis on investment decisions. Table 2-6 shows the percentage of funds that have a significant and positive β_{4i} based on Equation (2.5) between September 2009 and December 2019.

Table 2-6 Performance comparison tests

Panel A: Before reporting dates

Event periods	10%	5%	1%

[32] Like Kempf and Osthoff (2008), we do not know when the fund managers adjust their portfolios for window dressing. Therefore, we apply 5, 10, 15 and 20 days before the quarterly report date as the event period.
[33] Only funds that have at least 2 years of data have been retained in the sample.

5	11.76%	10.29%	8.82%
10	15.44%	13.24%	6.62%
15	24.26%	18.38%	9.56%
20	18.38%	14.71%	4.41%

Panel B: After reporting dates

Event periods	**10%**	**5%**	**1%**
5	1.47%	0.74%	0.74%
10	2.21%	1.47%	0.74%
15	2.21%	1.47%	0.74%
20	8.09%	6.62%	0.74%

Note: This table summarises the results for Equation (2.5). Panel A reports the results **before** the reporting date. We summarise the percentage of funds that have a significant positive β_{4i} before the reporting date for different event periods (5, 10, 15, and 20 days before the disclosure date) with different significant levels. For example, when applying 5 days before the disclosure date as the event period, 10.29% of RIFs in our sample show significant positive β_{4i} at the 5% significant significance level. Under our assumption, if RIFs apply window dressing in high ESG stocks, we should find a significant positive β_{4i}. Panel B summarises the percentage of funds that have a significant positive β_{4i} **after** the reporting date for different event periods with different significant levels.

Panels A and B of Table 2-6 report the results before and after the reporting dates, respectively. Fund numbers are summarized based on different event periods and significance levels. For example, in Panel A, when we examine 15 days before the disclosure date as the event period, 25 out of 136 (18.38%) RIFs show significantly positive β_{4i} at the 5% level. Panel A provides further evidence that some RIFs implement a window dressing strategy (shifting towards the orthogonalized ethical index) before the reporting date. This result contrasts with Kempf and Osthoff (2008), who find no indication of window dressing by RIFs between 2001 and 2004. Panel A also shows that the percentage for the 15-day event period is the highest relative to other periods, which may indicate a 'usual' time interval for RIF managers to adjust their holdings before the reporting date.

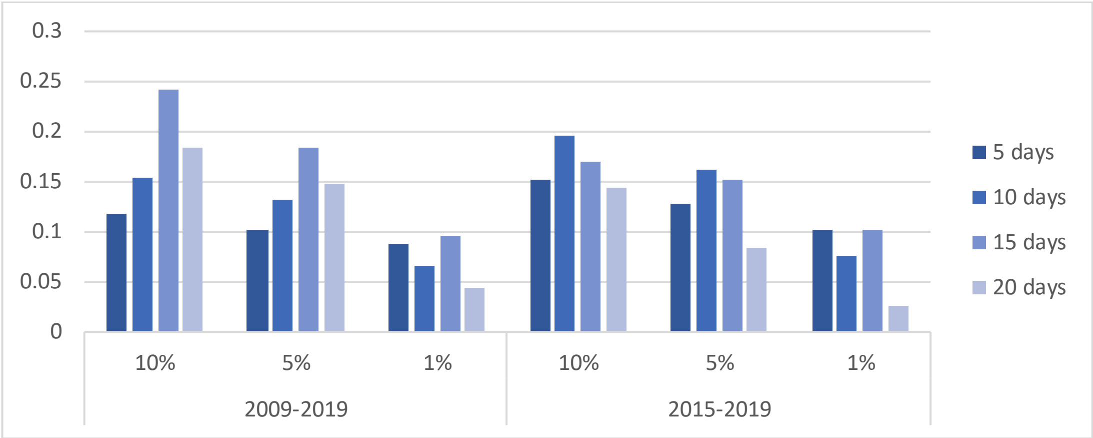
Panel B of Table 2-6 summarises the coefficients after the reporting date. The portion of funds with a significantly positive β_{4i} sharply drops after holdings disclosure. This may indicate that: 1) RIFs offload high ESG companies after the portfolio disclosure. Such a proportion reduction suggests that most of the funds with significant positive β_{4i} in Panel A are deliberately increasing holdings in high ESG companies before reporting, and 2) funds engaged in ESG window dressing quickly adjust their portfolios after disclosure, and the 'usual' post-disclosure adjustment time is about 10 days.

An interesting finding arises when we further trim the sample period to January 2015 to December 2019. Reducing the sample period decreases the sample size from 136 to 118 RIFs. Comparing 2015-2019 with the results for 2009-2019, the number of funds that show significant positive β_{4i} within the 5- and 10-day event periods before the reporting date increases, while the number of funds that show significant positive β_{4i} within 15- and 20-day event period decreases. The trend can be seen more directly as percentages (as shown in Figure 2-2 Panel A), with a higher proportion of funds showing significantly positive β_{4i} within the 5- and 10-day event period from 2015 to 2019, and a lower proportion of funds within the 15- and 20-day event period. This indicates that in more recent years, RIFs are more likely to make portfolio changes, buy (sell) higher (lower) ESG score companies, within a period that is closer to the disclosure date.[34] This finding may suggest that RIFs are facing more pressure to obtain attractive financial performance than in the earlier portion of the sample period, and thus they hold better financially performing but low ESG stocks for a longer period to maximize their financial gain.

Panel B of Figure 2-2 shows the proportion of funds with significantly positive β_{4i} within different event periods after reporting dates. Comparing to 2009-2019, fewer funds report significantly positive β_{4i} after the reporting date during 2015 and 2019. This indicates that within 2015-2019, funds exhibit quicker offload on high ESG companies after holdings disclosure.

Panel A: Before reporting dates

[34] The reasons behind this phenomenon are beyond the scope of this paper, but may relate to increased competition, managerial skills of fund managers or past performance of the RIFs.



Panel B: After reporting dates

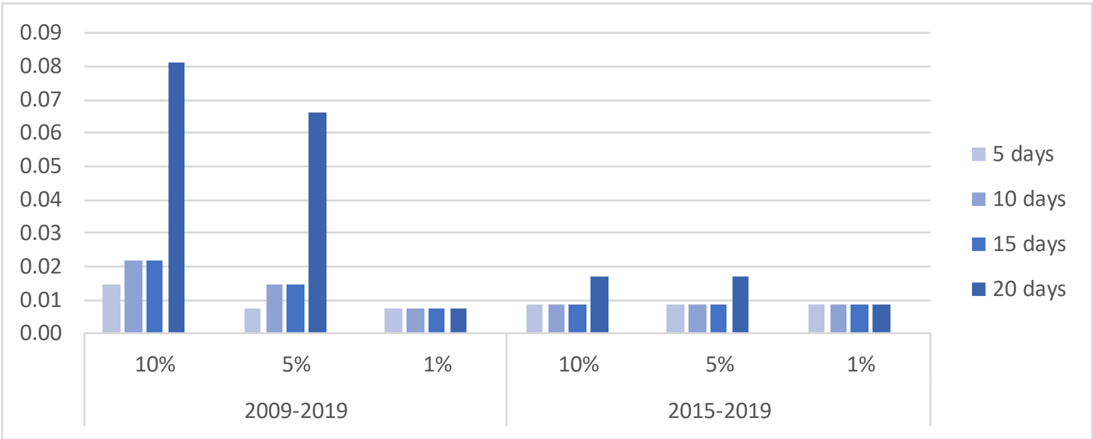


Figure 2-2 Performance comparison test (subsamples)

Note: Figure 2-2 reports results for Equation (2.5) for different sample periods. It presents the percentage of funds with significant positive β_{4i} for different event periods at different significant levels. The left part summarises the results of 136 RIFs between January 2009 and December 2019. The right part summarises the result for a sub-period between January 2015 and December 2019, and there are 118 RIFs within the sub-period.

2.5.4 Robustness Testing: Kalman Filter

The discussion so far has concentrated on standard asset pricing models to estimate coefficients. However, some literature argues that these models may have limitations since they impose stability on the beta parameter, which is usually unlikely in practice (Ortas et al., 2012; Swinkels & Van Der Sluis, 2006). To address this issue, rolling regressions are widely used to estimate the coefficients over a certain length of time. By deleting the first observation and adding the next observation, rolling regressions generate time-varying exposures. However, this approach still assumes that the exposure stays constant within the window (usually 24 or 36 months). Swinkels and Van Der Sluis (2006) propose using a Kalman filter to capture a more accurate time-varying exposure than traditional rolling window regressions. The Kalman filter was initially introduced by

Kalman (1960). It is a recursive algorithm for sequentially updating a one-step-ahead estimate of the state mean and variance given new information, used widely in the economics and finance fields.

In this paper, following Swinkels and Van Der Sluis' (2006) method, we use the Kalman filter and daily data to capture dynamic betas for RIFs to the ethical and conventional indices. Then, we plot the average coefficient to the ethical index for a 51-day-window (-25, +25) and examine if the coefficient exhibits patterns before and after reporting dates. The method may overcome the stated methodological limitation of our previous analysis.

Following Swinkels and Van Der Sluis (2006), the model can be expressed as:

$$R_{i,t}^{fund} = \alpha_{i,t} + \beta_{1,i,t} * R_t^{index\,1} + \beta_{2,i,t} * R_t^{index\,2} + \varepsilon_{i,t} \quad (2.6)$$

$$\alpha_{i,t} = \alpha_{i,t-1} \quad (2.7)$$

$$\beta_{1,i,t} = \beta_{1,i,t-1} + \xi_{1,i,t} \quad (2.8)$$

$$\beta_{2,i,t} = \beta_{2,i,t-1} + \xi_{2,i,t} \quad (2.9)$$

Where $R_{i,t}^{fund}$ is the fund excess return, $R_t^{index\,1}$is the excess return on the market index, and $R_t^{index\,2}$ is the excess return on the orthogonalized ethical index. $\varepsilon_{i,t}$ and $\xi_{i,t}$ are error terms $\varepsilon_{i,t} \sim$ NID $(0,\sigma_\varepsilon^2)$, and $\xi_{j,i,t} \sim$ NID $(0,\sigma_{j,i,\xi}^2)$. $\beta_{1,i,t}$and $\beta_{2,i,t}$ are time-varying exposures to the market index and the orthogonalized ethical index at time *t*. $\beta_{2,i,t}$ is the main indicator in this model, as it represents the sensitivity of RIFs to the ethical index. By looking at the value of $\beta_{2,i,t}$before and after the disclosure date, we infer whether RIFs change their exposure to the ethical index pre and post the holdings announcement date.

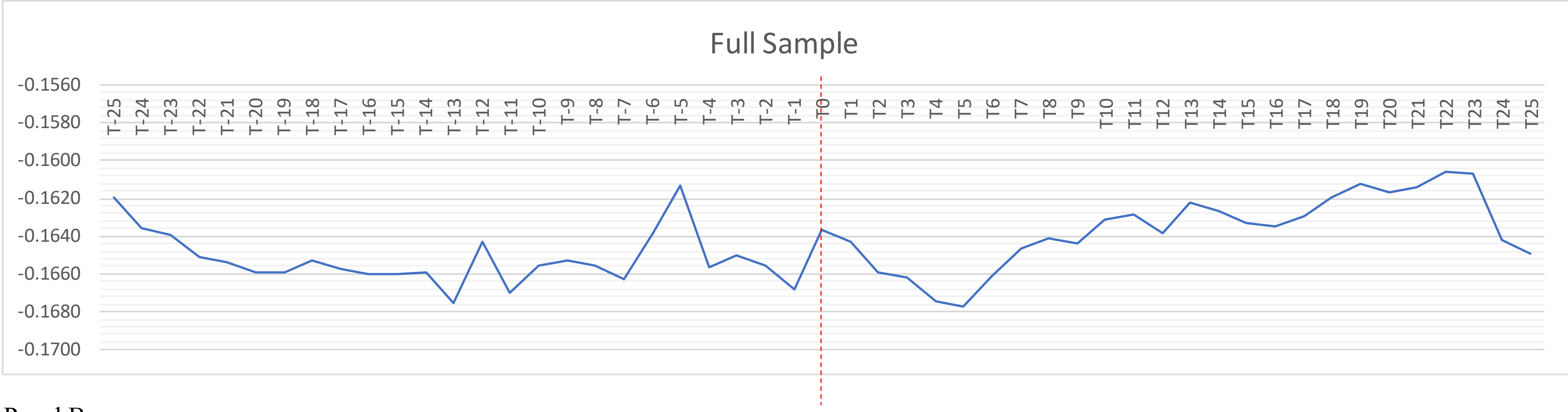
The model is in state-space form. Equation (2.6) is the measurement equation; it links RIFs' excess returns to the conventional and ethical indices. Equations (2.7), (2.8), and (2.9) are transition equations, which gives the state evolution process. We keep manager ability α_t constant over time. The exposure coefficients $\beta_{1,i,t}$ and $\beta_{2,i,t}$ are estimated based on exposure at the previous period (*t*-1) plus an associated error term that follows a normal distribution with mean zero and a variance $\xi_{i,t}$.

Figure 2-3 presents the average $\beta_{2,i,t}$ obtained from the Kalman filter (Equations 2.6 - 2.8) from 25 days before to 25 days after the reporting date (the last day of each quarter).[35] The average coefficient is negative, which means, on average, funds are negatively correlated to the orthogonalized ethical index. If the coefficient increases when the reporting date approaches, it means that funds are less negatively correlated to the ethical index, and this may indicate ESG-performance window dressing. Figure 2-3, Panel A reports the average $\beta_{2,i,t}$ for the entire sample. For the pre-disclosure window (-25, -1), average daily coefficients first gradually decrease and then increase with a small fluctuation. It then enters a fluctuating period, with three peaks at (-13, -12), (-7, -5) and (-1, 0). On the disclosure date, t_0, the coefficient reaches a relatively higher level (-0.1637) compared to the pre-disclosure window. For the post-disclosure window, the average coefficient immediately declines after the disclosure date from -0.1637 to -0.1677 at $t+5$ and then rises to a peak (-0.1606) until it starts decreasing from $t+22$.

The three peaks that happen within (-13, 0) in Panel A might be an indication of potential window dressing behaviour, as they are obvious changes in the coefficient before the reporting date. However, as Panel A displays the entire sample of RIFs, the overall result might be offset by funds within the sample that are unlikely to window dress. Therefore, a sub-sample is created using the funds that are more likely to be engaged in window dressing, with results shown in Panel B. This subsample includes RIFs with a significantly positive coefficient on the ESG factor in Equation (2.3). The average daily coefficient for the subsample shows a more obvious increasing trend between (-12, 0), reaching the highest level across the period at the reporting date (t_0). This upward trend indicates potential window dressing, which supports our finding in Table 2-4 that some funds exhibit ESG window dressing behaviour.

[35] There are some outliers that appear at the start of the sample period. This is caused by the Kalman filter procedure's learning period before it becomes stable. Therefore, the first 7 observations for each fund have been removed.

Panel A



Panel B

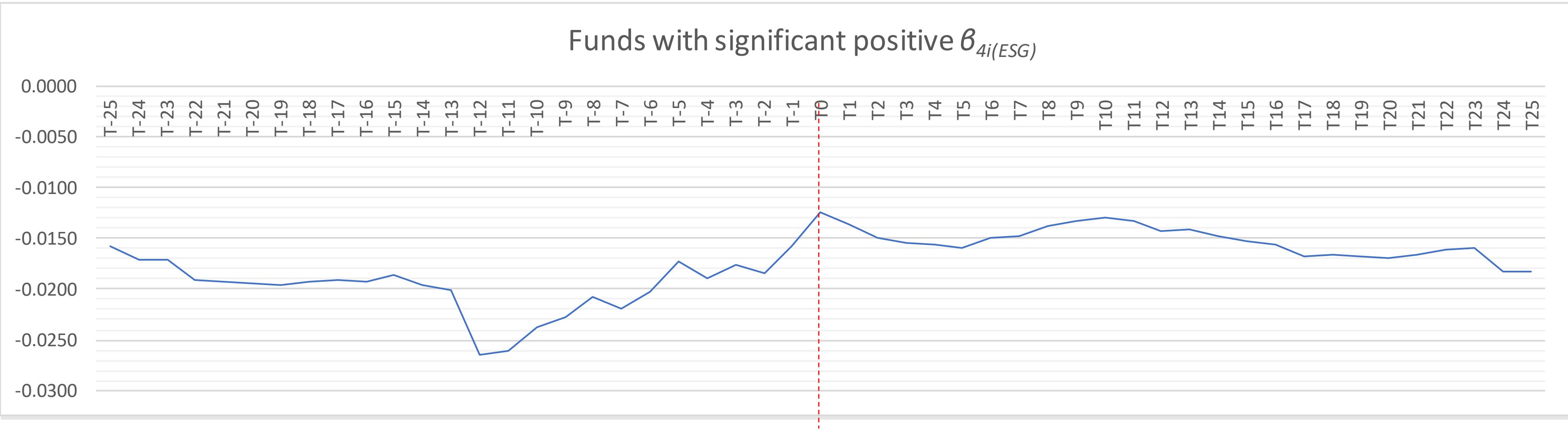


Figure 2-3 Average exposure obtained from Kalman filter for the 51-day-window

Note: Figure 2-3 This figure reports the average of Equation (2.6) for the 51-day-window. Panel A shows the results for 136 funds that have daily data. Panel B shows the results for the subsample, which includes the funds that have significant positive $\beta_{4i(ESG)}$ based on Equation (2.3). The red dash line indicates T0.

2.5.5 Determinants of Window Dressing

The extant literature on window dressing demonstrates that financial return window dressing may be related to poor past performance (Agarwal et al., 2014) and some unobserved influences at the fund management company level (Gil-Bazo et al.,2010). Morey and O'Neal (2006) point out that funds with higher risk exposure are more likely to change their risk characteristics prior to the disclosure date. However, whether these factors also play roles in interpreting the possibility of ESG window dressing is still unknown. To test the potential determinations of ESG window dressing, we run a logistic regression:

$$WD_{it} = \gamma_0 + \gamma_1 specialist\ level_{i,t} + \gamma_1 12\ month\ alpha_{i,t} + \gamma_2 tracking\ error_{i,t} + \gamma_3 age_{i,t} + \gamma_4 size_{i,t} + v_i + \varepsilon_{i,t} \quad (2.10)$$

where the dependent variable, WD_{it} is a binary variable that equals 1 when ESG window dressing exists (significant positive β_{4i} in a 24-month rolling window), and 0 otherwise. $specialist\ level_{i,t}$ is fund i's management company's expertise in responsible investing in month t, measured by the fund management company's percentage of assets under management in RIFs.[36] Following the work of Gil-Bazo et al. (2010), we hypothesize that management companies' specialization levels in the management of RIFs is key in explaining the differences between RIFs and conventional funds. $12\ month\ alpha_{i,t}$ is the fund's annualized alpha obtained using monthly raw returns and the 4-factor model in a 12-month rolling window, used to control for past performance (Ammann, et al, 2019). $tracking\ error_{i,t}$ is the past 12-month's cumulative R-squared, estimated from the 4-factor model by using a 12-month rolling window, and proxies return volatility. We additionally control for $age_{i,t}$ and $size_{i,t}$, which is the number of months since the oldest share class was established, and the logarithm of fund size for RIF i in month t. v_i is fund fixed effects and $\varepsilon_{i,t}$ denotes the error term.

Table 2-7 Determinates of ESG window dressing

[36] Our sample reduces to 156 RIFs after considering information at the fund management company level due to data availability.

Specialist level	12-month alpha	Tracking error	Age	Size	N
-0.9547*	-5.7364***	0.3745***	0.0075***	-0.7177***	7313

Note: Table 2-7 reports the results of logistic regression (Equation 2.10) for the determinates of ESG window dressing. Dependent variable: binary variable of ESG window dressing

Table 2-7 presents the results of our logistic regression in (2.10). The estimated coefficients of the management company's specialization level, past performance and size are significantly negative. Tracking error and age exhibit significant positive relationships. These results indicate that RIFs managed by companies with lower specialist levels and poor past performance are more likely to exhibit ESG window dressing. For volatility, RIFs with higher tracking errors are more likely to engage in ESG window dressing. The size coefficient is significantly negative at the 1% level, and the age coefficient is significantly positive at the 1% level. This indicates that controlling for more factors, in particular age, results in a change from window dressing firms being larger (as shown in Table 2-5) to smaller funds (as shown in Table 2-7).

2.6. Conclusion

Extensive research has been conducted on the financial and non-financial returns of RIFs based on their self-reported information. However, the accuracy of this information is relatively unknown. This paper attempts to address the issue. We examine the presence of financial and ESG window dressing of US domestic equity RIFs between 2005 and 2019 using the rank gap, backward holding return gap and factor model methods. The analysis delivers several novel findings. First, by comparing the rank difference between performance-based rank and the rank based on the proportions of winner and loser stocks reported by funds, we find that a proportion of RIFs exhibit financial performance-based window dressing. This finding is supported by the difference between the funds' hypothetical holding return calculated using a buy and hold strategy and the actual return reported by the funds. Second, RIFs' return differences between the reported portfolio and actual returns show a preference for high ESG companies, which indicates the existence of ESG window dressing. Third, both recorded actual and backtracked returns from disclosed holdings of funds are tilted towards companies with lower ESG scores. This finding may validate investor and regulator concerns regarding the reliability of some RIFs' attitudes to their stated ESG considerations.

Our performance comparison test suggests that over a quarter of funds shift towards the ethical index just before reporting their holdings, and the main result is robust to alternative specifications. This finding helps refute the possibility that our detected ESG window dressing is caused by normal portfolio adjustment. We also find that funds are leaving it later to window dress their portfolios in more recent periods, moving from 15 days prior to the reporting date to 5 or 10 days in 2015-2019. We argue this result may reflect that RIFs face more competition and suffer more pressure to obtain better dual performance, forcing managers to adjust holdings regarding better ESG performance closer to the reporting date than in the past.

This paper also investigates what drives ESG window dressing. Much like financial return window dressing, RIFs with poor past performance, higher tracking errors and those managed by companies with lower specialist levels, are more likely to exhibit ESG window dressing. The results may have interesting implications. There is a possibility that RIFs are not fulfilling their announced ESG objectives, in which case investors need to be very careful in selecting RIFs to achieve their non-financial goals. At the same time, regulators, such as the SEC, should pay close attention to funds that exhibit indicators of ESG window-dressing to ensure they are being honest with investors.

Appendix 2-1

Results of *t*-test

	Size		**Age**		**Average turnover %**	
	subsample 1	***subsample 3***	***subsample 1***	***subsample 3***	***subsample 1***	***subsample 3***
Mean	8417.13	1173.81	283.13	175.55	46.12	61.32
Variance	542607286.82	15244207.86	50059.43	16805.85	1116.89	1902.01
Observations	68.00	121.00	68.00	121.00	68.00	117.00
Hypothesized Mean Difference	0.00		0.00		0.00	
df	69.00		93.00		169.00	
t Stat	2.54		3.64		-2.66	
P(T<=t) two-tail	0.0132		0.0005		0.0086	
t Critical two-tail	1.99		1.99		1.97	

Note: Two-sample *t*-test assuming unequal variances for the comparison between subsamples 1(Funds significantly positive β_{4i}) and 3(Funds significantly negative β_{4i}).

Chapter 3 (Manuscript 2): Responsible Investment Funds and their Management Companies' Emphasis on ESG Performance: First Priority or Icing on the Cake?

Abstract

In this paper, we investigate the potential impact of Fund Management Companies' (FMCs) commitment to responsible investing on their responsible investment funds' ESG performance. Using a comprehensive dataset of US domestic equity Responsible Investment Funds (RIFs) over the period from 2005 to 2020, we find improvement in fund-level ESG scores is treated as the "icing on the cake" and will be promptly sacrificed if the fund suffers outflows. We also find that RIFs managed by FMCs with either the lowest (≤20%) or the highest (>80%) ESG commitment levels are more likely to put extra effort toward enhancing funds' ESG scores. Additionally, we observe that investors who choose FMCs with the highest ESG commitment level are less sensitive to financial returns when considering ESG performance.

JEL classifications: G10, G11, G12

Keywords: Responsible investment funds, Fund management company, ESG scores, Fund Flows

3.1. Introduction

In recent years, Responsible Investment Funds (RIFs) – defined as funds that consider Environmental, Social and Governance (ESG) objectives in their investment decision-making – have drawn increasing attention from investors and academics. According to the US Forum for Sustainable and Responsible Investment (US SIF) (2022), the total US-domiciled assets under management (AUM) invested sustainably grew from $639 billion in 1995 to $8.4 trillion at the start of 2022. In a ninefold increase from 2018, and over twofold increase from 2019, $51.1 billion flowed into US mutual funds with stated ESG objectives in 2020 (Hale, 2021). At the end of 2020, Morningstar reported a 23% increase in the number of RIFs from 2019, signalling that responsible investment is an increasingly important segment of the fund management industry, driven by strong investor demand for these products. Nearly 80% of investors consider ESG an essential factor when making their investment decisions, and 50% express a willingness to divest from companies that do not take sufficient action on ESG concerns (PricewaterhouseCoopers LLP, 2020).

Currently, research on RIFs is dominated by studies assessing the return implications of investing sustainably, documenting mixed results: some studies find outperformance (Lean et al., 2015, among others), others underperformance (El Ghoul & Karoui, 2017, among others), and others find no difference in returns (Climent & Soriano, 2011; Thompson et al., 2011, among others). In a recent meta-analysis, Whelan et al. (2021) found that 59% of investment studies assessing portfolio's risk-adjusted attributes between 2015 and 2020 demonstrated similar or better financial performance compared to conventional investments. In recent years, the research focus has shifted beyond financial performance. For instance, scholars have investigated the drivers of ESG performance for RIFs, including the impact of screening strategies, and have attempted to assess how intensively they consider ESG criteria during asset allocation (Capelle-Blancard & Monjon, 2014; D'Apice et al., 2021; Humphrey & Lee, 2011). Other studies investigate the development and/or characteristics of RIFs (Alda, 2020; Ferriani & Natoli, 2021; Nakai et al., 2016; Nofsinger & Varma, 2014; Pavlova & de Boyrie, 2022; Revelli, 2017), while another strand of literature focuses on the behaviour of RIF investors (both individual and institutional), such as investors' motivation, investment patterns, and decision making (Fernandez-Perez et al., 2022; Gibson Brandon et al., 2020; Hartzmark & Sussman, 2019; Ilhan et al., 2021).

To date, however, there has been little investigation into how fund management companies (FMCs, also known as 'fund families'[37]) impact the financial and ESG performance of RIFs. Our study addresses this question. We focus on the financial and ESG considerations of fund families as opposed to individual mutual funds for three reasons.

First, fund families focus on the overall profit of the entire family (i.e., either by increasing overall fee income or investor inflow) and, therefore, may sacrifice the benefit of some funds if the overall family stands to benefit, known as cross-fund subsidisation (Adrianto et al., 2018). In their efforts to improve ESG performance, individual RIFs may be influenced by the resources allocated by the FMC (or fund family), e.g., fund managers, research resources, or marketing opportunities. RIFs in FMCs with supportive (discouraging) policies may find it easier (harder) to enhance ESG performance. Therefore, it is worthwhile to investigate fund family attitudes toward improving the ESG performance of individual RIFs.

Second, Belghitar et al. (2017) find that for mutual funds, FMCs differ in their investment practices, available resources, ability to attract and retain talented managers, working culture, and intellectual freedom. They conclude that these differences at the FMC level may impact the fund investment decision-making process and consequently translate into differences in fund performance. However, it is unknown whether the same differences exist for RIFs, which have dual goals of pursuing both financial and ESG performance. Specifically, whether the FMCs' attitude toward ESG impacts RIFs' ESG performance.

Third, compared to the ESG performance of individual RIFs, the FMC's ESG preferences are likely to be highly influential in setting fund managers' priorities. For instance, financial returns rely partly on managerial skills (stock selection and market timing) and are often rewarded via the fund managers' bonus structure. According to Ma et al. (2019), 89% of US mutual fund managers are paid based on their fund's financial performance. However, a report from ShareAction in 2023, finds that in 2020 only 7% of RIF managers had financial incentives related to responsible investment (Vrublevskis & Zorila, 2023). That is to say, ESG

[37]A fund family is defined as a group of funds with diverse investment objectives provided by one fund management company (Nasdaq Inc, 2022). Fund families act as financial intermediaries offering a variety of mutual funds under a common brand name and via common marketing and distribution channels (Bani Atta & Marzuki, 2019).

performance, which may come at a cost to returns or may increase management costs, may not be explicitly recognised in bonus structures or performance incentives. It remains to be seen whether strong ESG performance can directly generate benefits for the manager. The FMCs' requirements and policies regarding ESG will influence managers' decisions in the asset selection process, with ESG intensity depending on the FMC.

In this paper, we argue that FMCs' ESG commitment level may represent the exposure of responsible investment to an FMC and thus reflect the importance the FMC places on ESG. In a sample of 118 US equity RIFs managed by 53 FMCs between 2005 and 2020, we proxy FMCs' ESG commitment level[38] by the proportion of AUM engaged in responsible investment and test its potential impact on fund ESG performance.

To test our hypotheses, we analyse the different relationships between three components of RIFs: fund flow, fund risk-adjusted returns and fund ESG performance (proxied by fund-level ESG score). These analyses are progressive and interdependent, each of them contingent upon the preceding ones for their context and results. We first confirm a significant positive relationship between fund flows and lagged returns for RIFs, as well as asymmetric reactions (i.e., positive returns garner more new flows than those lost to negative returns). We then find this relationship is predominantly driven by RIFs that are managed by FMCs with the lowest (≤20%) and highest (>80%) ESG commitment levels. When separately considering fund inflows and outflows, RIFs managed by FMCs with the lowest ESG commitment level, on average, only react to positive returns, while the RIFs managed by FMCs with the highest ESG commitment level react to both positive and negative returns, with a larger magnitude on positive returns. Since the flow-return relationship explains fund's incentive to alter the portfolio to perform well, the findings we obtained from this part support the idea that FMCs' ESG commitment level impacts funds' reaction to past returns in the RIF field.

We then take funds' ESG performance, measured by fund ESG (E, S and G) scores, into consideration and test its effect on the fund flow-return relationship. When we do not control for FMCs' commitment to ESG, we find that ESG scores do not impact RIFs' flow-return relationship. However, after controlling for FMC

[38] Gil-Bazo et al. (2010) use a similar approach to split FMCs into generalist companies (less than 50% of assets engaged in RIFs) and specialists (more than 50% of assets invested in RIFs).

commitment, we observe that investors who choose FMCs with the highest ESG commitment level are less sensitive to financial returns.

Lastly, we analyse the flow-ESG performance relationship by testing the relationship between the change in ESG scores and lagged fund flows. Empirical studies investigating the relationship between ESG performance and fund flows implicitly argue that ESG performance drives fund flow. However, this relationship could also be reversed. For instance, we could argue that funds with high ESG scores represent higher social responsibility levels, which may attract fund flows from investors who value responsible investment. Alternatively, funds attracting greater fund inflows might have better management teams or stronger research resources and, therefore, can improve the fund's ESG score by investing in higher ESG companies. We find that after considering the FMCs' ESG commitment, RIFs managed by FMCs with the lowest ESG commitment level (≤20%) report significant positive coefficients in response to fund inflows but no significant changes for outflows, while funds managed by FMCs with the highest commitment level (>80%) decrease their ESG performance when suffering fund outflows but no significant changes when facing fund inflows.

This paper contributes to the existing literature in three ways. First, we analyse the relationship between investors' interests (proxied by fund flows) and fund management companies' reactions based on the FMC's ESG commitment. We find that RIFs managed by FMCs with the lowest (≤20%) and highest (>80%) ESG commitment levels exhibit different responses to investor flows. This may indicate the existence of some unobserved factors at the FMC level that affect RIFs' attitude to their ESG performance and willingness to cater to changes in fund flows.

Secondly, this paper contributes to the literature analysing the impact of fund management firms' characteristics (Franch et al., 2008; Gil-Bazo et al., 2010) on their responsible investment strategy or financial performance. Rather than simply splitting FMCs into two groups (generalist and specialist companies, as Gil-Bazo et al., 2010), this paper divides fund families into quintile groups based on the FMC's commitment to responsible investment. The more nuanced classification allows for the exploration of FMCs' varying degrees of ESG commitment. Our results confirm the presence of differences and demonstrate that new inflows get invested in better ESG companies for only the most and least committed FMCs.

This paper also contributes to the literature on sustainable investors' behaviour (Christiansen et al., 2020; Riedl & Smeets, 2017). Extant studies track investors' incentives and attitudes to sustainable investment and describe investor characteristics. They answered questions about who chooses RIFs and why they do so. Our study is different in that we test the possible consequences of investing in a RIF. Specifically, we explore if investor inflows encourage RIFs to improve their ESG performance. Our findings provide insight into how investors might influence fund decisions through 'voting with their feet'.

3.2. Literature Review and Hypotheses

3.2.1 Fund Management Companies

Most existing mutual fund studies focus on fund-level factors, while comparatively fewer studies have been done at the fund management companies' level. Nanda et al. (2004) is one of the seminal studies on fund families. They employ US equity funds between January 1992 and December 1998 and identify the existence of fund family spillover effects, whereby a star fund's success leads to greater cash inflows for both the star fund and other funds in the same family. In more recent years, fund management companies' characteristics and decisions have also been shown to drive funds' financial performance. For instance, Belghitar et al. (2017) argues that the FMC plays a major role in explaining why UK-based RIFs and their characteristic-matched conventional counterparts outperformed the market index about 50%. In addition, Hunter et al. (2020) find that a fund family's attributes, including marginal fee economy of scale, offer of star fund, the mixture of high- and low-risk product offerings, within-family manager scope, and manager outsourcing, may improve a fund family's returns and attract more fund flows. More recently, Fu et al. (2021) find a positive performance effect from within-fund family information sharing, using 3,009 US-domiciled open-end equity mutual funds spanning the period from 1981 to 2018. Evans et al. (2020) state that FMCs encouraging cooperation among their managers tend to exhibit more coordinated behaviour, such as cross-trading and cross-holding, and have less volatile cash flows. On the other hand, FMCs with competitive incentives are more likely to have superior performing funds, a larger portion of "star funds", and greater performance dispersion across funds within the fund family. These articles support that differences in FMC policies, strategies, and incentives may impact managers' behaviour and have fund-level performance effects.

Fewer studies have considered how FMCs influence the ESG-related aspects of RIFs, especially for FMCs that manage both RIFs and conventional funds. One pioneering work is Franch et al. (2008), who sent surveys to Spanish FMCs that managed and/or marketed RIFs to identify what motivated FMCs to offer RIFs. For the 47 FMCs that responded, they found management companies with an internal Corporate Social Responsibility (CSR) policy or a positive attitude toward implementing and improving CSR policies are more likely to offer RIFs. Kim and Yoon (2020) highlight that FMCs with a higher number of funds (both RIFs and conventional) in the family are more likely to sign the United Nations Principles for Responsible Investment (UNPRI), which is currently the largest initiative in the asset management industry to incorporate ESG issues. However, they later find that signatories of these internationally recognised Principles do not show improvements in their ESG scores (Kim & Yoon, 2022). These articles emphasize FMCs' impact on financial performance and ESG-related investment practices for their RIFs.

To capture FMC influence, a variety of measures are used. Franch et al. (2008) employ binary variables based on FMC-level CSR policy implementation. Fu et al. (2021) assess the degree of information sharing within the fund family through common holdings, defined as the proportion of an individual fund's family communal stocks relative to its total stock holdings value. Belghitar et al. (2017) summarized several FMC-level attributes, such as the capacity to obtain resources, the ability to attract and retain talented managers, organizational culture, and intellectual freedom. They believe these attributes impact the fund-level investment decision-making process and consequently translate into differences in individual fund performance. However, Belghitar et al. (2017) did not deeply explore these characteristics. To account for FMC influences, they 1) use the FMC as a selection criterion for matching fund pairs and 2) use the cumulative total expense ratio to reflect the FMC's influence on investment practices.

In the context of our study, we seek a measure at the FMC level that may influence funds' attitudes toward improving their ESG performance. One such measure may be the FMC's responsible investment capability. Their capability, in turn, may be affected by the ability or willingness to resource and/or hire competent managers for their responsible investment funds. While FMCs' internal managerial policies and activities are not publicly available, it may be possible to infer an FMC's capability using proxies. For example, Gil-Bazo et al. (2010) examine US actively managed, retail, and domestic equity funds by splitting FMCs into generalists (which have less than 50% assets engaged in RIFs) and specialists (which have more than 50% assets in RIFs). They find that RIFs run by generalist companies underperform characteristic-matched conventional funds, while RIFs run by responsible investment specialist companies outperform their matched conventional peers, thus establishing that FMC ESG specialization may impact a RIF's financial performance. However, the impact of the FMC specialization level on fund ESG performance is still unclear. Most RIFs are managed by FMCs that operate both conventional and responsible funds, but do so with varying commitment to ESG-based funds. With different ESG commitment levels, the impact of the RIFs' performance on the FMCs' overall profit may differ, and thus, FMCs may respond differently to improving RIFs' ESG performance. Therefore, we extend Gil-Bazo et al. (2010) by splitting our sample of RIF management companies into quintiles to investigate FMCs' impact more thoroughly. The first (fifth) quintile includes the companies with the lowest (highest) proportion of AUM invested in socially responsible investment.

3.2.2 Relationship between Fund Flows and Performance

The mutual fund literature has extensively examined the flow-return relationship. This relationship illustrates the implicit incentive of mutual funds: funds charge management fees based on their assets under management, and this creates incentives for them to attract new fund flows (Chevalier & Ellison, 1997). This relationship has also been interpreted as a reflection of fund investors updating their knowledge about managers' skills and adjusting their expected financial performance (Berk & Green, 2004). The prior work documents that fund flows into and out of funds are strongly positively related to a variety of return measures. For instance, Chevalier and Ellison (1997) and Sirri and Tufano (1998) use market-adjusted returns, Coval and Stafford (2007) employ raw monthly returns, and Gil-Bazo and Ruiz-Verdú (2009) and Huang et al. (2007) utilize alpha from Carhart's (1997) four-factor model. Despite this variety, all provide evidence that mutual fund investors chase performance, and their investment decisions (purchase and sell) respond to past fund financial performance.

In the RIF context, a few studies have shed light on differences in the flow-return relationship between RIFs and conventional funds. Bollen (2007) investigates the relation between fund flows and lagged annual returns, finding that cash flows into RIFs exhibit lower volatility and are more (less) sensitive to lagged positive (negative) returns compared to their matched conventional peers. Benson and Humphrey (2008) also test the flow-performance relationship for RIFs and conventional funds. However, their results suggest that RIF flows are less sensitive to financial returns and exhibit stronger persistence than conventional funds. In the global comparison study, Renneboog et al. (2011) find that RIF investors seem less sensitive to past returns, especially negative returns, than investors in conventional funds.

As mentioned above, RIFs have dual investment objectives, and market themselves as maintaining both financial returns and ESG objectives. With the development of RIFs in the past decade, recent RIF literature investigates the relationship between fund flow and various past ESG performance measures, including ESG score, ESG ratings, and ESG-related labels, to reveal the impacts of ESG performance on fund flow. For instance, El Ghoul, and Karoui (2017) utilize fund level value-weighted ESG scores computed from holding companies' ESG scores and find that funds with higher ESG scores, compared to low-ESG score funds, exhibit worse performance, stronger performance persistence, weaker financial performance-flow relationship, and similar persistence in fund flows. Hartzmark and Sussman (2019) investigate the fund flow reaction to the publication of the Morningstar sustainability ratings, which they treat as an exogenous shock, and find that the fund's total net assets of the lowest rated RIFs decreased by 5.4% per year, while the highest rated funds increased about 3.6% per year. Similarly, Ammann et al. (2019) investigate the effect of the introduction of Morningstar's Sustainability Rating on actively managed US domestic equity mutual funds. They find during the first year after the launch of the Sustainability Rating, high-rated retail funds obtained higher net flow than both average- and low-rated funds.

Other studies have also demonstrated that investors are attracted to ESG-related labels. For instance, El Ghoul and Karoui (2021) found the 28 US mutual funds that changed their names to a sustainability-related appellation between 2003 and 2018 experienced larger fund inflows with no substantial changes in fund return or risk level. Moreover, Ceccarelli et al. (2022) looked at the introduction of Morningstar's "low carbon designation" and found that active funds labelled as "low-carbon" by Morningstar experienced a substantial increase in net inflows relative to conventional funds. In this paper, we follow the method of El Ghoul and Karoui (2017) and Gibson Brandon et al. (2021) and assume RIFs' ESG considerations are reflected in their holding companies' ESG performance. Our fund-level ESG scores are computed as the value-weighted sum of holding companies' ESG scores.

3.2.3 Hypotheses Development

Previous studies on the mutual fund flow-return relationship have found strong evidence that a fund's financial performance positively impacts its subsequent flows. The relationship tends to be asymmetric. Poorly performing funds are not punished to the same magnitude as better performers are rewarded. In the context of RIFs, ESG considerations underpin one of the RIFs' main goals and need to be considered alongside financial goals when investigating fund flow. Compared to conventional funds which only consider past returns, RIFs' natural dual goals may weaken the flow-return relationship. Thus, as a fund invests more in stocks with better ESG performance, the investor's sensitivity to the fund's financial performance should weaken. Therefore, our first hypothesis is that:

Hypothesis 1: Better ESG performance will weaken funds' flow-return relationship.

As discussed above, FMC-level decisions, especially those related to ESG emphasis, may affect RIFs' ESG investment practices. Such impacts are relatively hard to observe for two reasons:

1) Decisions at the FMC level are more likely to be confidential and not publicly available.

2) Policies and strategies at the FMC level tend to present as guiding principles and practice recommendations rather than as quantitative metrics, posing challenges for empirical research.

Therefore, we attempt to detect the FMC's emphasis on ESG through their ESG commitment level, which we define as the percentage of assets under management committed to RIFs. The rationale behind this measure is that this percentage reflects the influence of responsible investment on the entire FMC. A higher proportion of assets dedicated to responsible investment means that FMCs' requirements/policies regarding ESG will impact a more substantial segment of their assets under management. Thus, we hypothesize that:

Hypothesis 2: The ESG commitment level of fund management companies significantly impact the relationship between a fund's ESG score and its flow-return dynamics.

The existing literature focuses on the impact of ESG performance on fund flows. Specifically, whether improving a fund's ESG performance can attract greater fund inflows from investors, which benefits funds via higher fee revenue. This, in turn, may give funds an incentive to use the additional inflows to further increase/decrease their ESG performance to continue attracting additional inflows, setting up a virtuous cycle. We argue that funds attracting greater fund inflows might have better management teams or stronger research resources and, therefore, are able to improve the overall fund's ESG scores. We also argue that FMC-level ESG policies or attitudes will affect their managed RIFs' degree of ESG implementation and thus show a different response regarding ESG performance following fund inflows. Whether RIFs and their FMC react to additional inflows by increasing their ESG performance has not been empirically tested. Our study aims to fill this gap, leading to our final hypothesis:

Hypothesis 3: Responsible investment funds managed by fund management companies with the highest ESG commitment level increase (decrease) their ESG performance in response to fund inflows (outflows)

3.3. Data

3.3.1 Data Sources

To understand whether the FMC has an impact on a RIF's ESG performance, we obtain data from three sources: US SIF, Morningstar Direct, and Refinitiv. To identify RIFs, we use the Forum for Sustainable and Responsible Investment (US SIF)[39] reports, which are commonly used in the literature (Humphrey et al., 2016; In et al., 2014; Joliet & Titova, 2018). We identify RIFs using the US SIF trend reports spanning from 2007 to 2020. To avoid survivorship bias, we follow Humphrey et al. (2016) and keep RIFs in the sample once they appear in one of the report lists.

We retrieve information about fund holdings, fund returns, and other characteristics, such as share classes, net assets, and expense ratios from Morningstar Direct. From the US SIF report, we initially identify 310 RIFs (1,246 share classes) managed by 117 fund management companies in Morningstar Direct. We only include

[39] US SIF is a non-profit membership association that focuses on sustainable investment practices in the US and is one of the most widely used providers of RIF information in the literature.

funds identified as US Equity Large Cap Blend, US Equity Large Cap Growth, US Equity Large Cap Value, US Equity Mid Cap, and US Equity Small Cap based on the Morningstar Global Category (Agarwal et al., 2014; In et al., 2014; Kempf & Osthoff, 2008). Some of the funds in our sample have multiple share classes. The main differences between share classes managed by the same fund are their loadings and expense ratios, while the holding portfolio remains the same (Alda, 2020; Ibikunle & Steffen, 2017; Joliet & Titova, 2018). Since we analyse the portfolio composition of RIFs, including different classes may result in double counting. Following Livingston et al. (2019) and Alda (2021), we aggregate each share class to the fund level by taking the share-class total net assets weighted average and obtain the fund-level monthly return and annual expense ratio.

Consistent with Leite and Cortez (2015), funds with less than 36 monthly returns or 12 quarterly holdings information within the observation period are excluded. We also exclude funds where less than 60% of their holdings can be successfully matched with the stock ESG score from Refinitiv, formerly known as Asset4 (Dorfleitner et al., 2021).[40,41] These exclusions result in a final sample of 118 RIFs managed by 53 fund management companies, spanning January 2005 through to December 2020 (see Appendix 3-1 for a summary).

Information on the companies held by the funds, including ESG scores and ICB industry code, is obtained from Refinitiv. The Refinitiv ESG score[42] is a comprehensive score that evaluates a company's ESG performance and has been employed (or referenced) in more than 1,500 academic papers since 2003 (Berg et al., 2021). The calculation of Refinitiv's ESG score employs ten categories, such as resource use, innovation, emissions, human rights, workforce, and management, drawn from publicly available company-reported information (Refinitiv, 2022). Each category is given an individual score, and weighted into associated environmental, social, and corporate governance pillar scores. These adjusted scores are then aggregated to produce an overall ESG score for the company. The ESG score ranges from zero to one hundred, where a

[40] We also conduct analysis for 50% and 70%, the results are qualitatively similar to those reported in the paper.
[41] The portfolio holdings downloaded from Morningstar include company name, SECID and the proportion held by the fund. We match firms across Eikon (ISIN and Ticker) with Morningstar (SECID), using the identifiers and company name to match company information with the portfolio holding.
[42] Refinitiv provides two ESG scores: the ESG score, based on reported information in the ESG pillars, and the ESG combined score, which adjusts the ESG score according to the company's exposure to controversies and negative events as reported in global media. In this thesis, I use the ESG combined score to reflect the companies' overall ESG performance.

higher score indicates a firm has better ESG performance. In our sample, 3,631 companies (belonging to 11 industries) have ESG scores.

3.3.2 Descriptive Statistics

Table 3-1 summarizes descriptive statistics for the sample. Panel A contains the fund-level characteristics for the 118 RIFs in our sample between January 2005 and December 2020. The average fund is about 21 years (255 months) old,[43] has US$11.39 billion in assets under management, and an annual expense ratio of 0.83%. Size and age show considerable standard deviations, 32.86 billion and 190 months, respectively. The average fund ESG score is 35.98 (out of 100), with a standard deviation of 7.35, while the average E, S, and G scores are 39.29, 45.16, and 44.13, respectively.

Panel B (Table 3-1) presents the summary statistics for the FMC characteristics. The average size of our sample FMC is USD 270.81 billion, with 27.83 billion in assets belonging to RIFs. The average age of FMCs is 42.34 years (508 months), while on average, they have managed RIFs for approximately 24.43 years (293 months) as of December 2020.

Most RIFs belong to a 'mixed' FMC, in which the management company has both conventional funds and RIFs. For these mixed fund families, FMCs might not necessarily benefit from improving ESG performance if their RIFs only represent a small portion of their overall business. This may be especially true if the costs associated with improving ESG performance are high. Therefore, it is reasonable to suppose that different degrees of ESG commitment (proportion of assets belonging to responsible investments) may influence RIFs' ESG performance. Under this assumption, we set breakpoints at 20%, 40%, 60%, and 80% and split the 118 RIFs into five groups for each quarter. Figure 3-1 is a histogram of the FMCs' ESG commitment levels for each RIF.[44] The commitment level is re-calculated each year in June and assumed to be constant for the year.

[43] Some funds in our sample were very old (e.g., the Pioneer Fund was established on 10th February 1928). This may explain why the average fund is relatively old and large. As a robustness check, we excluded the five very old funds in the sample and our results are qualitatively similar. Results excluding them are available upon request.

[44] We conduct the main analysis at fund-level, therefore, we report this at the fund level, with a possibility of duplicates since more than one fund could belong to a given FMC.

Figure 3-1 shows three peaks, at each tail and the midpoint. Therefore, the first (fifth) group includes companies with less than 20% (greater than 80%) of AUM classified as responsible investment funds.[45]

Table 3-1 Descriptive statistics

	Mean	Median	Std. Dev.	Min	Max	N
Panel A: Summary statistics of RIFs						
i) Summary statistics for 118 funds as of December 2020						
Size (million)	11391.86	1016.85	32856.45	0.84	255669.5	118
Age (month)	255.18	218	190.45	38	1114	118
ii) Pooled summary statistics for the entire sample period						
Fund flow	0.0199	0.0005	0.0995	-0.1763	0.7359	5850
Return	-0.0046	-0.0042	0.0456	-0.2788	0.2852	5850
Expense ratio (%)	0.83	0.84	0.39	0.01	2.25	5842
ESG score	35.98	36.69	7.35	8.87	54.82	5850
E score	39.29	40.93	12.51	2.27	71.69	5850
S score	45.16	46.04	11.02	12.13	75.58	5850
G score	44.13	45.11	8.92	9.69	70.33	5850
Panel B: Summary statistics of 53 FMCs as of December 2020						
Total RIF AUM (million)	27827.06	935.58	99443.22	0	510320.3	53
FMC Total AUM (million)	270812.5	13589.85	906149.7	8.11	6281488	53
FMC age (month)	508.08	407	290.92	110	1157	53
Oldest RIF's age of FMC (month)	293.25	257	216.49	48	1114	53

Panel C Average ESG performance within five ESG commitment level groups

	Group 1 (≤20%)	Group 2 (21%-40%)	Group 3 (41%-60%)	Group 4 (61%-80%)	Group 5 (>80%)	Full sample
ESG score	37.34	34.42	35.72	35.42	35.38	35.98
E score	41.47	38.15	39.32	36.89	37.68	39.29
S score	47.04	42.73	45.23	44.19	43.65	45.16
G score	45.3	42.37	44.62	43.52	42.42	44.13

[45] For robustness, we also try 3 groups with breakpoints at 25% and 75%. Results are qualitatively similar, with significant ESG performance coefficients for the lowest and the highest commitment groups.

ESG score percentile ranking	53.14	45.11	49.02	45.5	48.1	-
E score percentile ranking	52.62	46.06	51.4	44.04	44.5	-
S score percentile ranking	52.73	44.31	51.18	45.25	44.8	-
G score percentile ranking	52.17	44.32	52.16	47.08	43.11	-
Size (million)	656.86	28147.96	12961.09	685.7	956.57	7086.03
Age (month)	183	313	261	115	167	213
Expense ratio (%)	1	1	0.62	0.88	0.98	0.83
FMC age	547	476	650	233	261	503
Oldest RIF's age of FMC	201	394	581	166	240	373
FMC Total AUM (billion)	181.85	151.56	309.72	7.32	4.08	182.61
N	1494	274	2412	370	1300	5850

Note: Table 3-1 summarises the descriptive statistics for the sample. Panel A provides fund-level summary statistics for 118 RIFs in our sample between January 2005 and December 2020. *Size* is the size of the RIF. *Age* is the number of months since the fund's oldest share class was established. *Fund flow* is the capital flow of fund, defined in Equation (3.3). *Return* is the fund's annualised alpha, obtained using monthly raw returns and the 4-factor model with a 12-month rolling window. *Expense ratio* is the annualized expense ratio which captures the funds' operating expenses and management fees. *ESG*, *E*, *S*, and *G scores* are the fund-level ESG, Environmental, Social, and Governance scores. They are calculated as the weighted sum of individual stocks' scores in fund's holding portfolio. Panel B describes the fund family-level summary statistics for the 53 FMC characteristics. *Total RIF AUM* is the total RIF assets under management belong to the FMC. *FMC Total AUM* is the total assets under management of Fund family. *FMC age* is the number of months since the first fund of FMC was established. *Oldest RIF's age of FMC* represents the age of the oldest RIF within FMC. Panel C reports the average level of ESG performance (includes raw scores and percentile rank of scores) and fund characteristics for five ESG commitment groups, defined in Section 3.4.1.

Panel C (Table 3-1) summarizes fund-quarter data for each commitment level group. The average ESG, E, S, and G scores show differences among the five groups (tests for differences in means between each group are presented in Appendix 3-2). Interestingly, on average, funds managed by FMCs with the lowest commitment level (≤20%) exhibit the highest combined ESG and E, S, and G scores, which suggests that RIFs managed by FMCs with the lowest ESG commitment may put more effort into investing in high ESG score companies. Group 2 (21%-40%) exhibits the lowest ESG, S, and G scores (34.42, 42.73, and 42.37, respectively), while Group 4 (61%-80%) reports the lowest average environmental (E) score (36.89). Additionally, the ESG performance of the RIFs in Group 5 (>80%), the group with the highest ESG commitment level, show average scores below the full sample's average, which may indicate: 1) these fund managers are implementing a more complex ESG strategy, which might not directly translate into immediate ESG score improvement; 2) there might be ESG-window dressing behaviour in my sample, raising the full sample average. As reported in Rows

(5)-(8), the percentile ranking differences also show that funds managed by the FMCs with the lowest commitment level (Group 1) exhibit the highest percentile rankings for ESG, environmental and social scores. In contrast, funds managed by relatively more ESG-dominated FMCs (Groups 4 and 5) have lower percentile rankings for all scores. The fund and FMC characteristics in different groups also show interesting results. RIFs in Groups 2 and 3 are relatively larger and older compared to other groups, but the expense ratio shows a large gap, which may suggest differences in management strategy. RIFs in Groups 4 and 5 are managed by relatively smaller and younger FMCs than those in Groups 1-3.

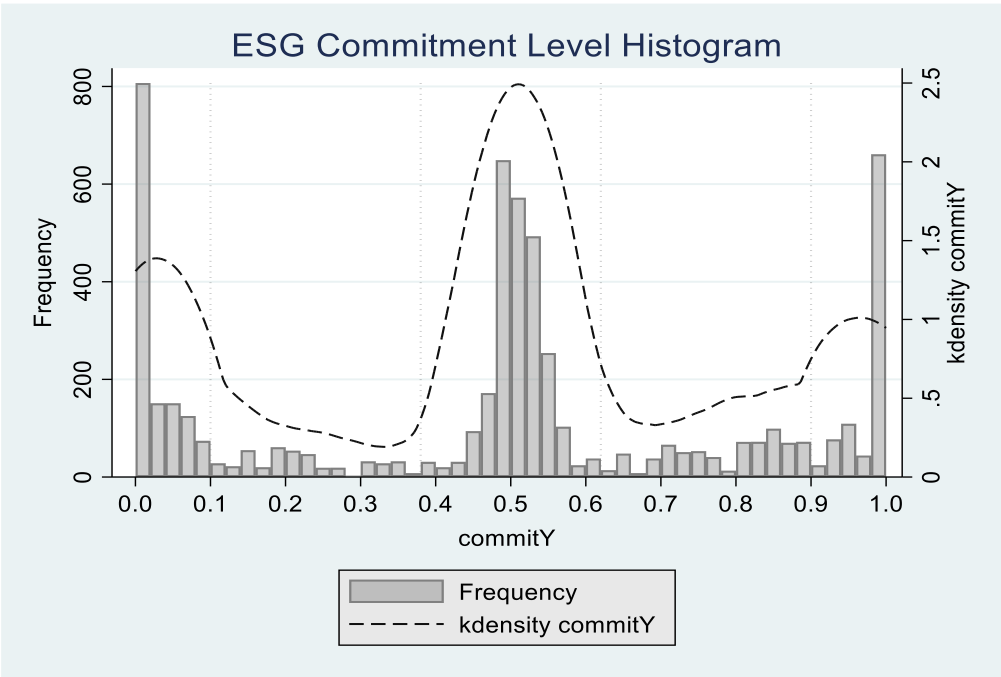


Figure 3-1 Histogram of the fund-quarters ESG commitment levels

Note: Figure 3-1 presents the histogram of the ESG commitment levels for 118 US RIFs between January 2005 and December 2020. The commitment level is calculated based on the proportion of AUM engaged in responsible investment of the fund management company. It is re-calculated in June for each year.

Figure 3-2 reports the quarterly number of firms with ESG scores and the average ESG scores from March 2005 to December 2020. The number of companies with ESG scores ranges from 635 in June 2006 to 2767 in

September 2019, an increase of 336%. The number of rated companies has continuously increased until the end of 2019, which indicates that US-listed companies have gradually adopted ESG reporting in line with growing investor interest. The average ESG score ranges from 29.78 in March 2005 to 39.84 in September 2014,[46] with some fluctuations. Interestingly, between December 2014 and March 2017, the average ESG score drops while the number of firms reporting ESG scores increases dramatically. For the rest of the sample period, before December 2014 and after March 2017, the number of firms and the average ESG score increased.

Figure 3-3 plots the trend of RIFs' average ESG, E, S, and G scores between 2005 and 2020. All four scores show an increasing trend between 2005 and 2009, with environmental scores exhibiting the most significant increase. Between 2010 and 2014, E, S, and G scores decreased while the ESG score remained largely unchanged. All four scores then increased from 2015 to 2020, while social scores exhibit the greatest rise. There are several notable features in Figure 3-3. The average ESG scores of companies increased from around 36 to 40 over the period 2009 to 2014; however, the average score for RIFs decreased by nearly one point. Additionally, from the trends of separate scores, it is interesting to note that the RIFs have responded differently to the material issues that investors have focused on over time. Between 2005 and 2009, we see strong emphasis across the board but greatest on environmental issues, while more recently, we see a greater emphasis on social issues along with the environment, and very little on governance, which has fallen.

[46] According to the Refinitiv (2022), Refinitiv applies ongoing adjustments to ESG scores without publicly announcing its changes. In addition, Refinitiv ESG scores had a one-time retroactive score rewriting (methodology changes that applied to newly created and historical scores) on April 6, 2020. Our Refinitiv ESG scores were obtained on 3 January 2022. The scores are rewritten scores after the methodology changes, which may result in a lower average level than earlier studies using the same ESG score provider.

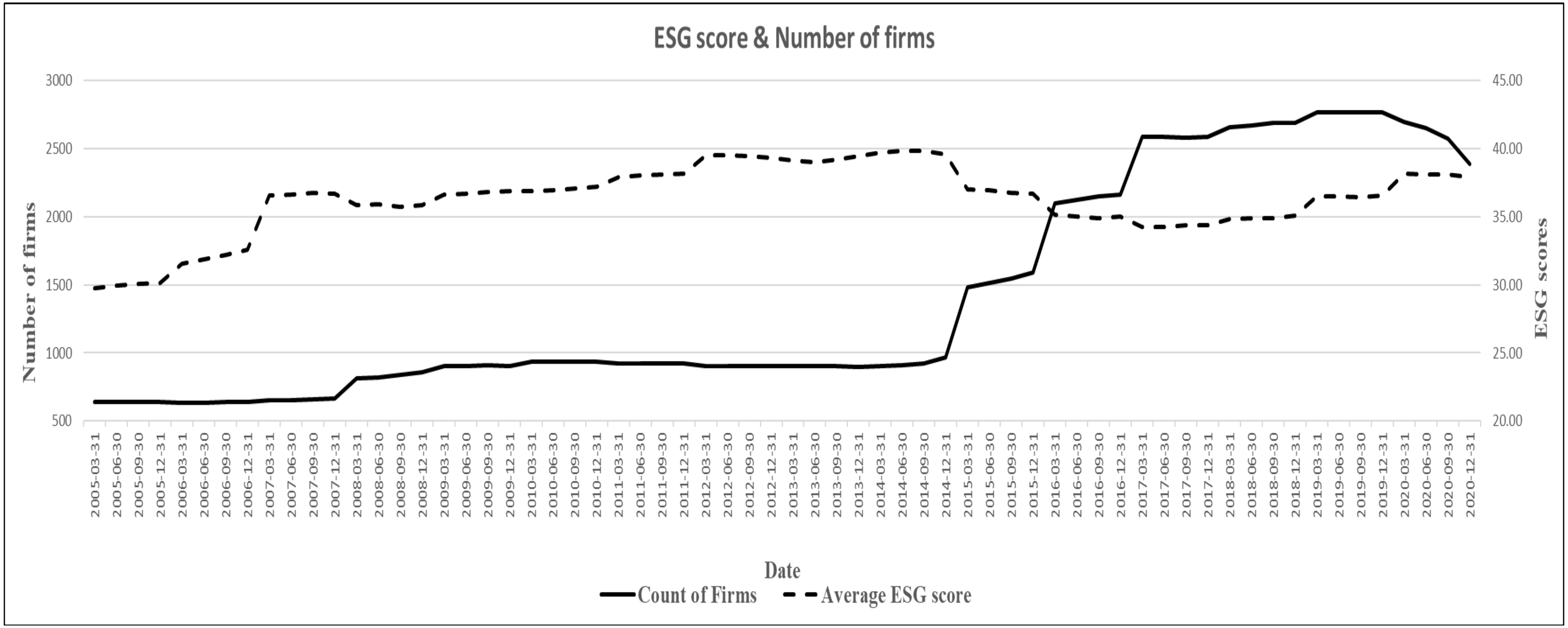


Figure 3-2 Number of firms reporting ESG scores and the average ESG scores

Note: Figure 3-2 reports the number of firms that report ESG scores and the average ESG scores by quarters from March 2005 to December 2020.

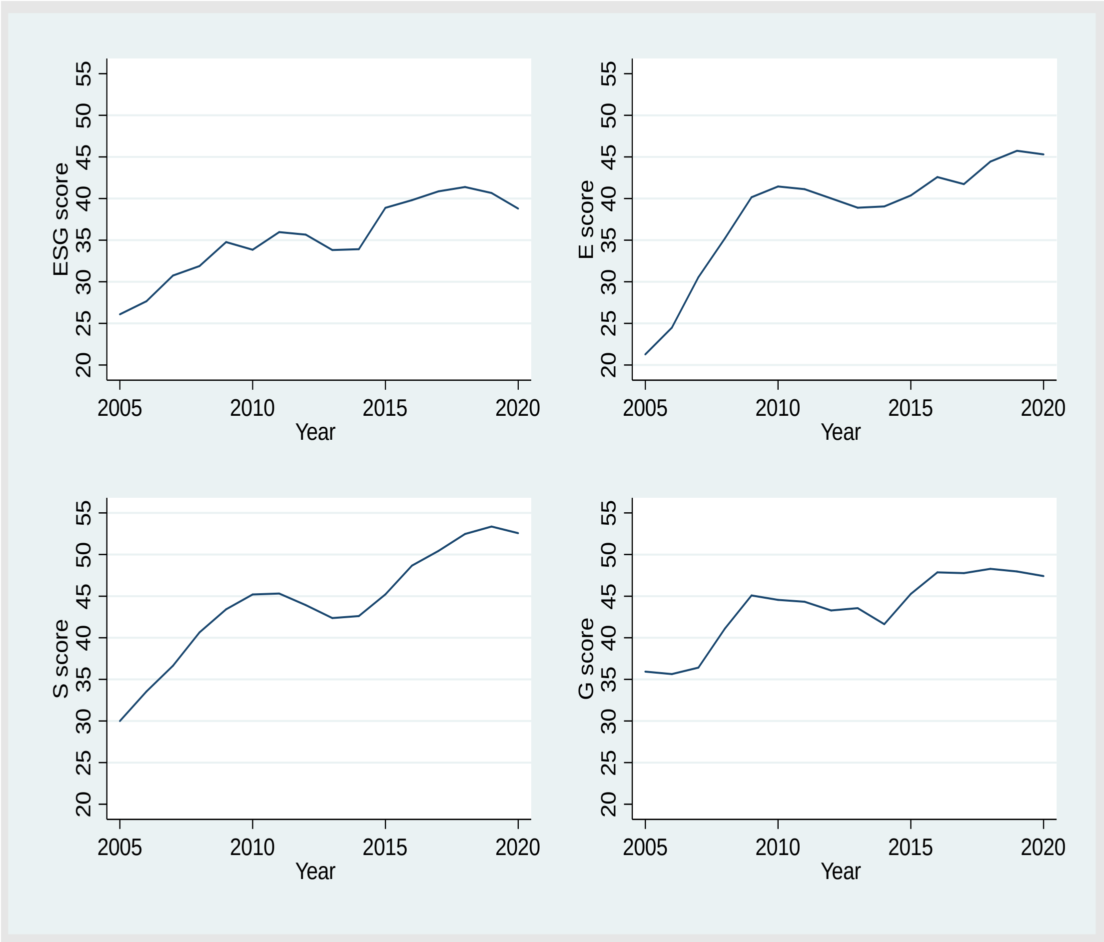


Figure 3-3 RIFs' average ESG scores (ESG, E, S, and G) between 2005 and 2020
Note: Figure 3-3 presents the trends of US RIFs' average ESG scores (ESG, E, S, and G) between 2005 and 2020.

3.4. Methodology and Results

To examine the potential impact of FMC-level factors on their RIFs, we first confirm the relationship between fund flow and fund financial performance by performing panel regressions for the entire sample and within the five ESG commitment level groups. The latter has not been addressed by the literature to date. Then, we analyse the relationship between flow and past ESG score (our measure of ESG performance) for RIFs. Lastly, to better understand the ESG reaction of FMCs to investors' flows, we examine the relationship between the change of ESG scores and the lagged fund flow (further discussed in Sections 3.4.3 and 3.4.4).

3.4.1 Flow-return Relationship Analysis

Similar to Bollen (2007) and Renneboog et al.(2011), we estimate the following flow-return regressions for all RIFs:

$$Fund\ Flow_{i,t} = \alpha + \beta Return_{i,t-1} + \gamma_1 SMB_{t-1} + \gamma_2 HML_{t-1} + \gamma_3 MOM_{t-1} + \gamma_4 volatility_{i,t-1} + \gamma_5 Expense\ ratio_{i,t-1} + \gamma_6 Size_{i,t-1} + \gamma_7 Age_{i,t-1} + \upsilon_i + \mu_i + \varepsilon_{i,t} \quad (3.1)$$

$$Fund\ Flow_{i,t} = \alpha + (\beta_1 R^+ + \beta_2 R^-) Return_{i,t-1} + \gamma_1 SMB_{t-1} + \gamma_2 HML_{t-1} + \gamma_3 MOM_{t-1} + \gamma_4 volatility_{i,t-1} + \gamma_5 Expense\ ratio_{i,t-1} + \gamma_6 Size_{i,t-1} + \gamma_7 Age_{i,t-1} + \upsilon_i + \mu_i + \varepsilon_{i,t} \quad (3.2)$$

The dependent variable, $Fund\,Flow_{i,t}$, is the capital flow of fund i during quarter t. It is measured as:

$$Fund\,Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1+R_{i,t})}{TNA_{i,t-1}} \quad (3.3)$$

where $TNA_{i,t}$ is the total net assets for fund i at the end of quarter t, and $R_{i,t}$ is the return of fund i during quarter t.

$Return_{i,t-1}$ is fund i's annualised lagged alpha, obtained using monthly raw returns and the 4-factor model with a 12-month rolling window (Ammann et al., 2019). We use fund returns lagged by one quarter to demonstrate the impact of the most recent holding information available to investors. To test whether there is an asymmetric flow-return reaction based on whether the lagged returns are positive or negative, we employ $R^+$and R^-as indicator variables that equal one if $Return_{i,t-1}$ is non-negative or negative, respectively. We also control for other variables that may influence fund flows. We include SMB, HML, and MOM, which are the quarterly size, book-to-market ratio and momentum factors obtained from Kenneth French's website. These factors are included to capture the potential effects on fund flows from style-based investment strategies (Frijns et al., 2016). We employ return volatility ($volatility_{i,t}$) as a measure of risk, which is the annualised standard deviation of monthly net returns over the previous 12 months (Ammann et al., 2019; Renneboog et al., 2011). $Expense\,ratio_{i,t}$ is the annualized expense ratio which captures the funds' operating expenses and management fees (Del Guercio et al., 2003). $Size_{i,t}$ is the logarithm of the fund size, $Age_{i,t}$ is the number of months since the oldest share class was established, and υ_i and μ_i are fund and year-fixed effects. We use White's (1980) heteroskedasticity-robust standard error estimation. The joint consideration of fixed effects and the White (1980) standard errors estimation is equivalent to the clustered standard error (considering the intragroup correlation).

The coefficients β, β_1, and β_2 in Equations (3.1) and (3.2) are the coefficients we are interested in. These coefficients capture the sensitivity of fund flow to past financial positive and negative returns, respectively. The coefficients γ_i capture the sensitivity of control variables.

Table 3-2 presents the estimation results for the flow-return relationship for the full sample of RIFs. Consistent with prior work, we find that the RIFs' flows are significantly positively associated (coefficient: 0.29) with past returns (Jiang & Yüksel, 2019; Marzuki & Worthington, 2015). Since flows can be incoming or outgoing, our results indicate that inflows are associated with superior past performance, holding everything else constant. In contrast, outflows are associated with lower past returns. We also find significant negative relationships between fund flow and fund size and age. This confirms the results of Jiang and Yüksel (2019) that fund flow decreases (increases) with an increase (decrease) in size and age.

We also find an asymmetric fund flow reaction to positive versus negative returns (as shown in column 2). The coefficient for positive returns is 0.50 and is significant at the 1% level, while the coefficient for negative returns is smaller but still positive (0.09) and significant at the 10% level. This suggests that RIFs exhibit a convex flow-performance relationship whereby better-performing funds receive greater money inflows, but funds with poor performance do not suffer money outflows of similar magnitude, consistent with Sirri and Tufano (1998).

Table 3-2 Regression results for the flow-return relationship

	(1)	(2)
Constant	0.6793***	0.6591***
	(0.1136)	(0.1094)
Lagged return	0.2916***	
	(0.0538)	
Lagged return (+)		0.5049***
		(0.1059)
Lagged return (-)		0.0921*
		(0.0552)
SMB	0.0013	0.0048
	(0.0359)	(0.0360)
HML	0.0129	0.0152
	(0.0221)	(0.0221)
MOM	-0.0251	-0.0212
	(0.0216)	(0.0211)
Volatility	0.0001	-0.0001
	(0.0006)	(0.0006)
Expense ratio	-0.0186	-0.0201
	(0.0267)	(0.0264)
Size	-0.0253***	-0.0251***
	(0.0050)	(0.0049)
Age	-0.0011***	-0.0010***
	(0.0003)	(0.0003)
Fund fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	5850	5850
R-squared	0.0938	0.0975
Number of fund ID	118	118

Note: This table summarises the regression results of Equations (3.1) and (3.2) for 118 US equity RIFs between 2005 and 2020. The dependent variable is *Fund Flow,* which is the capital flows of fund i during quarter t. *Lagged Return* is the fund's annualised lagged alpha obtained using monthly raw returns and the 4-factor model in a 12-month rolling window. The *Lagged return (+)* and *Lagged return (-)* are indicator variables that equal 1 if $Return_{i,t-1}$ is non-negative or negative, respectively. The SMB, HML and MOM are the quarterly size, book-to-market ratio and momentum factors. *Volatility* is annualised standard deviation of monthly net return over the previous 12 months. *Expense ratio* is the annualised expense ratio. $Size$ and Age are the size and age of fund. *, **, *** denote significance at 10%, 5% and 1%. Standard errors in parentheses.

Table 3-3 summarizes the coefficients of flow-return relationships at different ESG commitment levels.[47] Panel A summarizes the results for Equation (3.1), and Panel B reports the results for Equation (3.2). RIFs managed by FMCs with different ESG commitment levels show different flow-return relationships (Panel A, Table 3-3), which aligns with our expectations. RIFs managed by FMCs with the lowest (≤20%) and highest (>80%) ESG commitment levels exhibit significant positive relationships between fund flows and previous returns. Groups 2 and 4 report insignificant coefficients on lagged financial return. In addition, the groups show differing results for the control variables. For instance, for RIFs in Group 1 (lowest ESG commitment), fund flows are negatively related to expense ratio, fund size, and fund age. For Group 5, fund flows are only negatively associated with fund size.

Equation (3.2) splits the lagged return into positive and negative returns, with all groups displaying positive relationships between fund flows and previous positive returns, albeit with insignificant coefficients for Groups 2 and 3 (Panel B, Table 3-3). Only RIFs managed by FMCs with the highest (>80%) ESG commitment show significant positive coefficients to the previous negative return. These findings indicate that:

1) For some RIFs in our sample (e.g., funds in Group 1), past financial performance is a significant factor attracting fund inflow when facing a positive return, but its influence dissipates when the fund's return is negative.
2) For RIFs managed by FMCs with the highest ESG commitment level, their fund flows are positively related to both positive and negative returns, but are more sensitive to positive returns. The dual goals of RIFs may offer an explanation. Investors may make decisions influenced by financial returns but also non-financial considerations, which differ from one investor to another.

[47] To further support the existence of asymmetric fund flow reactions to positive or negative returns, we also test the following equation and report the results in Appendix 3-3:

$$Fund\ Flow_{i,t} = \alpha + \beta Return_{i,t-1} + \beta_1 * R^- * Return_{i,t-1} + \gamma_1 SMB_{t-1} + \gamma_2 HML_{t-1} + \gamma_3 MOM_{t-1} + \gamma_4 volatility_{i,t-1} + \gamma_5 Expense\ ratio_{i,t-1} + \gamma_6 Size_{i,t-1} + \gamma_7 Age_{i,t-1} + \upsilon_i + \mu_i + \varepsilon_{i,t} \quad (3.A1)$$

Table 3-3 Regression results for the flow-return relationship (five ESG commitment groups)

	Panel A: Equation (3.1)					Panel B: Equation (3.2)				
	Group 1 (≤20%)	Group 2 (21%-40%)	Group 3 (41%-60%)	Group 4 (61%-80%)	Group 5 (>80%)	Group 1 (≤20%)	Group 2 (21%-40%)	Group 3 (41%-60%)	Group 4 (61%-80%)	Group 5 (>80%)
Constant	0.7886***	2.3896	0.9488***	0.5876	0.5086**	0.7784***	2.3641	0.9297***	0.6069	0.4840**
	(0.2345)	(1.4805)	(0.2450)	(0.5087)	(0.1865)	(0.2326)	(1.4775)	(0.2271)	(0.5066)	(0.1787)
Lagged return	0.3218***	-0.0116	0.1726*	0.1545	0.4878***					
	(0.0714)	(0.0911)	(0.1016)	(0.1174)	(0.1104)					
Lagged return (+)						0.7010***	0.156	0.303	0.2930*	0.6913***
						(0.1866)	(0.1420)	(0.2168)	(0.1416)	(0.1763)
Lagged return (-)						0.0898	-0.1676	0.0203	0.0172	0.2842**
						(0.0762)	(0.1302)	(0.1118)	(0.166)	(0.1267)
SMB	-0.0645	-0.1822	0.019	-0.1778**	0.1251	-0.0595	-0.1784	0.0209	-0.1736**	0.1272
	(0.0569)	(0.1228)	(0.0490)	(0.0852)	(0.1041)	(0.0581)	(0.1221)	(0.0495)	(0.0835)	(0.1040)
HML	0.0508	-0.1464**	0.0106	-0.0079	-0.0085	0.0537	-0.1391*	0.0123	-0.0099	-0.0047
	(0.0555)	(0.0635)	(0.0293)	(0.0779)	(0.0516)	(0.0563)	(0.0664)	(0.0288)	(0.0799)	(0.0516)
MOM	-0.0121	-0.1142*	0.0046	0.0156	-0.1009**	-0.0072	-0.1124*	0.0059	0.0182	-0.0926**
	(0.0331)	(0.0583)	(0.0400)	(0.0394)	(0.0448)	(0.0337)	(0.0605)	(0.0389)	(0.0412)	(0.0445)
Volatility	-0.0013	0	0.0004	0.0017	0.0007	-0.0015	-0.0002	0.0002	0.0015	0.0004
	(0.0011)	(0.0012)	(0.0008)	(0.0015)	(0.0014)	(0.0011)	(0.0013)	(0.0008)	(0.0015)	(0.0014)
Expense ratio	-0.0721*	0.0336	-0.0628	0.0805	0.0714	-0.0733*	0.0312	-0.062	0.0815	0.0661
	(0.0413)	(0.0881)	(0.043)	(0.0998)	(0.0784)	(0.0417)	(0.0870)	(0.0428)	(0.0978)	(0.0770)
Size	-0.0305**	-0.0864	-0 .0336***	-0.0334	-0.0257***	-0.0309**	-0.0857	-0.0334***	-0.0348	-0.0249***
	(0.0131)	(0.0617)	(0.0099)	(0.0243)	(0.0058)	(0.0132)	(0.0616)	(0.0096)	(0.0244)	(0.0054)
Age	-0.0012**	-0.0026***	-0.0011**	-0.0002	-0.0006	-0.0011*	-0.0026***	-0.0010**	-0.0001	-0.0005
	(0.0005)	(0.0009)	(0.0005)	(0.0010)	(0.0010)	(0.0006)	(0.0009)	(0.0005)	(0.0010)	(0.0011)

Fund fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1494	274	2412	370		1494	274	2412	370	1300
R-squared	0.1183	0.2737	0.1094	0.1265		0.1242	0.2772	0.1113	0.1302	0.1608
Number of funds	41	17	56	23		41	17	56	23	26

Note: This table summarises the regression results of Equations (3.1) and (3.2) for 118 US equity RIFs for the five ESG commitment levels. The dependent variable is *Fund Flow,* which is the capital flows of fund i during quarter t. *Lagged Return* is the fund's annualised lagged alpha obtained using monthly raw returns and the 4-factor model in a 12-month rolling window. The *Lagged return (+)* and *Lagged return (-)* are indicator variables that equal one if $Return_{i,t-1}$ is non-negative or negative, respectively. The SMB, HML and MOM are the quarterly size, book-to-market ratio and momentum factors. *Volatility* is annualised standard deviation of monthly net return over the previous 12 months. *Expense ratio* is the annualised expense ratio. *Size* and *Age* are the size and age of fund. *, **, *** denote significance at 10%, 5% and 1%. Standard errors in parentheses.

3.4.2 ESG Impacts on the Flow-return Relationship

RIFs pursue dual investment goals: they aim to maximise financial returns while investing according to their ESG mandate. Prior surveys have indicated that some investors will accept sacrificing financial returns for societal or environmental benefits (PricewaterhouseCoopers LLP, 2020). To account for these investors, we follow the method of El Ghoul and Karoui (2017), and include an interaction term of the fund ESG score and the prior return to examine how the flow-performance relationship is affected by holdings-based ESG scores.

$$Fund\,Flow_{i,t} = \alpha + \beta_1 Return_{i,t-1} + \beta_2 ESG_{i,t-1} + \beta_3 Return_{i,t-1} * ESG_{i,t-1} + \gamma_1 SMB_{t-1} + \gamma_2 HML_{t-1} + \gamma_3 MOM_{t-1} + \gamma_4 volatility_{i,t-1} + \gamma_5 Expense\,ratio_{i,t-1} + \gamma_6 Size_{i,t-1} + \gamma_7 Age_{i,t-1} + v_i + \mu_i + \varepsilon_{i,t} \tag{3.4}$$

The calculation of the ESG score for fund *i* at quarter *t* ($ESG_{i,t}$) follows the method of Dorfleitner et al. (2012), which is shown in Equation (3.5). An individual company's ESG score is updated yearly; the fund-level ESG scores are calculated as the weighted sum of individual stocks' ESG scores in the portfolio. Therefore, to improve the fund-level ESG score, funds might consider increasing the holding percentage of high ESG companies, reducing the assets allocated in companies with low ESG scores, or adopting a combination of both strategies.

$$ESG_{i,t} = \sum_{j=1}^{n} w_{j,t} * ESG_j \tag{3.5}$$

where, w_j is the weight of stock *j* at the quarter *t* and ESG_j is the ESG score of stock *j*. FMCs may have different focuses regarding separate E, S, and G aspects to target different investor segments (at different times). We, therefore, use a similar method to obtain the E, S, and G scores for each RIF.

Table 3-4 Estimation results for the flow-return relationship impacted by ESG

	(1) ESG score	(2) E score	(3) S score	(4) G score
Constant	0.6995***	0.6557***	0.6936***	0.7147***
	(0.1150)	(0.1161)	(0.1157)	(0.1168)
Lagged return	0.3824*	0.2766*	0.3735*	0.4649*
	(0.2267)	(0.1577)	(0.2020)	(0.2415)
Lagged ESG scores	-0.0024***	-0.0016**	-0.0023***	-0.0024***
	(0.0008)	(0.0006)	(0.0007)	(0.0007)
Lagged return*ESG measurement	-0.0033	0.0002	-0.0024	-0.0047
	(0.0063)	(0.0041)	(0.0044)	(0.0055)
SMB	-0.0234	-0.0041	-0.0036	-0.0057
	(0.0352)	(0.0361)	(0.0362)	(0.0361)
HML	0.0015	0.004	0.0033	0.0074
	(0.0214)	(0.0215)	(0.0213)	(0.0211)
MOM	-0.0454**	-0.0430**	-0.0425**	-0.0453**
	(0.0205)	(0.0202)	(0.0203)	(0.0205)
Volatility	0.0002	0.0002	0	0.0002
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Expense ratio	-0.0304	-0.0275	-0.0319	-0.0316
	(0.0241)	(0.0247)	(0.0236)	(0.0234)
Fund size	-0.0238***	-0.0237***	-0.0240***	-0.0233***
	(0.0050)	(0.0050)	(0.0050)	(0.0050)
Age	-0.0009**	-0.0008**	-0.0007**	-0.0009**
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Fund fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Observations	5732	5732	5732	5732
R-squared	0.0969	0.0935	0.0985	0.1001
Number of fund ID	118	118	118	118

Note: Table 3-4 summarizes the regression results of Equation (3.4) for the sample of 118 US equity RIFs. Results in columns (1) to (4) show the four ESG measures, namely ESG, E, S, and G scores. The calculation of the ESG score for fund i at quarter t ($ESG_{i,t}$) follows the method of Dorfleitner et al. (2012), which is the weighted sum of individual stocks' ESG scores in the portfolio, as shown in Equation (3.5). We use a similar method to obtain the E, S and G scores for each RIF. *, **, *** denote significance at 10%, 5% and 1%. Standard errors in parentheses.

Table 3-4 presents Equation (3.4) coefficient estimates for the full sample of RIFs. Results in columns (1) to (4) show that for all four ESG measurements (ESG, E, S, and G scores), RIFs in our sample, on average, have significantly negative relationships between the scores and fund flows.[48] This suggests that, on average, an increase in ESG (E, S, and G) score is followed by fund outflows. While the coefficient is relatively small (-0.0024), a one standard deviation increase in raw ESG score is associated with a 0.89 decrease in fund flow. Moreover, the interaction terms of fund returns and the ESG measurements show insignificant results, suggesting that changes in ESG score do not impact the fund-flow relationship, which contrasts with Hypothesis 1. These findings differ from El Ghoul and Karoui (2017), who find that an increase in the ESG score weakens the flow-performance relationship for US RIFs between 2003 and 2011. A potential explanation for the disparate findings might be attributed to sample differences. El Ghoul and Karoui (2017) analyse 2,168 US domestic equity funds between 2003 and 2011, whereas our study is specifically centred on RIFs between 2005 and 2020. We focus on a rapidly growing subset of equity funds with distinct ESG criteria and objectives, which may inherently exhibit different results.

To further address this issue, we split the RIFs into quintiles based on their FMCs' ESG commitment. The investor may not be able to precisely assess a fund's ESG score but should be able to distinguish the relatively more "responsible" FMCs by reading the fund prospectus and website. Therefore, we interact $Return_{i,t-1} * ESG_{i,t-1}$ with ESG commitment level quintile dummies. The results are reported in Table 3-5. Rows (1)-(5) present the results when using the overall ESG score as the ESG performance measurement for each of the five commitment quintiles. Group 5 (the highest FMC commitment level) shows a significant negative coefficient on the interaction term, suggesting that for RIFs managed by ESG-dominated companies, an increase in ESG score weakens the flow-return relationship, which partly supports hypothesis 2. In supplementary tests, we also observe that RIFs in Group 1 (lowest ESG commitment) and Group 5 (highest), lagged ESG scores are negatively related to fund flow (Appendix 3-4 Panel B). Combining findings from Table 3-5 and Appendix 3-4 suggests that investors may be less sensitive to financial performance when they choose higher ESG commitment levels, which is consistent with the work of El Ghoul and Karoui (2017).

Table 3-5 Results of the flow-return relationship impacted by ESG (five ESG commitment groups)

[48] To support this conclusion, we report the regression results with only ESG measurements (no return and interaction term) in Appendix 3-4.

			Lagged return		Lagged ESG measurement		Lagged return*ESG measurement	
ESG score	**1**	Group 1	0.1193	(0.2055)	-0.0027**	(0.0013)	0.0056	(0.0062)
	2	Group 2	-0.6758	(0.4947)	-0.0019	(0.0022)	0.022	(0.0141)
	3	Group 3	-0.0143	(0.2874)	-0.0011	(0.0009)	0.0058	(0.0065)
	4	Group 4	0.538	(0.4861)	-0.0001	(0.0013)	-0.0116	(0.0125)
	5	Group 5	1.2360***	(0.3747)	-0.0038***	(0.0013)	-0.0242**	(0.0112)
E score	**6**	Group 1	-0.0392	(0.1601)	-0.0014	(0.0011)	0.0097**	(0.0045)
	7	Group 2	-0.4062	(0.3619)	-0.0032	(0.0025)	0.0115	(0.0089)
	8	Group 3	0.0918	(0.2324)	-0.0013**	(0.0006)	0.0027	(0.0046)
	9	Group 4	0.2652	(0.2561)	-0.0011	(0.0012)	-0.0038	(0.0065)
	10	Group 5	0.8813***	(0.2719)	-0.0024**	(0.0010)	-0.0127	(0.0076)
S score	**11**	Group 1	-0.1026	(0.1888)	-0.0015	(0.0011)	0.0099**	(0.0047)
	12	Group 2	-0.5331	(0.4289)	-0.0024	(0.0022)	0.014	(0.0097)
	13	Group 3	0.0139	(0.2761)	-0.0018**	(0.0007)	0.004	(0.0050)
	14	Group 4	0.4021	(0.3821)	0	(0.0011)	-0.0063	(0.0078)
	15	Group 5	1.2344***	(0.2943)	-0.0040***	(0.0011)	-0.0203***	(0.0066)
G score	**16**	Group 1	0.0672	(0.2207)	-0.0024**	(0.0012)	0.0061	(0.0053)
	17	Group 2	-0.7216	(0.5377)	-0.0003	(0.0023)	0.0187	(0.0125)
	18	Group 3	0.0234	(0.3024)	-0.0016**	(0.0007)	0.0037	(0.0057)
	19	Group 4	0.5115	(0.5086)	-0.0005	(0.0011)	-0.0087	(0.0107)
	20	Group 5	1.3594***	(0.3751)	-0.0035***	(0.0012)	-0.0232**	(0.0088)

Note: Table 3-5 summarizes the coefficients of the *Lagged return*, *Lagged ESG* and the interaction term *(Lagged return***ESG measurement*) in Equation (3.4) for US equity at five different FMC ESG commitment levels. Control variables are omitted for brevity. *, **, *** denote significance at 10%, 5% and 1%. Standard errors in parentheses.

Rows (6)-(10), (11)-(15), and (16)-(20) report the results of separate environmental, social, and governance scores. For Group 5, the results are relatively consistent, i.e., the relationship between fund flows and past financial returns weakens when scores increase. This may be because investors in Group 5 are prepared to tolerate relatively poorer financial performance as returns may be a secondary consideration in comparison to ESG performance. In addition, as FMCs' ESG commitment level increases, it may be more difficult for investors to find alternative RIFs that fit their ESG goals, and therefore, investors may be reluctant to transfer their investments even suffering lower comparative financial returns (Benson & Humphrey, 2008). The significant positive coefficients of the interaction term for environmental and social scores in Group 1 may suggest that funds managed by FMCs with a lower ESG commitment level are more sensitive to the flow-return relationship when the E and S scores increase.

3.4.3 Does Past Fund Flow Impact RIFs' ESG Performance?

Our previous regressions primarily consider the impact on fund flow related to financial returns or ESG performance. These analyses tend to explain the relationship from the funds' perspective and examine how investors adjust their investments based on past returns and ESG performance. However, for investors, the opposite relationship, how the past fund flows impact RIFs' ESG performance, maybe more important. This relationship attempts to link investors' capital flow and the change in ESG performance to answer the question: *Can investors' investment (proxied by fund flows) encourage RIFs to improve their responsible investment performance?* The ESG score of a fund is not publicly available for all investors, especially retail investors. However, both RIF managers and FMCs can obtain ESG scores for the funds they manage and can improve their ESG scores by investing in companies with higher ESG scores and/or selling down those with lower ESG scores if they wish to. Therefore, it is interesting to assess if the RIFs alter their holding companies to improve the fund level ESG scores *in response to* fund flows. To examine whether RIFs react to investors' money flows by altering their ESG performance, we examine the relationship between lagged fund flows and the change in ESG scores using the following model:

$$\Delta ESG_{i,t} = \alpha + \beta_1 Fund\,Flow_{i,t-1} + \beta_2 Return_{i,t-1} + \gamma_1 SMB_{t-1} + \gamma_2 HML_{t-1} + \gamma_3 MOM_{t-1} + \gamma_4 volatility_{i,t-1} + \gamma_5\, Expense\,ratio_{i,t-1} + \gamma_6 Size_{i,t-1} + \gamma_7 Age_{i,t-1} + \upsilon_i + \mu_i + \varepsilon_{i,t} \quad (3.6)$$

$\Delta ESG_{i,t}$ is the change in ESG score of fund *i* in quarter *t*. It can be used to capture the improvement of ESG scores and is defined in Equation (3.7). We use the same method to obtain $\Delta E_{i,t}$, $\Delta S_{i,t}$ and $\Delta G_{i,t}$.

$$\Delta ESG_{i,t} = ESG_{i,t} - ESG_{i,t-1} \quad (3.7)$$

We also employ $ESGpctrank_{i,t}$, the percentile ranking[49] of a fund's ESG score, as an alternative measure of a fund's ESG performance. In essence, this looks at whether new fund inflows motivate a greater change to a

[49] Percentile ranking of ESG score is obtained in three steps: 1) we rank all the companies with ESG (E, S and G) scores in descending order in each year; 2) use the rank of each company divided by the total number of the companies with a score in each year, then subtract this quotient from one; 3) multiply the difference by 100. We use percentile ranking as an alternative measure of a fund's ESG performance to indicate how well a RIF performs for ESG, relative to other funds.

fund's ESG performance relative to its competitors and accounts for the fact that ESG scores, on average, tend to increase over time. It is calculated by dividing the number of funds in quarter t by the ESG rank of fund i in quarter t, subtracting the quotient from 1, and multiplying by 100. $\Delta ESGpctrank_{i,t}$ captures the change in ESG score percentile ranking for fund i in quarter t. It can be calculated as:

$$\Delta ESGpctrank_{i,t} = ESGpctrank_{i,t} - ESGpctrank_{i,t-1} \qquad (3.8)$$

We obtain the $\Delta Epctrank_{i,t}$, $\Delta Spctrank_{i,t}$ and $\Delta Gpctrank_{i,t}$ using the same method.The coefficient β_1 in Equation (3.6) captures the sensitivity in the change of ESG performance to fund flow. It reflects the ESG performance adjustment in response to investment flow.[50]

Table 3-6 summarizes the results of Equation (3.6). At first glance, the results of Panel A confirm there is a significantly positive relationship between lagged fund flow and the four ESG performance scores. However, these results should be interpreted with care. As shown in Figure 3-2, firms' ESG scores have naturally and gradually increased over time. As such, the increase in a fund's aggregate numerical values of the ESG scores following new inflows may not be exclusively driven by investing in higher ESG companies but by the natural upward trend in ESG scores over time. Therefore, we retest Equation (3.6) using the percentile ranking of ESG scores. In Table 3-6, columns (5)-(8), we observe that the coefficients on the percentile ranking of ESG, E, S, and G scores for the entire sample are positive and significant at the 1% level. Taken together, we find evidence that when RIFs experience fund inflows (outflows) in the previous quarter, they will increase (decrease) both their raw and relative ESG performance, on average.

Our factor exposures in Table 3-6 show varied but interesting findings across the different ESG performance measures. Past performance, $Return_{i,t-1}$, yields insignificant negative coefficients for all regressions. Thus, past returns do not impact ESG scores and ESG percentile ranking. Return volatility is negatively related to changes in ESG, E, and G scores. The fund expense ratio is positively associated with the ESG score, E score,

---

[50] Equation (3.6) does not imply reverse causality with Equation (3.4) due to the difference in timing of the variables. For instance, if we assume September as time t, Equation (3.4) tests the impact of June's ESG score on September's fund flow (flows between June and September). In contrast, Equation (3.6) examines how the change in the ESG score between June and September is influenced by June's fund flow (flows between March and June).

and G score, suggesting that more expensive funds have better ESG performance, which may reflect that the higher fees are used to fund higher research costs. Fund size is positively related to changes in all four score types (except for the insignificant relationship between fund size and the change of the G score). Fund age exhibits negative relationships with changes in all four score types.

It is worth noting that the significant positive coefficient on fund flows also indicates that funds experiencing outflows may reduce their investment in companies with high ESG scores. To investigate further, we split fund flows into in- and outflows and employ FF^{+} and FF^{-} as indicator variables that equal one if $Flow_{i,t-1}$ is positive or negative, respectively.

$$\Delta ESG_{i,t} = \alpha + (\beta_1 FF^{+} + \beta_2 FF^{-}) Fund\ Flow_{i,t-1} + \beta_3 Return_{i,t-1} + \gamma_1 SMB_{t-1} + \gamma_2 HML_{t-1} + \gamma_3 MOM_{t-1} + \gamma_4 volatility_{i,t-1} + \gamma_5\ Expense\ ratio_{i,t-1} + \gamma_6 Size_{i,t-1} + \gamma_7 Age_{i,t-1} + \upsilon_i + \mu_i + \varepsilon_{i,t}$$

(3.9)

Table 3-6 Estimation results for the relationship between change on ESG performance and fund flows

	(1) ESG score	(2) E score	(3) S score	(4) G score	(5) ESG % ranking	(6) E % ranking	(7) S % ranking	(8) G % ranking
Constant	3.3212***	9.7889***	7.1189***	2.8210**	-12.3135**	-9.2127**	-12.2033***	-8.7347*
	(1.0545)	(1.2685)	(1.3388)	(1.4004)	(5.3806)	(3.7289)	(4.3237)	(5.2146)
Lagged Fund Flow	1.2320***	1.3676***	1.7580***	1.8607***	6.4569***	3.2788**	4.2535***	4.7831***
	(0.3335)	(0.4485)	(0.4470)	(0.4226)	(1.7519)	(1.2995)	(1.3877)	(1.4847)
Lagged return	-0.7016	-1.0996	-0.384	-1.2297	-3.531	-3.1316	-2.4554	-3.7741
	(0.6182)	(0.7729)	(0.7901)	(0.8310)	(2.6182)	(1.9077)	(2.2549)	(2.3795)
SMB	5.1203***	-1.8215**	-1.5677*	0.0256	0.6218	1.1775	1.1821	0.8829
	(0.7122)	(0.8803)	(0.8155)	(0.8537)	(3.8176)	(2.7956)	(3.0052)	(3.5934)
HML	0.5658	0.77	0.8593	-1.8679***	0.6502	1.9833	1.5781	1.706
	(0.4607)	(0.5719)	(0.6059)	(0.5945)	(2.8212)	(1.7718)	(2.2846)	(2.5214)
MOM	0.8930*	1.5540**	0.0818	0.7959	-0.1657	0.5097	0.1165	0.267
	(0.5039)	(0.6528)	(0.6729)	(0.6765)	(2.6766)	(1.9531)	(2.2206)	(2.5042)
Volatility	-0.0424***	-0.0963***	-0.0397***	-0.0965***	0.0125	0.0173	0.0053	0.0032
	(0.0088)	(0.0122)	(0.0111)	(0.0148)	(0.0470)	(0.0293)	(0.0338)	(0.0419)
Expense ratio	0.4566**	0.5661**	0.6329***	0.3013	1.2809	1.1882	1.8093**	0.8866
	(0.1819)	(0.2610)	(0.2111)	(0.2530)	(1.0393)	(0.8478)	(0.8166)	(0.9430)
Size	0.0579**	0.0525*	0.1128***	0.0477	0.4359***	0.2894***	0.3702***	0.2543***
	(0.0252)	(0.0299)	(0.0306)	(0.0311)	(0.1145)	(0.0830)	(0.0919)	(0.0952)
Age	-0.0379***	-0.0902***	-0.0786***	-0.0294***	0.025	0.022	0.0314	0.0292
	(0.0082)	(0.0095)	(0.0103)	(0.0105)	(0.0408)	(0.0276)	(0.0336)	(0.0396)
Fund fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5730	5730	5730	5730	5730	5730	5730	5730
R-squared	0.1016	0.117	0.0885	0.0793	0.006	0.006	0.0063	0.0047
Number of fund ID	118	118	118	118	118	117	118	118

Note: This table summarises the results of Equation (3.6) for all 118 US equity RIFs in the sample. Columns (1)-(4) summarize the results of raw ESG (E, S, G) scores. Columns (5)-(8) report results of percentile ranking of scores. *, **, *** denote significance at 10%, 5% and 1%. Standard errors in parentheses.

Table 3-7 Relationship between change on ESG scores and fund inflows or outflows

	(1) ESG score	(2) E score	(3) S score	(4) G score	(5) ESG % ranking	(6) E % ranking	(7) S % ranking	(8) G % ranking
Constant	3.4578***	9.9865***	7.2539***	2.9752**	-11.5540**	-8.6129**	-11.7545***	-8.27
	(1.0763)	(1.2676)	(1.3502)	(1.4317)	(5.4197)	(3.6682)	(4.2945)	(5.2380)
Lagged Fund Flow (+)	1.0138**	1.0521**	1.5423***	1.6145***	5.2442***	2.3211	3.5368**	4.0411**
	(0.3882)	(0.5251)	(0.5044)	(0.5052)	(1.9438)	(1.5120)	(1.5158)	(1.7224)
Lagged Fund Flow (-)	2.4998***	3.2006***	3.0108***	3.2908***	13.5027***	8.8433**	8.4174**	9.0941**
	(0.7857)	(1.0525)	(1.0901)	(1.2023)	(4.5884)	(3.6409)	(3.7638)	(4.4121)
Lagged return	-0.7397	-1.1547	-0.4216	-1.2727	-3.7427	-3.2989*	-2.5806	-3.9036
	(0.6185)	(0.7734)	(0.7923)	(0.8238)	(2.6270)	(1.9184)	(2.2652)	(2.3660)
SMB	5.1382***	-1.7956**	-1.5501*	0.0457	0.7211	1.256	1.2408	0.9436
	(0.7144)	(0.8844)	(0.8190)	(0.8571)	(3.8275)	(2.7994)	(3.0144)	(3.6040)
HML	0.5728	0.7802	0.8663	-1.8599***	0.6895	2.0143	1.6014	1.73
	(0.4614)	(0.5723)	(0.6070)	(0.5957)	(2.8258)	(1.7742)	(2.2863)	(2.5270)
MOM	0.8970*	1.5598**	0.0859	0.8005	-0.1431	0.5275	0.1299	0.2809
	(0.5038)	(0.6530)	(0.6729)	(0.6759)	(2.6749)	(1.9513)	(2.2202)	(2.5011)
Volatility	-0.0420***	-0.0957***	-0.0392***	-0.0960***	0.0148	0.0191	0.0067	0.0046
	(0.0089)	(0.0122)	(0.0111)	(0.0148)	(0.0468)	(0.0293)	(0.0337)	(0.0417)
Expense ratio	0.4500**	0.5566**	0.6264***	0.2939	1.2443	1.1593	1.7877**	0.8643
	(0.1800)	(0.2592)	(0.2095)	(0.2525)	(1.0288)	(0.8401)	(0.8103)	(0.9457)
Size	0.0527**	0.0449	0.1077***	0.0418	0.4068***	0.2664***	0.3530***	0.2365**
	(0.0261)	(0.0297)	(0.0309)	(0.0325)	(0.1160)	(0.0805)	(0.0923)	(0.0974)
Age	-0.0380***	-0.0903***	-0.0787***	-0.0294***	0.0247	0.0218	0.0312	0.029
	(0.0082)	(0.0095)	(0.0103)	(0.0105)	(0.0408)	(0.0276)	(0.0336)	(0.0396)
Fund fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Observations	5730	5730	5730	5730	5730	5730	5730	5730
R-squared	0.1019	0.1175	0.0888	0.0796	0.0064	0.0066	0.0065	0.0049
Number of fund ID	118	118	118	118	118	117	118	118

Note: Table 3-7 summarises the results of Equation (3.9) for the full sample of 118 US equity RIFs. We use four ESG scores (ESG, E, S and G scores) and the percentile ranking of four scores as the dependent variable and obtain the results. *, **, *** denote significance at 10%, 5% and 1%. Standard errors in parentheses.

Table 3-7 reports ESG score changes relative to lagged fund flows based on whether flows are positive or negative.[51] The changes in ESG score relate positively to both inflows and outflows but show greater sensitivity to fund outflows (coefficients to inflow and outflow are 1.01 and 2.50, respectively). This may suggest that for the RIFs in our sample, the ESG score serves as an added value proposition. It is more like the "icing on the cake", and will be sacrificed quickly if the fund suffers outflows. Similar results are shown for the changes in separate E, S, and G scores. We find similar asymmetric relationships between ESG rankings and fund flows when using ESG percentile ranking as our dependent variable, except for the insignificant relationship between fund inflow and the E score percentile ranking. This indicates that RIFs appear to invest in companies with lower E scores (reducing their environmental ranking relative to their peers) in response to fund outflows but do not adjust their E ranking when receiving fund inflows.

3.4.4 ESG-lagged Flow Analysis based on Fund Management Companies' ESG Commitment Levels

As discussed above, FMCs with varying ESG commitment levels might not see additional benefits in improving ESG scores further, especially if it comes with greater costs, such as research. Therefore, it is reasonable to believe that with varying degrees of ESG commitment (proportion of assets belonging to responsible investment), RIFs may react differently to fund flows by changing ESG scores due to FMC-level factors. We test the relationship between the fund flows and the changes in ESG scores within each commitment level group using Equations (3.6) and (3.9) and summarise the results in Table 3-8.

Table 3-8 Relationship between change on ESG performance and fund flows (five ESG commitment groups)

[51] We also test the following equation (as reported in Appendix 3-5) to further support the different impacts within groups (especially the asymmetric impact in the Group 5):

$$\Delta ESG_{i,t} = \alpha + \beta_1 Fund\ Flow_{i,t-1} + \beta_2 FF^{-} * Flow_{i,t-1} + \beta_3 Return_{i,t-1} + \gamma_1 SMB_{t-1} + \gamma_2 HML_{t-1} + \gamma_3 MOM_{t-1} + \gamma_4 volatility_{i,t-1} + \gamma_5\ Expense\ ratio_{i,t-1} + \gamma_6 Size_{i,t-1} + \gamma_7 Age_{i,t-1} + \upsilon_i + \mu_i + \varepsilon_{i,t} \quad (3.A3)$$

Panel A: Dependent variables: Change on ESG measurements; Independent variable: Lagged fund flows

	Group 1 (≤20%)	Group 2 (21%-40%)	Group 3 (41%-60%)	Group 4 (61%-80%)	Group 5 (>80%)
ESG score	1.7988***	2.1357*	0.1263	-1.0867	1.5970**
	(0.5957)	(1.0196)	(0.4258)	(1.7580)	(0.6289)
E score	1.8429**	3.3368**	-0.1276	-1.6880	2.0507**
	(0.7386)	(1.3084)	(0.6611)	(3.4540)	(0.7885)
S score	2.0767**	3.5344**	0.5303	-1.1444	2.4290***
	(0.7715)	(1.3607)	(0.6583)	(2.8004)	(0.8052)
G score	2.4039***	2.1562	0.8697	2.0997	2.0533**
	(0.8537)	(1.4080)	(0.6550)	(2.1364)	(0.7620)
ESG score percentile ranking	9.2506***	12.0946**	4.3909	-2.9097	6.3112*
	(2.9105)	(5.1632)	(3.3245)	(10.2583)	(3.2501)
E score percentile ranking	4.1913**	7.1863	1.7329	-19.6743	4.9888*
	(1.6725)	(6.1123)	(2.0510)	(16.1868)	(2.5168)
S score percentile ranking	5.4784**	6.7848	2.2624	-12.2974	5.6348**
	(2.0396)	(4.7510)	(2.4677)	(11.8752)	(2.6168)
G score percentile ranking	6.4328**	5.3995	3.2132	-6.0560	5.2823*
	(2.4999)	(5.0475)	(2.9382)	(14.8898)	(2.6960)

Panel B: Dependent variables: ESG measurements; Independent Variables: Lagged fund inflows and outflows

		Group 1 (≤20%)	Group 2 (21%-40%)	Group 3 (41%-60%)	Group 4 (61%-80%)	Group 5 (>80%)
ESG score	Lagged Fund Flow (+)	1.8780**	1.4994	-0.0164	-1.7762	1.0367
		(0.7055)	(0.8831)	(0.4758)	(2.6513)	(0.7410)
	Lagged Fund Flow (-)	1.3956	4.4263	1.1732	0.4652	5.0741***
		(1.7970)	(4.1694)	(1.2918)	(3.6054)	(1.4072)
E score	Lagged Fund Flow (+)	1.9465**	2.8447**	-0.2052	-4.3705	1.2940
		(0.9225)	(1.1359)	(0.8123)	(5.4943)	(0.8906)
	Lagged Fund Flow (-)	1.3154	5.1082	0.4423	4.3494	6.7465***
		(1.9926)	(6.9022)	(1.7215)	(4.1481)	(1.5584)
S score	Lagged Fund Flow (+)	2.3457**	3.4434***	0.3915	-3.1464	1.7605*
		(0.9253)	(0.9103)	(0.7442)	(4.7095)	(0.8918)
	Lagged Fund Flow (-)	0.7076	3.8618	1.5483	3.3614	6.5768***
		(2.2897)	(7.0673)	(2.1058)	(4.3245)	(1.4333)
G score	Lagged Fund Flow (+)	2.6784**	1.5590*	0.7361	-0.1446	1.4203
		(1.0497)	(0.8255)	(0.7200)	(3.6280)	(0.9217)
	Lagged Fund Flow (-)	1.0069	4.3061	1.8500	7.1508*	5.9815***
		(2.4521)	(5.9344)	(2.4894)	(3.8958)	(2.0269)
ESG score percentile ranking	Lagged Fund Flow (+)	8.3396***	1.5492	3.8603	-4.1562	4.4533
		(3.0405)	(5.6813)	(3.8533)	(15.2396)	(3.5252)
	Lagged Fund Flow (-)	13.9464	50.1260**	8.2190	-0.1051	18.0426**
		(11.3337)	(18.4318)	(7.3170)	(23.1422)	(6.8631)
	Lagged Fund Flow (+)	4.3685**	1.9531	1.2566	-32.8229	2.8157

E score percentile ranking		(2.1601)	(4.1126)	(2.6476)	(23.1242)	(2.6706)
	Lagged Fund Flow (-)	3.3007	26.3447	5.3027	11.1846	18.7374***
		(7.0052)	(30.3322)	(6.4410)	(12.0815)	(5.6691)
S score percentile ranking	Lagged Fund Flow (+)	5.5529**	0.8131	2.0873	-20.6821	3.9603
		(2.3437)	(2.7503)	(2.8366)	(19.8267)	(2.6445)
	Lagged Fund Flow (-)	5.0962	28.3920	3.5289	7.0501	16.4174**
		(7.1543)	(22.6165)	(7.4433)	(13.6082)	(6.9453)
G score percentile ranking	Lagged Fund Flow (+)	7.0377**	-3.3148	2.1172	-14.7432	4.2083
		(2.7205)	(4.4968)	(3.3058)	(25.8988)	(2.9975)
	Lagged Fund Flow (-)	3.4422	36.7597*	11.3524	12.9025	11.8690
		(9.3371)	(19.8499)	(7.8854)	(17.8653)	(8.3064)

Note: Table 3-8 summarizes the coefficients of fund flows in Equations (3.6) and (3.9) for five ESG commitment level groups. Panel A reports the results for Equation (3.6), while Panel B reports the results for Equation (3.9). *, **, *** denote significance at 10%, 5% and 1%. Standard errors in parentheses.

We find evidence that the relationship between past fund flow and change in ESG performance differs based on the FMC's ESG commitment level. Panel A of Table 3-8 reports the coefficients on $Flow_{i,t-1}$ using the change in raw scores and percentile rankings for ESG, E, S, and G scores as the dependent variable. We find significant positive coefficients for all four scores and percentile rankings for the funds managed by the highest (>80%) ESG committed FMCs. This finding supports our hypothesis 3 that RIFs managed by FMCs with the highest ESG commitment level increase (decrease) their ESG performance in response to fund inflows (outflows). Interestingly, funds managed by the lowest ESG committed FMCs ($\leqslant$20%) also show significant positive coefficients. Panel B of Table 3-8 reports different reactions for fund inflows and outflows. The RIFs managed by FMCs with the lowest ESG commitment level (Group 1) report significant positive coefficients across all ESG measures in response to fund inflows but no significant coefficients for outflows. This indicates that funds managed by companies with the lowest ESG commitment level take action to improve their ESG performance when they have increasing fund inflows but make no significant adjustments when suffering outflows. Interestingly, the FMCs in Group 5 (with the highest ESG commitment level) show the opposite reaction to Group 1. Funds managed by FMCs with the highest commitment level decrease their ESG performance when suffering fund outflows but appear to make no significant changes when enjoying inflows (except for S scores).

To summarize, our results suggest that RIFs managed by FMCs with different ESG commitment levels generate different reactions to fund flows. Specifically:

1) With the increase in the number of RIF providers, it has become more difficult for existing RIFs to maintain their market share, especially for the relatively ESG-dominated families (i.e., FMCs in Group 5). These funds families appear to pay more attention to retaining investors. They are more likely to take action when facing fund outflows (indicating loss of existing investors). Our findings in Table 3-8 Panel B suggest they decrease the fund-level ESG score in response to fund outflows. Funds' ESG performance is determined by the weighted ESG scores of the firms they hold. These funds may attempt to obtain better financial performance by decreasing (increasing) holding in companies with a high (low) ESG score but low (high) return firms. In addition, we find that an increase in ESG score weakens the flow-return relationship (as shown in Tables 3-4 and 3-5).

Conversely, a lower ESG score strengthens the flow-return relationship, which may, in turn, enhance the effects of improving financial returns. Both explanations indicate that ESG performance will be quickly sacrificed when facing fund outflows in Group 5, even though these fund families are more likely to have the 'true believer' investors who are prepared to sacrifice returns for ESG performance.

2) For RIFs in Group 1 (≤20%), they are managed by relatively old and large FMCs and charge the highest fees, as reported in Table 3-1 Panel C. Therefore, these RIFs likely need to show a better ESG performance (this group reports the highest average ESG score) to build a reputation for responsible investment and enhance their market share. Therefore, they are more likely to improve their ESG performance after receiving fund inflows, aiming to attract investors who value responsible investment.
3) Funds in Group 3 (40%-60%), are managed by comparatively older, larger, and likely well-established fund families (as shown in Table 3-1 Panel C). Investors in these funds may be more attracted to the family's reputation rather than their RIFs' ESG performance. Therefore, because of the limited impact of RIFs' ESG performance on the overall benefits for the entire fund family, they are the least likely to put extra effort into improving funds' ESG scores.

3.5. Conclusion

In recent years, assets under management and the number of Responsible Investment Funds (RIFs) have increased. However, relatively little is known about the impact of Fund Management Companies (FMCs), also known as 'fund families', on fund ESG performance. In this paper, we focus on US domestic equity RIFs between 2005 and 2020 and consider their FMC's ESG commitment level to analyse: 1) flow-return relationships; 2) the effects of ESG scores on the flow-return relationship; and 3) the relationship between funds' ESG performance and past fund flows. FMC commitment level is a useful proxy; we posit that a higher proportion of assets under management engaged in responsible investments suggests an FMC is more likely to be a 'true believer', while FMCs with a lower proportion suggest a lower commitment to responsible investment.

We find evidence confirming our hypothesis that FMCs' ESG commitment influences RIFs' willingness to cater to changes in fund return and flows, impacting their ESG performance. For example, in addition to confirming the previously addressed negative flow-return relationships and the asymmetric impacts of positive and negative past returns (Renneboog et al., 2011), we also find that the negative flow-return relationship is driven by RIFs managed by FMCs with the lowest (≤20%) and highest (>80%) ESG commitment levels.

In terms of financial performance, we find that for RIFs managed by FMCs with the highest ESG commitment level, an increase in ESG score weakens the flow-return relationship, suggesting investors who choose FMCs with higher ESG commitment levels are less sensitive to financial performance.

We then test the relationship between funds' ESG performance and past fund flows. In essence, we examine whether fund flows encourage RIFs to further increase their ESG performance by buying high ESG companies and/or selling low ESG companies. Evidence of this relationship is important as it speaks to the ability of investors to drive improvements in ESG. We find a significant positive effect for previous fund flows on ESG performance in the next period, with results suggesting that ESG (E, S and G) scores are more sensitive to outflows than inflows. Lastly, we consider whether FMCs' ESG commitment levels impact RIFs' efforts to improve ESG performance. Based on our results, funds managed by companies with the lowest ESG commitment level (≤20%) are more likely to take action to improve their ESG performance when receiving fund inflows but no action when suffering outflows. Conversely, FMCs with the highest ESG commitment levels (>80%) decrease their ESG performance when suffering fund outflows but exhibit no significant change when facing fund inflows.

By assessing whether investors' investments can improve funds' ESG performance, our paper provides insight into the ESG dimension of the fund flow-performance relationship. Our findings may also be helpful for regulators, such as the SEC, who monitor and promote transparency and the public's trust in the capital market.

Appendix 3-1

Sample cleaning process

Initially identify 353 funds (in total contains 1332 share classes) managed by 117 FMCs.

↓ Exclude funds with no FMC-level information

310 funds (1246 share classes) managed by 117 FMCs

↓ 13 FMCs have no available information

292 funds (1203 share classes) managed by 104 FMCs

↓ Filter for US equity funds

195 funds (819 share classes) managed by 81 FMCs

↓ Filter for funds at least have 60% holding companies can be matched with ESG scores

120 funds (567 share classes) managed by 55 FMCs

↓ At least have 36 months data between 2005 and 2020

Final sample: 118 funds managed by 53 FMCs

Appendix 3-2

Results of *t*-test

	GROUP1 VS GROUP2		GROUP1 VS GROUP3		GROUP1 VS GROUP4		GROUP1 VS GROUP5		GROUP2 VS GROUP3	
ESG score	2.922***	(-5.98)	1.621***	(-6.89)	1.928***	(-4.47)	1.964***	(-6.92)	-1.301**	(-2.88)
E score	3.317***	(-4.42)	2.155***	(-5.35)	4.581***	(-6.80)	3.794***	(-8.23)	-1.162	(-1.44)
S score	4.312***	(-6.04)	1.806***	(-5.14)	2.849***	(-4.52)	3.389***	(-8.01)	-2.505***	(-3.68)
G score	2.930***	(-5.16)	0.674*	(-2.37)	1.774***	(-3.52)	2.883***	(-8.33)	-2.256***	(-4.12)
ESG score percentile ranking	8.025***	(-4.23)	4.121***	(-4.37)	7.637***	(-4.65)	5.038***	(-4.58)	-3.904*	(-2.12)
E score percentile ranking	6.555***	(-3.63)	1.220	(-1.29)	8.583***	(-5.39)	8.114***	(-7.51)	-5.335**	(-2.87)
S score percentile ranking	8.414***	(-4.48)	1.541	(-1.63)	7.475***	(-4.54)	7.927***	(-7.22)	-6.873***	(-3.77)
G score percentile ranking	7.852***	(-4.25)	0.0175	(-0.02)	5.097**	(-3.11)	9.064***	(-8.32)	-7.834***	(-4.30)
	GROUP2 VS GROUP4		**GROUP2 VS GROUP5**		**GROUP3 VS GROUP4**		**GROUP3 VS GROUP5**		**GROUP4 VS GROUP5**	
ESG score	-0.994	(-1.63)	-0.958	(-1.89)	0.307	(-0.78)	0.343	(-1.38)	0.036	(-0.08)
E score	1.264	(-1.29)	0.477	(-0.56)	2.427***	(-3.41)	1.639***	(-3.71)	-0.788	(-1.03)
S score	-1.463	(-1.63)	-0.922	(-1.20)	1.043	(-1.75)	1.583***	(-4.20)	0.540	(-0.80)
G score	-1.156	(-1.69)	-0.047	(-0.07)	1.100*	(-2.29)	2.209***	(-7.15)	1.109*	(-2.00)
ESG score percentile ranking	-0.388	(-0.17)	-2.987	(-1.52)	3.515*	(-2.21)	0.917	(-0.92)	-2.599	(-1.53)
E score percentile ranking	2.028	(-0.97)	1.560	(-0.81)	7.363***	(-4.54)	6.894***	(-6.81)	-0.468	(-0.28)
S score percentile ranking	-0.939	(-0.43)	-0.487	(-0.25)	5.933***	(-3.73)	6.386***	(-6.42)	0.453	(-0.27)
G score percentile ranking	-2.755	(-1.27)	1.212	(-0.64)	5.079**	(-3.17)	9.046***	(-9.09)	3.967*	(-2.34)

Note: t-test of means for ESG performance within each commitment level groups. *, **, *** denote significance at 10%, 5% and 1%. t-statistics in parentheses.

Appendix 3-3

Regression results of Equation 3.A1

Note: This table summarises the regression results of Equation 3.A1 for 118 US equity RIFs and five subsamples based on

	Full Sample	**Group 1**	**Group 2**	**Group 3**	**Group 4**	**Group 5**
Constant	0.6591***	0.7784***	2.3641	0.9297***	0.6069	0.4840**
	(0.1094)	(0.2326)	(1.4775)	(0.2271)	(0.5066)	(0.1787)
Lagged return	0.5049***	0.7010***	0.156	0.303	0.2930*	0.6913***
	(0.1059)	(0.1866)	(0.1420)	(0.2168)	(0.1416)	(0.1763)
Lagged return (-)	-0.4128***	-0.6111**	-0.3236	-0.2827	-0.2759	-0.4071*
	(0.1325)	(0.2260)	(0.2118)	(0.2959)	(0.1941)	(0.2188)
SMB	0.0048	-0.0595	-0.1784	0.0209	-0.1736**	0.1272
	(0.0360)	(0.0581)	(0.1221)	(0.0495)	(0.0835)	(0.1040)
HML	0.0152	0.0537	-0.1391*	0.0123	-0.0099	-0.0047
	(0.0221)	(0.0563)	(0.0664)	(0.0288)	(0.0799)	(0.0516)
MOM	-0.0212	-0.0072	-0.1124*	0.0059	0.0182	-0.0926**
	(0.0211)	(0.0337)	(0.0605)	(0.0389)	(0.0412)	(0.0445)
Return volatility	-0.0001	-0.0015	-0.0002	0.0002	0.0015	0.0004
	(0.0006)	(0.0011)	(0.0013)	(0.0008)	(0.0015)	(0.0014)
Annul expense ratio	-0.0201	-0.0733*	0.0312	-0.062	0.0815	0.0661
	(0.0264)	(0.0417)	(0.0870)	(0.0428)	(0.0978)	(0.0770)
Fund size	-0.0251***	-0.0309**	-0.0857	-0.0334***	-0.0348	-0.0249***
	(0.0049)	(0.0132)	(0.0616)	(0.0096)	(0.0244)	(0.0054)
Age	-0.0010***	-0.0011*	-0.0026***	-0.0010**	-0.0001	-0.0005
	(0.0003)	(0.0006)	(0.0009)	(0.0005)	(0.0010)	(0.0011)
Fund fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5850	1494	274	2412	370	1300
R-squared	0.0975	0.1242	0.2772	0.1113	0.1302	0.1608

ESG commitment level of their FMC.

$$Fund\ Flow_{i,t} = \alpha + \beta Return_{i,t-1} + \beta_1 * R^- * Return_{i,t-1} + \gamma_1 SMB_{t-1} + \gamma_2 HML_{t-1} + \gamma_3 MOM_{t-1} + \gamma_4 volatility_{i,t-1} + \gamma_5 Expense\ ratio_{i,t-1} + \gamma_6 Size_{i,t-1} + \gamma_7 Age_{i,t-1} + \upsilon_i + \mu_i + \varepsilon_{i,t} \quad (3.A1)$$

Where $Return_{i,[t-1]}$ is fund i's annualised lagged alpha that obtained using monthly raw returns and the 4-factor model in a 12-month rolling window. The R^- is an indicator variable that equals one if $Return_{i,[t-1]}$ is negative. The SMB, HML and MOM are the quarterly size, book-to-market ratio and momentum factors. $volatility_{i,t}$ is annualised standard deviation of monthly net return over the previous 12 months. $Expense\ ratio_{i,t}$ is the annualised expense ratio. $Size_{i,t}$ is the logarithm of the fund size. $Age_{i,t}$ is the number of months since the oldest share class was established. υ_i and μ_i are fund-fixed effects and year effects. $\varepsilon_{i,t}$ denotes the error term.

*, **, *** denote significance at 10%, 5% and 1%. Standard errors in parentheses.

Appendix 3-4

Regression results of Equation 3.A2

Panel A

	ESG score	E score	S score	G score
Constant	0.7214***	0.6708***	0.7139***	0.7363***
	(0.1198)	(0.1200)	(0.1201)	(0.1214)
Lagged ESG measurement	-0.0026***	-0.0016**	-0.0023***	-0.0025***
	(0.0008)	(0.0006)	(0.0007)	(0.0007)
SMB	-0.0264	-0.0054	-0.0051	-0.0076
	(0.0346)	(0.0359)	(0.0359)	(0.0358)
HML	0.0023	0.0054	0.0044	0.0085
	(0.0213)	(0.0214)	(0.0212)	(0.0211)
MOM	-0.0275	-0.0248	-0.0237	-0.0261
	(0.0196)	(0.0195)	(0.0195)	(0.0195)
Return volatility	-0.0003	-0.0003	-0.0005	-0.0003
	(0.0005)	(0.0006)	(0.0006)	(0.0006)
Annul expense ratio	-0.0281	-0.0246	-0.0294	-0.029
	(0.0250)	(0.0258)	(0.0246)	(0.0243)
Fund size	-0.0247***	-0.0245***	-0.0250***	-0.0243***
	(0.0051)	(0.0051)	(0.0051)	(0.0051)
Age	-0.0008**	-0.0008**	-0.0007*	-0.0008**
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Year	Yes	Yes	Yes	Yes
Observations	5732	5732	5732	5732
R-squared	0.0812	0.0768	0.0824	0.0837
Number of fund ID	118	118	118	118

Panel B

	Group 1	Group 2	Group 3	Group 4	Group 5
Constant	0.7568***	2.577	0.8988***	0.326	0.7209***
	(0.236)	(1.570)	(0.247)	(0.439)	(0.177)
Lagged ESG measurement	-0.0027**	-0.0021	-0.0011	0.0001	-0.0042***
	(0.0013)	(0.0023)	(0.0008)	(0.0013)	(0.0014)
SMB	-0.0704	-0.189	-0.0074	-0.1851**	0.0801
	(0.0568)	(0.1210)	(0.0480)	(0.0809)	(0.102)
HML	0.0260	-0.1506**	0.0022	-0.0240	-0.0089
	(0.0542)	(0.0663)	(0.0296)	(0.0834)	(0.0470)
MOM	-0.0018	-0.1295*	-0.0190	0.0207	-0.0639
	(0.0287)	(0.0617)	(0.0366)	(0.0386)	(0.0379)
Return volatility	-0.0024**	0	0.0003	0.0020	0.0008
	(0.0010)	(0.0012)	(0.0006)	(0.0015)	(0.0013)
Annul expense ratio	-0.0708*	0.0070	-0.0561	0.1060	0.0203
	(0.0420)	(0.09720	(0.0401)	(0.0874)	(0.0705)
Fund size	-0.0274**	-0.0915	-0.0307***	-0.0209	-0.0282***

	(0.0115)	(0.0640)	(0.0102)	(0.0202)	(0.0065)
Age	-0.0006	-0.0026***	-0.0009**	-0.0006	-0.0006
	(0.0006)	(0.0009)	(0.0005)	(0.0010)	(0.0010)
Fund fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	1461	270	2367	358	1276
R-squared	0.103	0.285	0.0915	0.100	0.141

Note: This table summarises the regression results of Equation 3.A2. Panel A reports the results for 118 RIFs between 2005 and 2020; Panel B reports results for the 5 subsamples of different ESG commitment levels. For brevity, we only report these results for the ESG score.

$$Fund\ Flow_{i,t} = \alpha + \beta_1 ESG_{i,t-1} + \gamma_1 SMB_{t-1} + \gamma_2 HML_{t-1} + \gamma_3 MOM_{t-1} + \gamma_4 volatility_{i,t-1} + \gamma_5 Expense\ ratio_{i,t-1} + \gamma_6 Size_{i,t-1} + \gamma_7 Age_{i,t-1} + \upsilon_i + \mu_i + \varepsilon_{i,t} \quad (3.A2)$$

*, **, *** denote significance at 10%, 5% and 1%. Standard errors in parentheses.

Appendix 3-5

Regression results Equation 3.A3

Dependent variables: ESG measurements.
Independent variables: Lagged fund flows and Lagged fund out flows.

		Full sample	Group 1	Group 2	Group 3	Group 4	Group 5
ESG score	Lagged Fund Flow	1.0138**	1.8780**	1.499	-0.0164	-1.776	1.037
		(0.388)	(0.706)	(0.883)	(0.476)	(2.651)	(0.741)
	Lagged Fund Flow (-)	1.486	-0.482	2.927	1.190	2.241	4.0374**
		(0.921)	(2.078)	(4.346)	(1.438)	(5.333)	(1.644)
E score	Lagged Fund Flow	1.0521**	1.9465**	2.8447**	-0.205	-4.370	1.294
		(0.525)	(0.922)	(1.136)	(0.812)	(5.494)	(0.891)
	Lagged Fund Flow (-)	2.1485*	-0.631	2.264	0.647	8.720	5.4525***
		(1.245)	(2.443)	(7.438)	(2.174)	(8.769)	(1.732)
S score	Lagged Fund Flow	1.5423***	2.3457**	3.4434***	0.392	-3.146	1.7605*
		(0.504)	(0.925)	(0.910)	(0.744)	(4.710)	(0.892)
	Lagged Fund Flow (-)	1.468	-1.638	0.418	1.157	6.508	4.8163***
		(1.230)	(2.690)	(7.526)	(2.362)	(8.260)	(1.529)
G score	Lagged Fund Flow	1.6145***	2.6784**	1.5590*	0.736	-0.145	1.420
		(0.505)	(1.050)	(0.826)	(0.720)	(3.628)	(0.922)
	Lagged Fund Flow (-)	1.676	-1.672	2.747	1.114	7.295	4.5612*
		(1.411)	(2.938)	(6.107)	(2.708)	(6.931)	(2.388)
ESG score percentile ranking	Lagged Fund Flow	5.2442***	8.3396***	1.549	3.860	-4.156	4.453
		(1.944)	(3.041)	(5.681)	(3.853)	(15.24)	(3.525)
	Lagged Fund Flow (-)	8.259	5.607	48.5768**	4.359	4.051	13.5894*
		(5.058)	(12.12)	(18.73)	(8.953)	(32.41)	(7.331)
E score percentile ranking	Lagged Fund Flow	2.321	4.3685**	1.953	1.257	-32.82	2.816
		(1.512)	(2.160)	(4.113)	(2.648)	(23.12)	(2.671)
	Lagged Fund Flow (-)	6.522	-1.068	24.39	4.046	44.01	15.9217**
		(4.184)	(8.182)	(31.44)	(8.157)	(32.45)	(5.874)
S score percentile ranking	Lagged Fund Flow	3.5368**	5.5529**	0.813	2.087	-20.68	3.960
		(1.516)	(2.344)	(2.750)	(2.837)	(19.83)	(2.644)
	Lagged Fund Flow (-)	4.881	-0.457	27.58	1.442	27.73	12.4571*
		(4.089)	(8.029)	(23.20)	(8.514)	(31.49)	(6.844)
G score percentile ranking	Lagged Fund Flow	4.0411**	7.0377**	-3.315	2.117	-14.74	4.208
		(1.722)	(2.720)	(4.497)	(3.306)	(25.90)	(2.998)
	Lagged Fund Flow (-)	5.053	-3.595	40.0745*	9.235	27.65	7.661
		(5.022)	(10.25)	(20.86)	(9.047)	(41.36)	(9.071)

Note: This table summarises the regression results of Equation 3.A3 for the entire sample and five groups with different ESG commitment levels of FMCs.

$$\Delta ESG_{i,t} = \alpha + \beta_1 Fund\ Flow_{i,t-1} + \beta_2 FF^- * Flow_{i,t-1} + \beta_3 Return_{i,t-1} + \gamma_1 SMB_{t-1} + \gamma_2 HML_{t-1} + \gamma_3 MOM_{t-1} + \gamma_4 volatility_{i,t-1} + \gamma_5\ Expense\ ratio_{i,t-1} + \gamma_6 Size_{i,t-1} + \gamma_7 Age_{i,t-1} + \upsilon_i + \mu_i + \varepsilon_{i,t} \quad (3.A3)$$

*, **, *** denote significance at 10%, 5% and 1. Standard errors in parentheses.

Chapter 4 (Manuscript 3): Do Responsible Investment Fund (RIF) Managers' Career Paths Impact their Fund's ESG Performance?

Abstract

This paper focuses on how the past career path of responsible investment fund managers impacts their funds' ESG performance. Using a dataset of 47 US domestic equity funds from 2005 to 2020, we contribute to the growing mutual fund literature on the impact of managerial characteristics on the funds they manage. Our results suggest that for the majority of our ESG measurements, RIFs with a wholly conventional experience management team exhibit the best ESG performance, suggesting these funds are more likely to invest in companies with higher ESG scores. However, when considering joint ESG and financial performance, the proportion of managers with exclusive RIF work experience positively impacts the joint efficiency of the fund. In addition, we find insignificant differences in financial returns between funds with purely RIF managers and those where all managers have conventional experience.

JEL classifications: G10, G11, G12

Keywords: Responsible investment funds, Funds management, Fund manager characteristics, ESG performance, DEA model

4.1. Introduction

Responsible investment funds (RIFs) are defined as investment funds that consider environmental, social, and governance (ESG) benefits when making investment decisions. RIFs have experienced remarkable worldwide development in recent decades driven by strong demand from investors. Nearly 80% of investors consider ESG an essential factor when making their investment decision, and 50% express a willingness to divest from companies that do not take sufficient action on ESG concerns (PricewaterhouseCoopers LLP, 2020). As a result of investor demand, the total US-domiciled assets under management (AUM) invested sustainably reached $8.4 trillion at the start of 2022, representing 12.6% of total US assets under professional management (Forum for Sustainable and Responsible Investment, 2022).

A key difference between RIFs and conventional funds is that RIFs manage *both* their investors' investment aims, namely financial returns and ESG performance. As a result, it is reasonable to expect that RIF managers may also have differences relative to their conventional counterparts. Compared to conventional fund managers, who aim to maximize risk-adjusted returns, the multi-task nature of RIFs may weaken managers' incentives to simply pursue higher risk-adjusted returns (Renneboog et al., 2008), and likely requires a different set of skills.

The mutual fund literature has extensively studied how a fund manager's characteristics may impact a fund's financial performance. Prior studies have shown that fund performance and investment behaviours are affected by fund managers' characteristics, including managerial skill (Ferruz et al., 2010; Leite & Cortez, 2015; Jitmaneeroj, 2023), educational background (Chevalier & Ellison,1999; Gottesman & Morey, 2006), professional qualifications such as the CFA and CPA (Gottesman & Morey, 2006; Fang & Wang, 2015), behaviour biases (Baker et al., 2010; Pool et al., 2012), social networks (Hong et al., 2005; Gu et al., 2019) and physical characteristics like age and gender (Chevalier & Ellison, 1999; Özerol et al., 2011; Niessen-Ruenzi & Ruenzi, 2019).

Additionally, the extant literature finds that prior career experience may translate into differences in managers' performance or managerial skills. These articles study various aspects of a fund manager's career path, such as tenure (Golec, 1996), previous professional background (Chen et al., 2018), industry-specific (outside the financial sector) work experience (Cici et al., 2014), and prior performance before switching jobs (Deuskar et al., 2011). They document that fund managers' past experiences, successes, and even failures, shape their perspectives and play a crucial role in explaining mutual fund managers' performance, managerial skills, and investment decisions. However, the literature applying these findings to RIFs is limited.

This paper sheds light on the impact that the career paths of RIF managers have on how they manage their RIFs. The growth in responsible funds has resulted in managers from conventional funds managing responsible investments (Van Duuren et al., 2016). We are interested in whether managers with previous conventional fund management experience act differently from managers who have solely worked as RIF managers. Do managers' past work experiences offer insights into how they manage an RIF, which in turn impacts the funds' performance, including risk-adjusted return, ESG performance, and joint performance?

There are two reasons why the career path of a manager may be translated into differences in whether managers emphasize financial performance, fund ESG performance, or combined performance (consider financial and ESG performance simultaneously).

The first reason is related to the trade-off between financial and ESG performance. The majority of conventional fund managers are primarily motivated by the fund's performance. According to the work of Ma et al. (2019) on fund manager compensation contracts, 36.1% of fund managers obtain bonuses solely based on investment performance, 14.5% based only on the advisor's profits, and 0.9% based exclusively on AUM, which has been shown to be impacted by past returns. The remaining fund managers earn rewards through various combinations of these three metrics, with 11.3% receiving all three types simultaneously. This indicates that conventional fund managers are used to being focused primarily on financial return metrics which determine their bonuses. In recent years, the growth in the responsible investment industry has resulted in conventional fund managers participating in responsible investments (Van Duuren et al., 2016). However, a report from ShareAction in 2023 finds that in 2020, only 7% of RIF managers had incentives related to responsible investment (Vrublevskis & Zorila, 2023). As a result of fund managers' compensation structures, the original responsible investment goal of "doing good" may be watered down in the pursuit of returns, especially for those managers who have been accustomed to thinking solely about return performance. We proxy funds' ESG performance with their holdings' weighted average ESG scores to test if managers' different working backgrounds translate into variations in funds' ESG performance.

Second, fund managers play a decisive role in the ESG performance of RIFs. They have fundamental choices when pursuing ESG objectives. Specifically, RIFs may apply different ESG strategies.[52] Managers' choice of portfolio holdings may generate considerable variation in the funds' ESG performance. The understanding and implementation of ESG principles and practices requires knowledge and experience in responsible investment, which takes time to develop. In addition, for many RIFs the applied strategy is not explicitly stated, which opens up the possibility of managers engaging in potentially misleading behaviours such as greenwashing. It is, therefore, possible that fund managers coming from non-RIF backgrounds may make different choices in portfolio construction and asset allocation, at least initially, which will lead to differences in financial and ESG performance.

Based on the discussion above, we hypothesize that fund managers with prior conventional fund management experience may behave differently compared with those who only have RIF experience. To test this, we start by examining the potential differences in financial returns between three managerial groups.[53] We find insignificant differences in financial performance between funds with purely RIF managers and those where all the managers have conventional experience. Of note, those funds with a mix of career paths report a slightly better performance when solely considering financial returns.

Next, we shed light on fund ESG performance and use three different measures for ESG performance (fund-level ESG scores, the percentage of holdings invested in the high and low ESG score companies, and fund-level carbon emissions) to test differences in the ESG performance between the three managerial groups. Our results suggest that for the majority of our ESG measurements, RIFs with a management team that only has

[52] According to the Global Sustainable Investment Alliance (2021), ESG factors are typically addressed using one or more of several strategies, include negative/exclusionary screening, positive/best-in-class screening, norms-based screening, ESG integration, sustainability-themed investing, impact/community investing, and corporate engagement and shareholder action.

[53] Based on the managers' previous work experience, the sample has been split into three groups. Group 1 contains funds managed by a manager/team who do not have conventional fund work experience. Funds in Group 2 are managed by management teams with at least one manager who has conventional fund management experience. Group 3 includes funds where all of the managers have conventional work experience.

conventional experience exhibit the best ESG performance, suggesting these funds hold companies with higher ESG scores.

We then employ data envelopment analysis (DEA) to measure joint fund financial and ESG performance. DEA is a data-driven evaluation approach based on multiple inputs and outputs of decision-making units (DMUs). The DEA approach is considered one of the most effective tools for multi-dimensional evaluation and has been used previously to assess RIFs' performance (Xiao et al., 2022; Galagedera, 2019). Our results indicate that the proportion of managers with exclusive RIF work experience positively impacts the joint performance of RIFs. We then further test the length of RIF management experience on fund joint performance and find that, for management teams with less than 5-years' experience, on average, an increase in experience will result in higher joint performance.

This study contributes to the academic discussion of RIF managers (Humphrey et al., 2016; Przychodzen et al., 2016; Kiymaz, 2019). The existing literature examines several basic characteristics, such as age, gender, and tenure. We collect RIFs' management experience for their managers and build a unique dataset of RIFs and their managers' characteristics. By testing the potential relationship between previous funds management experience and ESG performance, my study extends existing analyses.

This chapter also contributes to the literature analysing the value of career experience on performance and skills in the mutual fund industry (Greenwood & Nagel, 2009; Huang et al., 2015; Chen et al., 2018). My study extends the literature by shedding light on the impact of a key aspect of RIF managers: their fund management experience. We examine not only the impact on managers' risk-adjusted returns but also the potential influence on funds' ESG performance, which should measure how responsible a given RIF is.

Our results may have potential implications for RIF retail investors when selecting asset managers[54] and allocating their investment assets. Compared with confidential or paywalled information, such as fund holdings, managerial compensation, and funds' internal policies, a manager's career paths are easier to access for investors, either from the fund prospectus, the SEC website, or LinkedIn. Moreover, this study may also

[54] Investors value and compare managers' qualifications, skills, and experience as part of their decision making (Financial Markets Authority, 2018).

provide suggestions for asset management companies in hiring and allocating RIF managers. By balancing investors' demand and managers' capacity, they can optimize resources and asset allocation, and improve their chances of growing their assets under management.

4.2. Literature Review and Hypothesis Development

4.2.1 Background

4.2.1.1 Fund Managers' Work experience

Extensive empirical studies have been conducted over the past few decades to examine the influence that fund managers' characteristics have on fund performance and investment behaviours. Work experience is one strand of this increasingly popular research area. Tenure, defined as the length of time a manager has held their current position, is one of the applied variables for proxying fund managers' work experiences in the literature (e.g., Lin et al., 2023; Graham et al., 2019; Patel & Sarkissian, 2017). People tend to acquire knowledge and expertise when they are involved in an activity for a longer time, and this knowledge should consequently result in better performance (Philpot & Peterson, 2006). However, studies about the influence of fund managers' tenure on financial performance show mixed results. Earlier articles find evidence that tenure has a positive relationship with fund performance (Golec, 1996). However, this result has been challenged in more recent articles (Prather et al., 2004). According to Kempf et al. (2017), previous experience is a valuable characteristic, but the process of gaining knowledge is not a simple (and linear) function of time.

More recently, researchers have moved their focus to more sophisticated measures of managers' past careers. Chen et al. (2018) claim that fund managers' managerial skills are impacted by their previous professional work experiences. They investigate Chinese mutual fund managers with past work experience as industry analysts or macroanalysts. They document that managers with experience as industry analysts are better at stock selection, while those who were macroanalysts tend to exhibit better market timing. Cici et al. (2014) state that industry-specific work experience (outside the financial sector) impacts fund managers' performance. Using a dataset of US domestic equity funds between 1996 and 2009, they find that fund managers with specific industry work experience exhibit better stock selection and market timing ability when investing in familiar industries compared with managers with no previous industry experience. Kempf et al. (2017) argue that people learn more in relatively more challenging environments than business-as-usual/typical periods. They employ the number of industry shocks a manager has experienced as a proxy of fund managers' experience, defining an industry shock as a period of severe underperformance in a specific industry. They test actively managed US equity funds managed by single managers between 1992 and 2012 and show that industry sub-portfolios managed by experienced fund managers substantially outperform those managed by inexperienced managers.

The prior literature documents how mutual fund managers' career path impacts fund performance. Given that RIFs are a subset of the mutual funds industry, it is reasonable to question whether fund managers' prior experience has implications for RIFs' performance, especially their ESG performance. To date, much of the RIF literature has focused on performance evaluation, while much less research analysis has been conducted on other aspects of RIFs, such as managerial characteristics and investment behaviours. Humphrey et al. (2016) conduct a relatively comprehensive analysis of fund manager characteristics in the RIFs field. They investigate how RIF managers differ from conventional fund managers and find that RIF managers have longer tenure and are more likely to be female. Regarding age, CFA charter, and the size of the management team in group-managed funds, RIF managers and conventional fund managers do not exhibit significant differences.

Existing research also includes managers' personal characteristics as control variables. For instance, Kiymaz (2019) includes managers' tenure in their RIF performance evaluation and finds that funds with experienced managers provide higher returns to investors. However, the differences between conventional and RI managers are still unclear. This study attempts to fill this gap by considering RIF managers' past careers and assessing their ESG and financial performance.

4.2.1.2 Data Envelopment Analysis (DEA)

Data Envelopment Analysis (DEA) was introduced by Charnes et al. (1978) to evaluate the relative efficiency of decision-making units incorporating multiple inputs and outputs. DEA builds an efficient frontier across all observations and measures the efficiency of individual decision-making units (DMUs) as the relative distance between the observed output and the efficient frontier. A DMU is classified as inefficient if its efficiency score is not equal to one, which means that outputs and inputs fall below the best practice frontier, with greater distances from the frontier indicating less efficiency. Murthi et al. (1997) propose the DEA portfolio efficiency index as a measure of mutual fund performance. Later, Basso and Funari (2001) propose the use of the traditional DEA methodology to evaluate mutual fund performance. Since then, the traditional DEA has been used in evaluating portfolio efficiency (e.g., Lin & Li, 2020). The basic DEA has three forms: the well-known basic Charnes, Cooper and Rhodes (CCR) model, the Banker, Charnes and Cooper (BCC) model, and the free disposal hull (FDH) model (Basso & Funari, 2003b). In the extant literature, both the CCR and the BCC have been employed in assessing fund performance. The CCR model applies constant returns to scale (Murthi et al., 1997; Basso & Funari, 2001), and the BCC model allows variable returns to scale and is more flexible (Glawischnig & Sommersguter-Reichmann, 2010).

In recent years, the DEA method has been utilized in the literature to evaluate the performance of RIFs including ESG performance as one of the model outputs. The main reason DEA is attractive in the field of evaluating sustainable fund performance is the ability to incorporate several different outputs simultaneously. As mentioned above, RIFs require an integrated consideration of both financial return and ESG performance; thus, multiple inputs and multiple outputs are engaged in the assessment process, making DEA an appropriate tool for evaluating the joint financial and responsible investment performance of RIFs. Basso and Funari (2001; 2003a) point out the importance of considering the ESG component when evaluating the performance of RIFs. They then employ traditional DEA models under constant and variable returns to scale, to assess the performance of 189 RIFs in various European countries between June 2006 and June 2009 (Basso & Funari, 2014). Galagedera (2019) develops a two-stage DEA model to assess the performance of RIFs. They treat ESG scores as the first stage outputs and financial indicators as the second. The inputs of stage 1 are turnover, management fees, and fund size, while the outputs are ESG score and benefit payment. The inputs for the second stage are total risk, downside risk, and systematic risk.

The traditional DEA[55] method can only model the cross-sectional efficiency frontier. However, in recent years, scholars have argued that the correlation over different time horizons should not be ignored. Consequently,

[55] In addition to DEA, free disposal hull (FDH) is a similar method of considering the efficiency frontier. Abdelsalam et al. (2014) consider the daily mean return and daily returns skewness as output and standard deviation of the daily returns, kurtosis, and expenses as inputs to calculate the FDH efficiencies to compare the performance difference between 636

some articles have started to investigate the application of the DEA methodology across multiple time periods under certain circumstances. For instance, Ren et al. (2021) develop a diversification-consistent DEA model with and without sustainability investment constraints over a multi-horizon framework, finding that responsibility constraints may impact both portfolio efficiency and portfolio ranking. Xiao et al. (2022) also propose some alternative multi-period diversification-consistent DEA models to assess the dynamic performance (both financial and ESG aspects) of RIFs. After selecting 45 Chinese RIFs between 2017 and 2020 and comparing overall efficiency with and without ESG scores, they conclude that the consideration of ESG scores results in a significant increase in the efficiency and the number of efficient RIFs.

4.2.2 Hypotheses

As previously mentioned, the prior work experience of fund managers can shape their preferences, which in turn can affect asset allocation and decision-making. We hypothesize that work experience is also likely relevant to ESG performance in the context of RIFs. That is, managers with a background in conventional funds management might behave differently compared to those who have exclusively worked in the RIF field in terms of financial, ESG and joint performance. To explore this, we test the following hypotheses.

Hypothesis 1:

H_0: RIFs managed by managers with exclusive RIF backgrounds may exhibit different financial performance when compared with RIFs managed by managers with a background in conventional fund management.

Hypothesis 2:

H_0: RIFs managed by managers with pure RIF experience may exhibit different ESG performance compared to those managed by managers with conventional fund experience.

Hypothesis 3:

RIFs and 138 Islamic funds. They find that for the most inefficient funds, RIFs exhibit significantly superior performance, while for the best mutual funds, Islamic funds outperform RIFs.

H_0: When considering both financial return and ESG performance simultaneously, RIFs managed by managers with pure RIF experience may exhibit differences in comparison to RIFs managed by those with conventional fund experience.

4.3. Data

4.3.1 Data Source

To understand whether previous conventional fund management experience has an impact on RIFs' ESG performance, we obtain data from various sources to (a) identify RIFs, (b) obtain fund-level data, and (c) build a database of fund managers' characteristics, including their previous work experience.

The (US) Forum for Sustainable and Responsible Investment (US SIF) reports provide lists of RIFs that are commonly used in the literature (Humphrey et al., 2016; In et al., 2014). Using the US SIF classification avoids issues with funds self-reporting, allowing us to identify RIFs reported in 2007-2020. To avoid survivorship bias, we keep RIFs in the sample once they appear in one of the report lists.

Morningstar Direct is used to retrieve information about fund holdings, fund returns, fund managers' information and other fund characteristics, such as share classes, net assets, and the expense ratio. From the US SIF reports, we initially identified 310 RIFs (1,246 share classes) managed by 117 fund management companies in Morningstar Direct. Some of the funds in our sample have multiple share classes. The main differences between share classes managed by the same fund are their loadings and expense ratios, while the holding portfolio remains the same (Alda, 2020; Ibikunle & Steffen, 2017; Joliet & Titova, 2018). Since we analyse the portfolio composition of RIFs, including different classes may result in double counting. Following Livingston et al. (2019) and Alda (2021), we aggregate each share class to the fund level by taking the share-class total net assets weighted average to obtain the fund level monthly return and the annual expense ratio. We only include funds that are identified as being US Equity Large Cap Blend, US Equity Large Cap Growth, US Equity Large Cap Value, US Equity Mid Cap, and US Equity Small Cap based on the Morningstar Global Category (Agarwal et al., 2014; In et al., 2014; Kempf & Osthoff, 2008). Then, consistent with Leite and Cortez (2015), funds with less than 36 monthly returns or 12 quarterly holdings information within the observation period are excluded. We also exclude funds where less than 60% of their holdings can be successfully matched with the stock ESG score and carbon emission intensity[56] information from Thomson Reuters Eikon (Dorfleitner et al., 2021; Rohleder et al., 2022). These exclusions result in a final sample of 47 RIFs managed by 25 fund management companies (we detail the cleaning process in Appendix 4-1; using carbon emissions sharply decreases our sample size) between January 2005 and December 2020.

We also obtain fund managers' information from Morningstar Direct, supplementing missing observations with further detail from LinkedIn, the SEC website, and the funds' official website (detailed processes of collecting and matching are provided in Appendix 4-2). For each fund manager, we collect the managers' past work experience (within the fund management industry). We use a binary variable that equals one if a manager starts their role in RIF management without prior experience in conventional funds, indicating their sole experience is in responsible investment. Given that most of our sample is team management, we compute the percentage of managers within each team who only have RIF management experience and use this percentage to proxy the previous work experience of the entire management team.

Other manager-level characteristics that have been discussed in the literature are also obtained from Morningstar Direct, such as their highest level of education attainment (Chevalier & Ellison, 1999; Gottesman & Morey, 2006) and gender (Niessen-Ruenzi & Ruenzia, 2019; Hu et al., 2012; Clare, 2017). We collect information about whether managers possess either the Chartered Financial Analyst (CFA) qualification or a Master of Business Administration (MBA) degree, which are widely recognized in the financial sector. The educational background of each management team is measured in three percentages (percentages of managers' highest education level for doctoral, master's and bachelor's degrees). Gender, CFA certification, and the MBA degree are also measured using percentages.

In this paper, we consider four proxies that capture fund-level ESG performance: 1) fund-level ESG scores (including individual environmental, social, and governance pillar scores), 2) the percentage of holdings invested in assets with high ESG scores, 3) the percentage of holdings invested in assets with low ESG scores,

[56] In this paper, we use total emissions (scope 1 and 2) per revenue as the carbon emission intensity.

and 4) carbon emission intensity. All proxies we use are based on fund holdings information.[57] Information at the holding company level, including ESG scores, carbon emission and ICB industry code, is obtained from Refinitiv Eikon. We acknowledge there are several agencies that provide company-level ESG scores, such as Kinder, Lydenberg, and Domini (KLD, now MSCI KLD), Sustainalytics, Moody's ESG (Vigeo-Eiris), S&P Global (RobecoSAM), Refinitiv, and MSCI.[58] However, the Refinitiv ESG[59] score is one of the most commonly employed measures for corporate sustainability performance in the literature, and has been employed (or referenced) in over 1,500 research articles since 2003 (Berg et al., 2021).

4.3.2 Summary Statistics

Table 4-1 provides summary statistics of RIFs in our sample. Panel A reports the pooled summary statistics of RIFs and their management team information. The average fund within our sample period has an average annualized return (alpha obtained using monthly raw returns and the 4-factor model with a 12-month rolling window [Ammann et al., 2019]) of -0.0046 with a standard deviation of 0.0309. The annualized return volatility (annualized standard deviation of monthly net returns over the previous 12 months [Ammann et al., 2019; Renneboog et al., 2011]) ranges from 3.47% to 36.15%, with a mean value of 13.37%. The average management team in our sample has 2.78 managers; 59.95% of managers have no previous conventional fund management experience. On average, approximately 19.23% of the management team is female. Most managers (73.03%) have obtained at least a master's degree, with about half (53.79%) CFA charter holders and 54.85% holding an MBA degree. Panel B presents the *size* and *age* of RIFs and their fund management company (FMC, also referred to as the 'fund family') information as of December 2020.[60] The average fund

---

[57] We acknowledge that there are limitations associated with holding-based analysis as identified by practitioners, including: 1) ignoring the fund managers' intentional ESG strategy (e.g., intentionally buying low ESG score companies and waiting for their score to improve); 2) ignoring managers' efforts in active engagement shareholder strategy; and 3) this method relies on backward-looking reported data. However, the first two limitations are hard to distinguish and quantitatively analyze; we therefore use the available metrics (ESG score) to proxy funds' ESG performance. In consideration of the increasing attention to climate risk and the carbon emission reporting requirements in recent years, we also employ carbon emission intensity to assess and compare the ESG performance of funds.

[58] Kinder, Lydenberg, and Domini Inc were acquired by Riskmetrics in 2009 and then in 2010, MSCI acquired Riskmetrics (Eccles et al., 2020). Morningstar acquired Sustainalytics in July 2020.

[59] According to Refinitiv (2021), the Refinitiv ESG score is a comprehensive score that evaluates a company's ESG performance by using ten main themes (including resource use, innovation, emissions, human rights, workforce, and management) based on publicly available company-reported data. The score ranges from 0 (worst ESG) – 100 (best ESG). Refinitiv (2021) states that their ESG score is designed in a way that "help[s] you make sound, sustainable investment decisions". In our sample, 3,631 companies (belonging to 11 industries) have ESG scores.

[60] For funds no longer active before December 2020, we use their last quarter's information.

in our sample is about 21 years (253 months) old,[61] has US$10.34 billion in assets under management, and is managed by an FMC that is about 48.8 years (586 months) old and where 41.7% of their AUM are classified as sustainable investment funds.[62]

To better understand the potential impacts of fund managers' past experience, we split the sample into three groups based on fund managers' past work experiences. Group 1, with 812 fund-quarter observations (25 RIFs fall into this group through the entire sample period), is managed by RIF-only managers (all the managers have no previous conventional fund management experience). Group 3, with 530 fund-quarter observations, contains RIFs that are managed by managers who all had or have conventional fund management experience. This group consists of 28 RIFs throughout the period. Group 2, comprising the remaining 725 fund-quarter observations over 23 RIFs, has both conventional and RIF-only managers on their management teams.

[61] Some funds in our sample were very old (e.g., the Pioneer Fund was established on 10th February 1928). This may explain why the average fund is relatively old and large.

[62] This paper focuses on US domestic equity RIFs, however, when calculating the percentage of AUM committed to sustainable investment, we consider all the available funds listed in the US SIF report, not only equity funds.

Table 4-1 Summary statistics of RIFs

Panel A

	Annualized alpha	Annualized return volatility	Annualized expense ratio	RIF manager %	Manager Team Count	CFA holder %	MBA%	Bachelor%	Master degree%	PHD%	Female %
Min	-0.1997	3.4673	0.0001	0	1	0	0	0	0	0	0
Mean	-0.0046	13.3669	0.0067	0.5995	2.7758	0.5379	0.5485	0.2417	0.7003	0.0301	0.1923
p50	-0.0024	11.8146	0.0065	0.6667	2	0.5	0.5	0	0.7143	0	0
Max	0.1251	36.1544	0.0225	1	12	1	1	1	1	1	1
SD	0.0309	6.1485	0.0040	0.4046	2.1573	0.3923	0.3723	0.2963	0.3154	0.1262	0.2948
N	2114	2114	2114	2114	2114	2114	2114	2114	2114	2114	2114

Panel B

	Size (billion)	Age	AUM of RIF within FMC (billion)	AUM of FMC (billion)	AUM of RIF/AUM of FMC	FMC Age	Oldest RIF age within FMC
Min	0.0130	43	0.0130	0.0633	0.0006	107	48
Mean	10.3376	253.28	122.8726	428.7463	0.4170	585.9787	403.6170
p50	1.0408	193	4.3940	126.1257	0.5044	458	282
Max	136.6499	1114	510.3203	6281.4870	1	1157	1114
SD	26.9271	253.47	192.6376	964.3436	0.3263	326.6163	326.1952
N	47	47	47	47	47	47	47

Note: Table 4-1 provides summary statistics of the 47 RIFs in our sample. Panel A reports the pooled summary statistics of RIFs and their management team information between 2005 and 2020. *Annualized alpha* is the annualized alpha obtained by the 4-factor model with a 12-month rolling window. *Annualized Return volatility* is an annualized standard deviation of monthly net returns over the previous 12 months. *Annualized expense ratio* captures the funds' operating expenses and management fees. *RIF manager %* represents the percentage of managers who only have RIF work experience. *Manager Team Count* represents the number of fund managers in the management team. We also report some fund management team characteristics, such as the percentage of managers who have an MBA degree (*MBA %*) or CFA certification (*CFA holder %*). *Bachelor%, Master degree%* and *PHD%* reflect the percentage of fund managers' highest education degree. *Female %* represents the percentage of female managers in the team. Panel B presents the size and age of RIFs and their FMC information as of December 2020. *Size* is the fund size. *Age* is the fund age, which is calculated as the number of months since the fund's oldest share class was established. *AUM of RIF within FMC* is the total RIF assets under management for the FMC. *AUM of FMC* is the total assets under management of FMC. *AUM of RIF/AUM of FMC* represents the percentage of RIF assets to the total assets under management of the FMC. *FMC Age* is the number of months since the first fund of the FMC was established. *Oldest RIF age within FMC* represents the age of the oldest RIF within the FMC.

Table 4-2 Summary statistics for the three management groups

Panel A

Managerial Group	Annualized alpha	Annualized return volatility	Annualized expense ratio	RIF manager %	Manager Team Count	CFA holder %	MBA%	Bachelor%	Master degree%	PHD%	Female%
1	-0.0033	13.4736	0.0057	0.9904	1.5936	0.6068	0.5397	0.2520	0.6525	0.0454	0.1991
2	-0.0030	13.4202	0.0073	0.5877	4.6234	0.4514	0.6016	0.2120	0.7322	0.0325	0.1716
3	-0.0088	13.3770	0.0071	0.0131	2.0698	0.5534	0.4924	0.2684	0.7290	0.0025	0.2058

Panel B

Managerial Group	Size (billion)	Age	AUM of RIF within FMC (billion)	AUM of FMC (billion)	AUM of RIF/AUM of FMC	FMC Age	Oldest RIF age within FMC	Number of funds in each group
1	4.6251	256.2727	159.2132	299.0127	0.543564	491.6364	445.9091	11
2	17.9596	326.4211	146.5326	336.6144	0.4015225	673.2105	469.4211	19
3	5.5152	169.5882	72.9145	615.6627	0.3524663	549.5294	302.7059	17

Panel C

	Group1 VS Group2		Group1 VS Group3		Group2 VS Group3	
Annualized alpha	-0.000207	(-0.14)	0.00556**	(-3.24)	0.00577**	(-3.01)
Annualized return standard deviation	0.0534	(-0.17)	0.0966	(-0.27)	0.0432	(-0.13)
Annualized expense ratio	-0.00158***	(-8.14)	-0.00143***	(-5.76)	0.000144	(-0.7)
RIF manager %	0.403***	(-59.67)	0.977***	(-198.91)	0.575***	(-69.21)
Manager Team Count	-3.030***	(-32.85)	-0.476***	(-9.15)	2.554***	(-21.54)

CFA holder %	0.155***	(-8.25)	0.0534*	(-2.15)	-0.102***	(-5.25)
MBA %	-0.0619***	(-3.52)	0.0474*	(-2.11)	0.109***	(-5.3)
Bachelor %	0.0400**	(-2.88)	-0.0164	(-0.87)	-0.0564***	(-3.59)
Master's degree%	-0.0797***	(-5.24)	-0.0765***	(-3.91)	0.00314	(-0.19)
PHD degree%	0.0129	(-1.75)	0.0428***	(-5.6)	0.0300***	(-6.74)
Female %	0.0275	(-1.9)	-0.00663	(-0.36)	-0.0341*	(-2.28)
N	1537		1342		1255	

Note: Table 4-2 provides summary statistics of the three groups. Panel A presents the pooled summary statistics for each group. *Annualized alpha* is the annualized alpha obtained by the 4-factor model with a 12-month rolling window. *Annualized Return volatility* is an annualized standard deviation of monthly net returns over the previous 12 months. *Annualized expense ratio* captures the funds' operating expenses and management fees. *RIF manager %* represents the percentage of managers who only have RIF work experience. *Manager Team Count* represents the number of fund managers in the management team. *MBA%* represents the percentage of managers who have an MBA degree. *CFA holder %* represents the percentage of managers who hold a CFA certification. *Bachelor%*, *Master degree%* and *PHD%* reflect the percentage of fund managers' highest education degree. *Female %* represents the percentage of female managers in the team. Panel B reports the funds and FMCs' characteristics of the three groups as of 31 December 2020. *Size* is the fund size. *Age* is the fund age, which is calculated as the number of months since the fund's oldest share class was established. *AUM of RIF within FMC* is the total RIF assets under management belonging to the FMC. *AUM of FMC* is the total assets under management of the FMC. *AUM of RIF/AUM of FMC* represents the percentage of RIF assets to the total assets under management of the FMC. *FMC Age* is the number of months since the first fund of the FMC was established. *Oldest RIF age within FMC* represents the age of the oldest RIF within the FMC. *Number of funds in each group* represents the number of funds in each group. Panel C reports the t-test results for differences between the groups. *, **, *** denote significance at 10%, 5% and 1%. t-statistics in parentheses.

We split the sample based on the management teams' information from the previous quarter, as we expect any changes in the management team may take some time to manifest in fund performance. The summary statistics of the three groups are reported in Table 4-2. Panel A presents the pooled summary statistics for the three groups (t-test results between each group are reported in Panel C). All three groups report negative average alphas. Group 1 reports a relatively low average alpha (-0.0033) and the highest return volatility (13.47), with the lowest annual expense ratio (0.57). RIFs in Group 2 show the highest annual return (-0.0030) and charge the highest expense ratio of 0.0073. Funds in Group 3 report the lowest return (-0.0088) and the lowest return volatility (13.37).

On average, the RIF-only management team in Group 1, has the highest rate (60.68%) of CFA certification and the smallest average management team size (1.59). Group 2, the mixed teams, has the highest proportion (76.47%) of managers who have at least obtained a master's degree, the lowest percentage (17.16%) of female managers and the largest management team with 4.6 members. Funds in Group 3, all conventional experience, report the highest percentage of female managers (20.58%).

Panel B reports the funds and FMCs' characteristics for the three managerial groups as of 31 December 2020. RIFs in Group 1 have the smallest average size (4.63 billion US$), are relatively older (256 months), and they are managed by the FMCs with the highest ESG commitment level (percentage of AUM classified as RIFs). The average RIF in Group 2 is the largest (18 billion) and the oldest (326 months). These funds are managed by the oldest FMCs and have the longest RIF operation time. RIFs in Group 3 are the youngest (16 years, or 196 months), but these funds are managed by the largest FMCs (615.66 billion), which also have the lowest average ESG commitment level (35.25%) and the shortest time in the RIF market (302 months).

4.4. Methodology and Results

4.4.1 Financial Performance Comparison

We start by assessing financial performance differences between the three groups of RIFs. Following the work of Ammann et al. (2019), we calculate alpha using the fund's raw return and the 4-factor model with a 12-month rolling window. We use this annualized alpha to measure financial performance. We then employ Equation (4.1), using the annualized alpha as the dependent variable, to test the potential performance difference between the three groups.

$$Annualised\ alpha_{i,t} = \alpha_i + \gamma_1 Group2_{i,t-1} + \gamma_3 Group3_{i,t-1} + \beta_1 Volatility_{i,t} + \beta_2 Expense\ ratio_{i,t} + \beta_3 Size_{i,t} + \beta_4 Age_{i,t} + \beta_4 MBA\%_{i,t-1} + \beta_5 CFA\%_{i,t-1} + \beta_6 PHD\%_{i,t-1} + \beta_7 Master\%_{i,t-1} + \beta_8 Bachelor\%_{i,t-1} + \beta_9 Female\%_{i,t-1} + \epsilon_{i,t} \qquad (4.1)$$

Where $Annualised\ alpha_{i,t}$ is the annualized alpha obtained by the 4-factor model with a 12-month rolling window of fund i at time t. We employ return volatility ($Volatility_{i,t}$) as a measure of risk, which is an annualized standard deviation of monthly net returns over the previous 12 months (Ammann et al., 2019; Renneboog et al., 2011). $Expense\ ratio_{i,t}$ is the annualized expense ratio which captures the funds' operating expenses and management fees (Del Guercio et al., 2003). $Size_{i,t}$ is the logarithm of the fund size and$Age_{i,t}$ is the number of months since the oldest share class was established. We also control for fund management team characteristics, such as the percentage of managers who obtain an MBA degree ($MBA\%_{i,t-1}$), or CFA certification ($CFA\%_{i,t-1}$). We use three percentages: $Bachelor\%_{i,t-1}$, $Master\%_{i,t-1}$ and $PHD\%_{i,t-1}$, to reflect the percentage of fund managers' highest education degree. We also consider the team's gender, with $Female\%_{i,t-1}$ used to represent the percentage of female managers in the team. $Group2_{i,t-1}$ and $Group3_{i,t-1}$ are indicator variables, equalling one if the fund has been classified as Group 2 or 3, and 0 otherwise (indicating Group 1). We assume the impact of the fund management team on the fund performance will take some time to occur, so all the manager-related information is one-quarter lagged.

Table 4-3 reports the regression results of Equation (4.1). Column 1 reports the monthly results, and column 2 reports the yearly results. For both data frequencies, the coefficient of Group 2 is significantly positive, indicating the financial return of Group 2 is higher than that of Group 1. Group 3 does not show a significant difference compared to Group 1, which is different from the univariate result in Table 4-2 when we simply compare the average annualized alpha. This difference makes sense, as we now control for other factors that impact fund performance. Our findings also reveal that alpha is negatively affected by return volatility in both yearly and monthly data. Furthermore, we observe some significant coefficients in the RIF and management team characteristics when considering the monthly data. We find that RIFs' fund size is significantly positively associated with alpha. Of note, the significant positive relationship between the annual expense ratio (coefficient: 0.0186) and alpha may indicate that RIFs charging higher expense ratios are able to deliver better financial returns, on average. We also observe positive relationships with the PhD degree percentage, and the MBA degree percentage.

We also find that RIFs' alpha is significantly positively related to the one-quarter lagged percentage of managers with a PhD degree as their highest degree (coefficient: 0.015), indicating that fund alpha increases (decreases) in response to an increase (decrease) in the percentage of managers who have PhD degrees. This finding differs from Clare et al. (2022), who observe a significantly negative coefficient between the PhD degree and alpha. The significantly positive coefficients for the percentage of MBA holders align with Fang and Wang (2015), who find that having an MBA degree or obtaining a CFA qualification is significantly associated with a fund manager having better stock-picking skills and better performance. However, our findings differ from theirs in terms of the insignificant coefficients for the CFA qualification.

Table 4-3 Financial performance comparison by managerial group

	Monthly	Yearly
Constant	-0.0559***	-0.0595
	(0.0141)	(0.0617)
Group 2	0.0079***	0.0154**
	(0.0017)	(0.0071)
Group 3	-0.0001	0.0022
	(0.0018)	(0.0073)
Annualized return volatility	-0.0277***	-0.0895***
	(0.0061)	(0.0261)
Annualized expense ratio	0.0202***	2.3737
	(0.0032)	(1.4832)
Size	0.0025***	0.003
	(0.0007)	(0.0030)
Age	-0.0000***	-0.0001
	(0.0000)	(0.0001)
Lagged MBA %	0.0051**	0.0016
	(0.0021)	(0.0090)
Lagged CFA holder %	-0.0033*	-0.0065
	(0.0019)	(0.0081)
Lagged PHD degree%	0.0145**	0.0236
	(0.0061)	(0.0260)
Lagged Master degree%	-0.0057	-0.0021
	(0.0052)	(0.0230)
Lagged Bachelor %	0.0037	0.0081
	(0.0050)	(0.0221)
Lagged Female %	-0.0025	-0.0056
	(0.0021)	(0.0085)
N	6022	529
R^2	0.0245	0.0575

Note: Table 4-3 reports the regression results of Equation (4.1) for the 47 RIFs between 2005 and 2020. The dependent variable is *Annualized alpha,* which is the annualized alpha obtained by the 4-factor model with a 12-month rolling window. *Group 2* and *Group 3* are indicator variables that equal one if the fund has been classified as Group 2 or 3. *Annualized Return volatility* is an annualized standard deviation of monthly net returns over the previous 12 months. *Annualized expense ratio* captures the funds' operating expenses and management fees. *Size* and *Age* are the fund size and age. *MBA %* represents the percentage of managers who have an MBA degree. *CFA holder %* represents the percentage of managers who hold a CFA certification. *Bachelor %*, *Master degree%* and *PHD %* reflect the percentage of fund managers' highest education degree. *Female %* represents the percentage of female managers in the team. *, **, *** denote significance at 10%, 5% and 1%. Standard errors in parentheses.

4.4.2 ESG Performance Comparison

We next compare ESG performance and test Hypothesis 2. To measure fund-level ESG performance, we rely on the most popular method in the extant literature, the weighted average ESG performance based on the RIFs' holding portfolio. We employ four metrics for fund ESG performance: 1) fund-level ESG scores (including individual environmental, social, and governance pillar scores), 2) the percentage of holdings invested in assets with high ESG scores, 3) the percentage of holdings invested in assets with low ESG scores, and 4) carbon emission intensity.

The first measurement (fund-level ESG scores) uses the Refinitiv ESG scores. According to Refinitiv (2021), the Refinitiv ESG company score is calculated based on verifiable reported ESG-related information in the public domain, and it captures over 450 firm-level ESG measurements, from which a subset of 178 of the most comparable and relevant indicators are selected for the overall scoring process. They also provide separate environmental, social, and governance pillar scores. The calculation of fund-level ESG scores at quarter t ($ESG_{p,t}$) follows the method of Dorfleitner et al. (2012), which is the weighted sum of individual stocks' ESG scores in the portfolio.

$$ESG_{p,t} = \sum_{j=1}^{n} w_{j,t} * ESG_{j,t} \qquad (4.2)$$

Where, $w_{j,t}$ is the weight of stock j at the quarter t, and ESG_j is the ESG measure (ESG score, individual E, S and G pillar score and the carbon emission intensity) of stock j at quarter t.

The second and third measures (holding percentage invested in high and low ESG assets, $\%\ high_{i,t}\ and\ \%\ low_{i,t}$) also rely on the Refinitiv ESG scores. Instead of considering the raw score, this method aggregates a fund's asset allocation. To assess the percentage of holdings allocated to firms with relatively high or low ESG scores, we first classify the companies into three portfolios using the best (worst)-in-class method. For each industry (based on the ICB industry code from Refinitiv), we sort companies based on their ESG scores each June and assign the 30% of companies with the highest ESG scores into the high ESG company group, and the lowest 30% into the low ESG company group. The high (and low) ESG groups are updated each year based on firms' yearly ESG score. Then, based on the holdings information, we obtain the percentage of assets invested in the high (low) ESG score companies by the fund in each quarter. The higher (lower) proportion of holdings invested in the high (low) ESG score firms refer to a better ESG performance.

Due to the lack of a well-defined and widely accepted measurement of ESG (Downar et al., 2021) and the increasingly complex ESG methodologies (Christensen et al., 2022), we also use reported greenhouse gas emission information as an alternative ESG performance measurement based on Thomä et al. (2018) and Popescu et al. (2021). Carbon emission is an aggregated score that involves physical measurements and the delineation of scope (e.g., so-called Scope 1, 2 and 3 emissions) to measure CO2 equivalents (Downar et al., 2021). It is a key measure, perhaps the single most salient measure of firms' environmental commitments in ESG (Garvey et al., 2018; Raghunandan & Rajgopal, 2022). Raghunandan and Rajgopal (2022) also point out that carbon emission is correlated with a firm's actual environmental performance as opposed to recent criticism of ESG scoring methods, which are correlated with the extent of voluntary ESG-related disclosures rather than the actual levels of carbon emissions by firms. Like the first measurement, our carbon emission intensity is calculated as the weighted sum of individual stocks' carbon emissions in the portfolio. In Equation (4.2), by using the individual firms' carbon emission intensity as ESG_j, we can obtain the overall emission intensity of the fund. A fund's carbon emission intensity is the total emission of scopes 1 and 2,[63] adjusted by company revenue. This method is a widely used proxy for environmental (or green) performance. We reverse the CO2 variable so that higher values indicate better ESG (less carbon emission intensity, greener companies) for ease of comparison with standard ESG scores.

Table 4-4 contains the summary statistics of all ESG performance measurements within the three groups. Surprisingly, Group 1 (managers with only RIF experience) reports the lowest quarterly average ESG performance across all ESG performance measurements, except for the G pillar score. Also, Group 1 shows the smallest range and the lowest standard deviation for the majority of measures, except for the percentage

[63] There are three scopes of emission data available. However, according to Busch et al. (2020), information on direct scope 1 emissions (from a company's direct operations) and indirect scope 2 emissions (electricity purchased from third parties for use in direct company operations) is largely available and shows a relatively good consistency between different data providers, while the information on indirect emissions (scope 3) is seldom provided and with generally low reliability. Therefore, we follow the work of Pedersen et al. (2021) and exclude scope 3 emissions in our analysis.

invested in low ESG companies and the carbon emission intensity. Group 3 (managers with only conventional fund experience) exhibits the highest quarterly average ESG performance level for all measures except the percentage of assets invested in low ESG score firms. Results from Table 4-4 indicate that RIFs managed by conventional managers are more likely to obtain a higher ESG score, invest more in high ESG score companies, and report less greenhouse gas emissions, on average. These results do not fit expectations that RIF experience only managed funds would have better ESG performance. However, the results of Utz and Wimmer (2014) appear to support our finding. They rank all the US mutual funds into quintiles based on their yearly ESG scores and find that conventional funds show better ESG scores than RIFs.

Table 4-4 Summary statistics of ESG performance measures by managerial group

Panel A

		ESG score	E score	S score	G score	% invested in high ESG assets	% invested in low ESG assets	Carbon emission intensity
Mean	Group 1	39.93	47.75	52.2	50.81	47.34	7.24	177.34
	Group 2	40.49	48.95	53.15	50.38	50.89	4.51	157.74
	Group 3	42.11	49.9	54.97	51.65	52.61	4.29	139.75
P50	Group 1	40.12	49.44	52.79	51.39	46.51	7.43	168.86
	Group 2	40.49	48.95	53.15	50.38	50.89	4.51	157.74
	Group 3	42.11	49.9	54.97	51.65	52.61	4.29	139.75
Min	Group 1	25.48	20.93	28.77	34.24	22.08	0	25.19
	Group 2	21.23	19.86	24.92	24.83	22.89	0	25.19
	Group 3	13.43	12.83	16.52	18.67	18.21	-1.17	25.19
Max	Group 1	50.43	61.59	67.66	61.16	77.25	25.45	428.68
	Group 2	52.99	64.86	72.97	63.48	80.26	24.32	428.68
	Group 3	54.82	71.69	75.58	70.33	77.5	18.12	428.68

Panel B

	Group1 VS Group2		Group1 VS Group3		Group2 VS Group3	
ESG score	-0.562*	(-2.42)	-2.183***	(-8.06)	-1.621***	(-5.38)

E score	-1.191**	(-2.97)	-2.148***	(-4.63)	-0.957*	(-1.98)
S score	-0.954**	(-2.69)	-2.774***	(-6.54)	-1.820***	(-3.95)
G score	0.431	(-1.63)	-0.838**	(-2.59)	-1.269***	(-3.45)
% invested in high ESG assets	-3.545***	(-6.51)	-5.264***	(-8.51)	-1.719**	(-2.59)
% invested in low ESG assets	2.734***	(-11.81)	2.957***	(-11.77)	0.223	(-0.97)
Carbon emission intensity	19.60***	(-4.05)	37.59***	(-7.29)	17.98***	(-3.41)
N	1537		1342		1255	

Note: Table 4-4 contains the summary statistics of all ESG performance measures in the three groups described in Section 4.3.2. ESG measures include fund-level ESG scores, Environmental, Social, and Governance pillar scores, the percentage of holdings invested in assets with high ESG scores, the percentage of holdings invested in assets with low ESG scores and carbon emission intensity. Panel B provides the differences between each group, with *, **, and *** denoting significance at 10%, 5%, and 1%, respectively. t-statistics in parentheses.

We then compare the ESG performance of the three groups, following the method of Utz and Wimmer (2014), in two ways: the yearly average ESG performance and the yearly minimum ESG performance.

a) The yearly average level of ESG

Here we test the yearly mean ESG performance of the different groups. While the SEC has required US mutual funds to disclose their complete portfolio quarterly since 2004, the ESG scores and carbon emission information of individual stocks are only updated yearly. Therefore, we average the four ESG_P to obtain the fund yearly ESG performance, ESG_Y, which represents the fund's average ESG performance in that calendar year. Then, we calculate the weighted average ESG_Y for the three manager groups (only conventional experience, no conventional fund experience, and mixed).

$$ESG_Y = mean\ ESG_P \quad (4.3)$$

Table 4-5 Panel A summarises the average ESG_Y for the three manager groups. RIFs in Group 3 (managed by teams where all the managers have conventional fund management work experience) show the highest average yearly ESG score (45.93). RIFs managed by managers with only RIF management experience (Group 1) have an average ESG score of 39.34, and Group 2 shows the lowest score (36.09). We also consider the separate E, S and G scores and the percentage of holdings invested in companies with high (low) ESG scores to compare the differences in the three subsamples. All alternative measures exhibit the same results. The pairwise differences are reported in Table 4-5 Panel C.

b) The minimum level of ESG

We then compare the lowest ESG performance of individual funds. The minimum ESG performance in the specific year is calculated as Equation (4.4), and then we calculate the weighted average $min\ ESG_Y$ for the three manager groups.

$$minESG_Y = min\ ESG_P \qquad (4.4)$$

By comparing $minESG_Y$, we are interested in whether the lowest ESG performance of RIFs run by managers with RIF-only backgrounds is higher than that of RIFs run by managers who have conventional fund work experiences.

Panel B of Table 4-5 summarises the $minESG_Y$ for the three manager groups. As the results in Panel A, Group 3 exhibits the highest minimum yearly ESG score of 44.56, followed by Group 1 (38.70) and then Group 2 with 35.16. Other ESG measures report similar results.

Together, the results suggest that RIFs managed by a team where all the members have conventional funds management work experience are inclined to exhibit better ESG scores and carbon emissions-based ESG performance. This may be explained by the potential trade-off of investment objectives for RIFs. Fund managers in conventional funds are adept at optimizing a single metric: financial returns. When managing an RIF, these managers may apply the same singular focus but switch emphasis to ESG performance. Such behaviour can (and appears to, on average) generate higher ESG performance but may come at the expense of the funds' financial performance, as shown in Section 4.4.1. It is possible that pure RIF managers are familiar with balancing dual goals. This finding may suggest that fund managers are able to achieve better ESG performance, but achieving a harmonious balance between ESG and financial performance remains a challenge, highlighting a need for a more integrated approach to measuring RIFs' performance.

Table 4-5 Average ESG_Y and the $minESG_Y$ for the three manager groups

Panel A yearly mean ESG measurements

	Yearly mean ESG score	Yearly mean E score	Yearly mean S score	Yearly mean G score	Yearly mean % invested in high ESG company	Yearly mean % invested in low ESG company	Yearly mean carbon emission intensity
1	39.34	48.58	50.54	50.29	49.65	3.72	309.15
2	36.09	43.74	46.36	44.83	44.30	3.46	124.16
3	45.93	66.49	69.09	63.07	55.82	5.51	82.17

Panel B yearly minimum ESG measurements

	Yearly minimum ESG score	Yearly minimum E score	Yearly minimum S score	Yearly minimum G score	Yearly minimum % invested in high ESG company	Yearly minimum % invested in low ESG company	Yearly minimum carbon emission intensity
1	38.70	47.73	49.61	49.43	45.73	2.76	290.09
2	35.16	42.51	45.26	43.75	40.65	2.31	117.24
3	44.56	64.67	67.19	61.12	50.35	4.03	77.80

Panel C Difference between groups

	Group1 VS Group2		Group1 VS Group3		Group2 VS Group3	
Yearly mean ESG score	3.255*	(-2.35)	-6.591***	(-5.31)	-9.846***	(-6.37)
Yearly mean E score	4.842*	(-2.07)	-17.91***	(-9.29)	-22.75***	(-11.67)
Yearly mean S score	4.177*	(-2.19)	-18.55***	(-11.64)	-22.72***	(-13.16)
Yearly mean G score	5.466***	(-4.05)	-12.78***	(-9.88)	-18.25***	(-11.61)
Yearly mean % invested in high ESG company	5.35	(-1.63)	-6.177	(-1.49)	-11.53**	(-2.93)
Yearly mean % invested in low ESG company	0.26	(-0.26)	-1.798	(-1.32)	-2.058	(-1.88)
Yearly mean carbon emission intensity	185.0***	(-11.06)	227.0***	(-14.4)	41.99***	(-5.12)
Yearly minimum ESG score	3.539*	(-2.6)	-5.864***	(-4.56)	-9.403***	(-6.03)

Yearly minimum E score	5.227*	(-2.15)	-16.93***	(-8.31)	-22.16***	(-10.37)
Yearly minimum S score	4.347*	(-2.25)	-17.58***	(-10.04)	-21.92***	(-11.55)
Yearly minimum G score	5.674***	(-4.14)	-11.69***	(-8.02)	-17.37***	(-10.18)
Yearly minimum % invested in high ESG company	5.084	(-1.51)	-4.623	(-1.02)	-9.706*	(-2.28)
Yearly minimum % invested in low ESG company	0.45	(-0.5)	-1.271	(-1.13)	-1.721	(-1.82)
Yearly minimum carbon emission intensity	172.9***	(-10.89)	212.3***	(-14.11)	39.44***	(-5.05)
N	30		30		30	

Note: Table 4-5 Panel A summarises the average yearly average level of ESG measures for the three manager groups. Panel B summarises the yearly minimum ESG measures for the three manager groups. Panel C reports the pairwise differences between groups, with t-statistics in paratheses. *, **, *** denote significance at 10%, 5% and 1%.

4.4.3 Data Envelopment Analysis (DEA)

The above discussion is mainly based on a multivariate regression analysis framework where we separately consider financial return and ESG performance. However, these two objectives are not mutually exclusive and, therefore, need to be considered together in the investment decision process. To deal with this, we employ the DEA method to estimate the overall efficiency of RIFs. This method allows us to jointly consider the financial and ESG performance as the outputs of the fund management process, based on selected inputs, and build an efficient frontier. This efficient frontier envelops all the decision-making units (DMUs, i.e., the individual RIFs in my sample) and defines a production possibility set. Then, each DMU obtains an efficiency score based on its relative distance from the frontier.

Charnes, Cooper, and Rhodes' (CCR) method assumes constant returns to scale and the efficiency is measured by assigning optimal weights to individual DMUs (a brief technical explanation is provided in Appendix 4-3). It measures the efficiency of different units by allowing each unit to select the most favourable weights for its inputs and outputs, while ensuring that efficiency scores are comparable across all units and have an upper bound (usually set to 1). This provides advantages in a performance evaluation situation that needs to assess which units are performing best and which may need improvement. Therefore, we employ the CCR model in this study. The CCR model has two forms: input-oriented and output-oriented. Since we aim to evaluate RIF performance, the model that maximizes the efficiency ratio of outputs to inputs (output-oriented CCR) is more suitable. To take both financial and ESG performance into consideration, we follow the work of Basso and Funari (2003a)[64] and employ the two-output format model. Our outputs are the capitalization factor, which is a non-negative return[65] and the ESG measures used previously (ESG score and carbon emission intensity).

[64] Basso and Funari (2007) propose two additional DEA models suitable for RIF evaluation. However, the extensions focus on dealing with the presence of negative data and a new measurement for ESG performance. The scope of this paper is to test the potential impact of fund managers' career paths on both financial returns and ESG, together. Therefore, we employ the simplest and most widely used CCR model.

[65] Due to the assumption that all the inputs and outputs in DEA are non-negative, we use capitalization factor, $\overline{U_J} = \overline{R_I} + 1$, instead of the mean return as an output in the DEA model, following Tavakoli Baghdadabad and Houshyar (2014) and Shahrour (2022).

In the funds' performance literature, DEA model inputs are typically the resources or costs that are used to generate returns. Following the literature, we select the year-end funds' size, yearly expense ratio (Solórzano-Taborga et al., 2020; Pérez-Gladish et al., 2013), turnover ratio (Pérez-Gladish et al., 2013) and the standard deviation of returns (Solórzano-Taborga et al., 2020; Basso & Funari, 2003a). Figure 4-1 illustrates our DEA model.

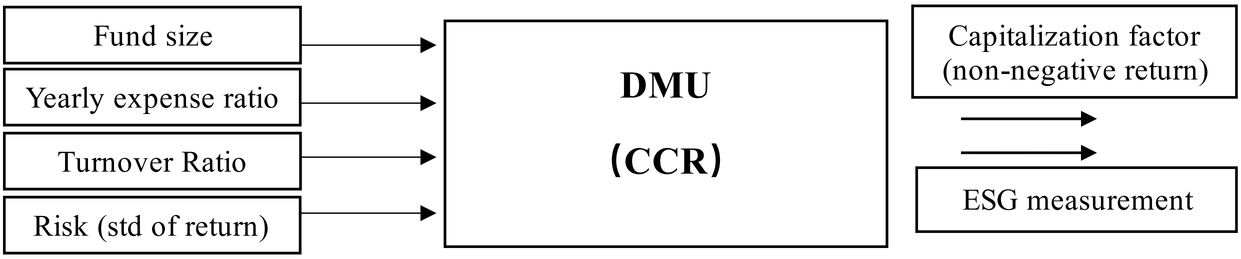


Figure 4-1 DEA model

Note: Figure 4-1 describes the inputs and outputs of our DEA model.

We begin by considering joint performance cross-sectionally[66] each year to investigate the relationship between managers' past work experience (proxied by the percentage of managers with pure RIF experience) and RIFs' joint performance (proxied by the overall efficiency score obtained from the DEA model). For each year, we obtain the efficiency score for each RIF (DMU) and then rank the RIFs each year; the most efficient funds (those on the frontier) have the lowest rank. The lower rank represents a higher efficiency score, meaning better joint performance. The efficiency rank is a count variable of only positive integers and therefore represents a discrete probability distribution, such as the Poisson. Specifically, we estimate the following Poisson regression model for every year:

$$Rank\ of\ efficiency\ score_i = exp\ \{\beta_1 * Lagged\ \%\ of\ pure\ RIF\ manager_i + \beta_2 * Size_i + \beta_3 * Age_i + \beta_4 * Alpha_i + \beta_5 * Volatility_i\} \tag{4.5}$$

[66] We notice that several recent papers argue the possibility of applying DEA model over multiple periods (Ren et al., 2021 and Xiao et al., 2022). In our paper, we use the rank of the efficiency score and the number of observations changes year by year (as shown in Table 4-6). Therefore, we focus on cross-sectional analysis.

Where, $Size_i$ is the logarithm of fund i's size, Age_i is the number of months since the oldest share class was established, $Alpha_i$ is the fund i's annualized lagged alpha, obtained using monthly raw returns and the 4-factor model with a 12-month rolling window (Ammann et al., 2019), and $Volatility_i$ is the annualized standard deviation of monthly net returns over the previous 12 months (Ammann et al., 2019; Renneboog et al., 2011).

Table 4-6 shows the results of the Poisson regression analysis, over the period 2006 to 2020. In Panel A, the ESG score is the ESG performance measurement. We find that 11 (out of 15) years report significantly negative coefficients on the lagged percentage of pure RIF managers. We then, following the spirit of Fama and MacBeth (1973), regress the coefficients of the lagged percentage of pure RIF managers obtained from Equation (4.5) with Newey-West standard errors, and report the results in the first row of Table 4-7. We obtain a negative coefficient of -0.40 with a t-statistic of -4.46. This suggests that an increase in the percentage of pure RIF managers will result in better joint performance (a lower efficiency rank indicates a higher efficiency score, which represents a better combined performance of ESG and return).

In Panel B of Table 4-6, which presents the efficiency rank based on carbon emission intensity and capitalization factors, we find similar results. Ten out of the 15 years reveal a significantly negative coefficient between the lagged percentage of pure RIF managers and the efficiency rank. The average coefficient is -0.43 (t-statistic = -6.8), as shown in the second row of Table 4-7. This indicates the proportion of pure RIF managers is positively related to RIFs' joint performance. These findings partly support Hypothesis 3. When combining financial return and ESG performance, RIFs managed by a team containing more managers with pure RIF experience exhibit higher efficiency scores.

Table 4-6 Results of the Poisson regression analysis

Panel A: ESG score as the ESG performance measure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	2006	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
lagged % of pure RIF manager	-1.2132***	0.124	-0.5792***	-0.8757***	-0.4652**	-0.0548	-0.00370	-0.3903**	-0.4261***	-0.4260***	-0.6812***	-0.3132**	-0.2452*	-0.4330***	-0.0501
	(0.397)	(0.480)	(0.199)	(0.258)	(0.183)	(0.175)	(0.186)	(0.172)	(0.143)	(0.150)	(0.164)	(0.144)	(0.134)	(0.141)	(0.146)
Size	0.3050***	0.103	0.2271***	0.1288***	0.1677***	0.1716***	0.3112***	0.1365***	0.1042***	0.1408***	0.3135***	0.2048***	0.0573*	0.2423***	0.0959***
	(0.102)	(0.0809)	(0.0441)	(0.0450)	(0.0503)	(0.0415)	(90.0513)	(0.0416)	(0.0394)	(0.0397)	(0.0422)	(0.0309)	(0.0295)	(0.0311)	(0.0341)
Age	-0.0013*	0.0004	0.0007*	0.0005	0.0004	0.0002	0.0006**	0.0001	0.0006**	0.0004	-0.0016***	0.0007**	0.0014***	0.0014***	0.0015***
	(0.0007)	(0.0006)	(0.0003)	(0.0004)	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0002)	(0.0003)	(0.0003)
Alpha	-9.6002**	9.1920**	9.6837***	-8.6378***	-2.801	-1.045	0.274	0.853	8.5728*	-6.3080**	-3.577	-8.6228***	1.041	11.9987***	1.610
	(4.464)	(4.320)	(3.673)	(2.458)	(4.710)	(3.996)	(3.614)	(4.625)	(4.711)	(3.185)	(3.305)	(1.267)	(1.893)	(2.166)	(1.016)
Volatility	0.0026	0.8936***	0.1960***	0.1193***	0.4670***	0.3334***	0.5300***	0.7496***	0.6090***	0.6547***	0.1240*	0.5458***	0.4543***	0.3864***	0.2502***
	(0.174)	(0.263)	(0.0374)	(0.0362)	(0.0830)	(0.0597)	(0.0801)	(0.117)	(0.140)	(0.104)	(0.0728)	(0.0858)	(0.0517)	(0.0423)	(0.0299)
Constant	-4.090	-10.1668***	-6.5564***	-2.7935***	-10.5377***	-7.0384***	-10.5424***	-7.3453***	-5.3010***	-9.7048***	-5.3849***	-5.0947***	-6.2396***	-8.2262***	-7.0509***
	(2.608)	(3.353)	(1.247)	(0.995)	(1.712)	(1.301)	(1.713)	(1.467)	(1.478)	(1.559)	(1.281)	(0.763)	(1.018)	(1.024)	(0.985)
N	24	23	25	27	29	29	29	33	33	33	37	41	47	45	41

Panel B: Carbon emission intensity as the ESG performance measure

	(1) 2006	(2) 2007	(3) 2008	(4) 2009	(5) 2010	(6) 2011	(7) 2012	(8) 2013	(9) 2014	(10) 2015	(11) 2016	(12) 2017	(13) 2018	(14) 2019	(15) 2020
lagged % of pure RIF manager	-0.8632**	-0.502	-0.4427**	-0.9228***	-0.4187*	-0.202	-0.345	-0.4955***	-0.6333***	-0.3532**	-0.5688***	-0.3257**	-0.2736**	-0.00290	-0.162
	(0.424)	(0.346)	(0.223)	(0.286)	(0.233)	(0.173)	(0.218)	(0.170)	(0.150)	(0.176)	(0.150)	(0.148)	(0.131)	(0.161)	(0.147)
Size	0.2362**	0.1840***	0.2556***	0.1659***	0.1767***	0.1373***	0.2826***	0.0871**	0.0634	0.1703***	0.1642***	0.2216***	0.0816***	0.3743***	0.2252***
	(0.107)	(0.0622)	(0.0486)	(0.0493)	(0.0593)	(0.0408)	(0.0592)	(0.0417)	(0.0404)	(0.0450)	(0.0348)	(0.0320)	(0.0296)	(0.0413)	(0.0400)
Age	-0.0009	0.0008*	0.0006*	0.0008*	0.0008**	0.0006	-0.0004	0.0007**	0.0010***	0.0007**	0.0002	0.0004	0.0005*	0	0.0003
	(0.0008)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)
Alpha	-13.314***	9.403***	13.585***	-11.138***	10.6085*	2.238	-6.248	-1.943	6.851	-6.0612*	-9.733***	-5.562***	1.284	3.9843*	0.837
	(4.775)	(3.337)	(4.166)	(2.818)	(5.710)	(3.946)	(4.489)	(4.559)	(4.900)	(3.674)	(2.787)	(1.330)	(1.909)	(2.349)	(1.144)
Volatility	0.0144	0.951***	0.178***	0.084**	0.399***	0.372***	0.533***	0.682***	0.400***	0.669***	0.0733	0.649***	0.289***	0.375***	0.282***
	(0.182)	(0.211)	(0.0413)	(0.0413)	(0.0863)	(0.0598)	(0.0995)	(0.117)	(0.141)	(0.119)	(0.0625)	(0.0868)	(0.0503)	(0.0506)	(0.0311)
Constant	-3.201	-11.561***	-7.072***	-3.046***	-9.749***	-6.964***	-9.808***	-5.823***	-2.733*	-10.940***	-1.956*	-5.827***	-3.902***	-11.034***	-10.397***
	(2.735)	(2.669)	(1.387)	(1.131)	(1.873)	(1.302)	(1.988)	(1.467)	(1.488)	(1.798)	(1.063)	(0.795)	(0.984)	(1.286)	(1.069)
N	24	23	25	27	29	29	29	33	33	33	37	41	47	45	41

Note: Table 4-6 shows the cross-sectional regression results of Equation (4.5) (Poisson regression) between 2006 and 2020. In Panels A and B, we report the results of employing the ESG score and carbon emission intensity as the ESG performance measurement, respectively. *, **, *** denote significance at 10%, 5% and 1%. Standard errors in parentheses.

Table 4-7 Results of Fama Macbeth regression

	Coefficient	Newey–West std. err.	t	P>t	[95% conf. interval]	N
Coefficients based on ESG score	-0.4022	0.0902	-4.46	0.001	[-0.59575, -0.20864]	15
Coefficients based on carbon emission intensity	-0.4341	0.0638	-6.8	0	[-0.57097, -0.29721]	15

Note: Table 4-7 reports the results of regressing the yearly coefficients obtained from Equation (4.5) with Newey-West standard errors. In the first and second rows, we report the results of employing the ESG score and carbon emission intensity as the ESG performance measures, respectively.

4.4.4 RIF Management Experience

Compared to financial returns, ESG performance is much harder to measure. A fund's ESG strategy and the intensity of that strategy vary between funds, and there is a lack of transparency around ESG strategy for most funds, which complicates ESG performance comparisons. Most of the current fund-level ESG measures are reliant on measuring ESG performance with ratings obtained from third-party providers. However, the investment decision-making process and balancing trade-offs between various ESG factors for a given stock holding within a portfolio is complex. It is therefore reasonable to assume fund managers' knowledge, skills and intuition used when making ESG-related decisions require experience, practice and refinement as time progresses. We thus test how managers' length of work experience in the RIF field (*RIF experience*) impacts funds' joint performance. For management teams, we understand that weighting tenure by the relative contribution of each team member would be the ideal method; however, such data is not available. Therefore, we calculate an equally weighted average of tenures for all managers in the team. A similar method has been used in several existing studies, including Patel and Sarkissian (2017), Humphrey et al. (2016) and Khorana et al. (2007).

Table 4-8 reports the descriptive statistics for *RIF experience*. Column (1) reports the RIF tenure at the individual manager level.[67] The average length of tenure for RIF managers is 7.96 years, with a median value of 5.5 years, suggesting the majority of managers are less experienced than the average. The range of experience varies significantly among individuals, with the least experienced manager having a mere 0.5 years in the field and the most experienced boasting a substantial tenure of 41.25 years. Column (2) of Table 4-8 reports team *RIF experience* by using the average tenure of the entire team. There are notable differences between the two measures. The team tenure has an average of 7.68 years and a standard deviation of 5.23 years. This may indicate that management teams commonly have at least one very experienced member who has a significantly longer tenure and some newer members with less experience. Additionally, the median of the two columns is relatively close (5.5 years and 6.67 years). Of note, in at least one case, an RIF is being managed by a manager or team with virtually no RIF experience as shown by the minimum value of 0.08 years of experience for the average team tenure. The histogram of the average tenure of management teams shows a significant skew with a very long tail (Figure 4-2).

Table 4-8 Summary statistics of tenure

	Individual tenure	**Team tenure (average)**
Mean	7.96	7.68
Median	5.5	6.67
Standard Deviation	7.02	5.23
Min	0.5	0.08
Max	41.25	29.83
N	224	2106

Note: Table 4-8 reports the descriptive statistics of managers' RIF experience for the sample of 47 RIFs. Column (1) reports the *RIF tenure* at the individual manager level, while Column (2) reports the *RIF experience* of the management team using the average tenure of all team members.

[67] The current managers' tenure is calculated as of 31st December 2020 (the end of our sample period). For managers who exited the market prior to this date, their length of work experience is computed based on their final date of service.

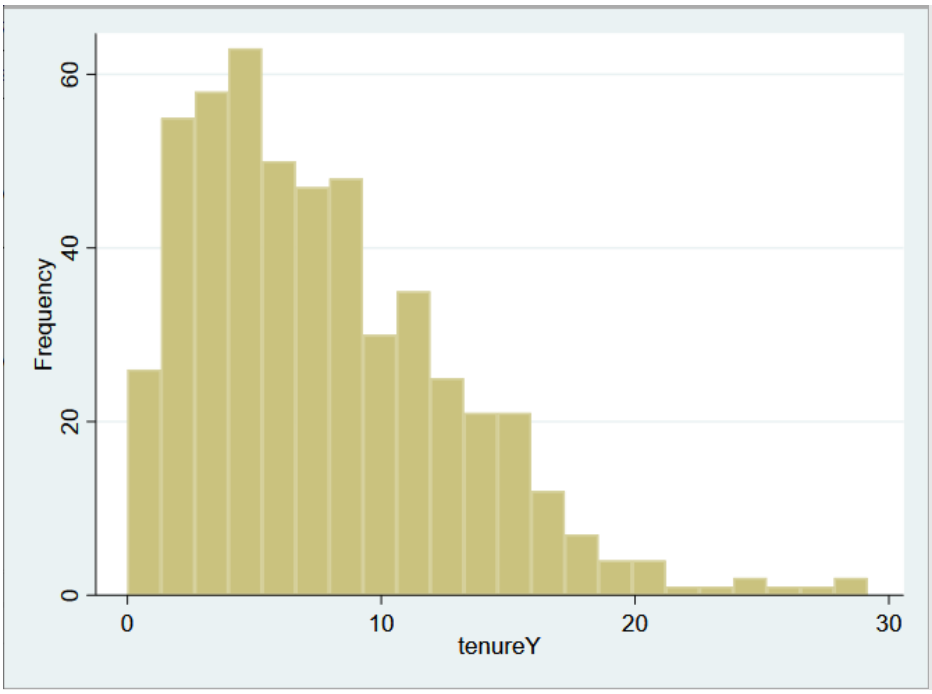


Figure 4-2 Histogram of average tenure

Note: Figure 4-2 describes the histogram of the average tenure of management teams.

We now employ several 5-year interval dummy variables (e.g., greater than 5 years, greater than 10 years, through to greater than 25 years) to examine the potential differences related to the varying lengths of experience. The equation is shown below:

$$Rank\ of\ efficiency\ score_{i,t} = exp\ \left\{\sum_{i=1}^{5}\gamma_i D_{i,t} + \beta_3 * Size_{i,t} + \beta_4 * Age_{i,t} + \beta_5 * Alpha_{i,t} + \beta_6 * Volatility_{i,t}\right\} \tag{4.6}$$

Table 4-9 Impact of experience on joint performance

ESG Performance Measure	(1) ESG score	(2) Carbon emission
Constant	-6.5804***	-6.8318***
	(1.1259)	(1.0150)
dummy>=5	0.0635	0.0366
	(0.0619)	(0.0560)
dummy>=10	-0.1387*	0.04
	(0.0770)	(0.1093)
dummy>=15	-0.1232	0.025
	(0.1289)	(0.1558)
dummy>=20	-0.2564	-0.2531
	(0.2397)	(0.2158)
dummy>=25	-0.3096**	-0.2495*
	(0.1379)	(0.1356)
Size	0.3386***	0.3393***
	(0.0598)	(0.0500)
Age	-0.0003	-0.0004
	(0.0005)	(0.0004)
Alpha	-1.9584	-1.3949
	(1.2993)	(1.0597)
Volatility	0.1671***	0.1761***
	(0.0201)	(0.0233)
2007.year	-0.8259***	-0.2114
	(0.2441)	(0.2234)
2008.year	-1.6021***	-1.7712***
	(0.4056)	(0.4366)
2009.year	-1.9448***	-2.1727***
	(0.4257)	(0.4209)
2010.year	-1.6025***	-1.9773***
	(0.3547)	(0.4199)
2011.year	-1.0139***	-0.9915***
	(0.3069)	(0.3237)
2012.year	-0.1275	-0.4315*
	(0.2584)	(0.2260)
2013.year	0.0754	0.1876
	(0.1933)	(0.1808)
2014.year	0.2386	0.2839
	(0.2166)	(0.2150)
2015.year	-0.6380**	-0.7728**
	(0.2827)	(0.3078)
2016.year	-0.3777	-0.0026
	(0.2366)	(0.2353)
2017.year	0.8012***	0.9507***

	(0.2065)	(0.2195)
2018.year	-0.6926**	-0.5819**
	(0.3167)	(0.2791)
2019.year	-0.3351	-0.5956**
	(0.3055)	(0.3025)
2020.year	-2.9482***	-3.0674***
	(0.5208)	(0.5501)
N	496	496

Note: Table 4-9 summarises the results for Equation (4.6). Dummies are equal to 1 if the tenure is greater than 5, 10, 15, 20, 25-year experience. *, **, *** denote significance at 10%, 5% and 1%. Standard errors in parentheses.

Table 4-9 summarises the results for Equation (4.6). For both measures of ESG performance (ESG score and carbon emissions), when the management team has less than 5 years (RIF) experience, an increase in experience will result in a lower efficiency ranking (coefficients: -6.58 and -6.83, all statistically significant at 1% level), indicating an increase in the joint performance of the fund. In column (1), we apply the ESG score as the proxy for ESG measurement and find that RIFs managed by teams with more than 10 years of RIF experience obtain better joint performance in comparison to their counterparts with less than 5 years of experience. Such positive impacts on joint performance still hold when the average team tenure is greater than 25 years. Employing carbon emissions as the ESG measure (column [2]) sees a similar increasing effect for the most experienced management teams (greater than 25 years).

4.5. Conclusion

In recent years, with the growth in both the number of RIFs and their assets under management, RIFs have been drawing increasing attention from investors. Naturally, this growth also means more fund managers are now in this market, including those with experience primarily managing conventional funds. However, the management of RIFs may require additional knowledge and expertise in ESG assets. Therefore, we hypothesize that fund managers with conventional fund management experience before managing RIFs may exhibit different performance than those with solely RIF management experience. To test our hypothesis, we conduct our analysis in three steps. First, we compare the financial performance and return volatility of three groups of RIFs, categorised by differences in their teams' past work experiences. We find that the financial returns of Groups 1 (pure RIF-experienced managers) and 3 (all managers with only conventional fund experience) are not significantly different, while Group 2 (fund managers with a mix of career paths) reports a slightly higher return.

Second, we assess the ESG performance (including ESG scores, asset allocation in high or low ESG score firms, and carbon emission intensity) between the three managerial groups. Our results suggest that for the majority of our ESG measurements, RIFs in Group 3 report the highest average ESG performance, indicating that funds managed by teams with conventional fund management experience are more likely to exhibit better ESG performance. While this finding confirms our hypothesis that managers' work experience influences their ESG performance, it does not align with our intuitive expectation that funds managed by managers with only RIF experience would have better ESG performance. A reasonable conjecture is that managers with a background in conventional funds may shift their singular focus from financial return to ESG considerations, whereas the pure RIF managers may be more adept at considering both financial return and ESG objectives.

Lastly, we combine the ESG performance and financial return into an efficiency score and use this score to test if managers' career paths influence their overall performance. Our findings support the idea that an increase in the proportion of managers with exclusive RIF work experience has positive effects on the overall efficiency of RIF management. We further test the impact of the length of RIF work experience and find that when the management team has less than 5 years of experience, additional experience tends to result in improved joint performance.

Our findings have potential implications for RIF retail investors when selecting asset managers and allocating their investment assets. Compared with some confidential or paywalled information (e.g., fund holdings, managers' compensation, and internal policy), managers' career paths are more accessible to retail investors. Investors can select managers and adjust their asset allocation based on their non-financial motivations. Moreover, our study may also provide suggestions for asset management companies in hiring and allocating RIF managers. By balancing investors' demands and managers' capabilities, they can better promote the growth of the assets under management.

However, this study has two limitations. First, the sample size is relatively small, driven by the availability of carbon emissions, which we used as an alternative proxy for ESG performance. As regulations and disclosure requirements around carbon emissions increase, data availability is likely to improve for future studies. Second, our sample period includes the onset of the Covid-19 pandemic crisis. Both Nofsinger and Varma (2014) and Boffo and Patalano (2020) claim that RIFs outperform their conventional peers in financial returns over this period. It is uncertain whether RIF managers change their predisposition toward ESG management during the crisis, and if so, to what extent. This, and other questions around ESG-based decision making of fund managers, is left for future research.

Appendix 4-1

Sample selection process.

Initially, identify 353 funds (in total contains 1332 share classes) managed by 117 FMCs

↓ Exclude funds with no FMC level information

310 funds (1246 share classes) managed by 117 FMCs

↓ 13 FMCs have no available information

292 funds (1203 share classes) managed by 104 FMCs

↓ Filter for US equity funds

195 funds (819 share classes) managed by 81 FMCs

↓ Filter for funds at least have 60% holding companies can be matched with ESG scores

120 funds (567 share classes) managed by 55 FMCs

↓ At least 36 months of data available between 2005 and 2020

118 funds managed by 53 FMCs

↓ Filter for funds at least 60% holding companies can be matched with carbon emission intensity.

Final sample: 47 funds managed by 25 FMCs

Appendix 4-2

Fund manager match process

We start by collecting fund managers' names, management period for each fund, career path within the fund management industry, and some fund level identification information, such as the fund ID and fund management company for each RIF. Using this data, we build our RIF manager dataset. Then, we obtain the same information for all the other mutual funds that are available in the Morningstar database to build our conventional fund manager dataset. We utilize three steps to match these two datasets and conclude if RIF managers have previous work experience in conventional funds.

For the first step, we use the fund manager's name and working time in RIFs to match the conventional funds' dataset. For the names that only appear in RIF managers' history, we treat them as pure RIF managers. To avoid the inconsistency of names recorded in Morningstar, such as using abbreviations to ignore the middle name in some funds, we also separately checked the first name and the last name to match the managers' information in two datasets.

For the names that appear in both datasets, we further match managers' career paths. For the managers with the same name and career path, we assume they are the same person. For some managers without detailed career paths in Morningstar, we try to build their career by collecting information from LinkedIn, the fund's official website and the SEC documents. Then, conduct the matching process.

After matching all the managers with available information, we then compare the starting time of managing RIF and the conventional funds. If a manager starts to manage the RIF with no previous work experience in conventional funds, we treat this manager as a RIF manager who only has responsible investment experience.

Appendix 4-3

A brief technical explanation of the DEA model

Following the prior literature (Charnes et al., 1978), the DEA model can be described in the following equations.

$$\max\{u_r, v_i\} = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \qquad (4.A1)$$

Subject to the following two constraints:

$$u_r \geq \varepsilon; r = 1, \ldots, s$$

$$v_i \geq \varepsilon; i = 1, \ldots, m$$

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1 \, ; j = 1, \ldots n \qquad (4.A2)$$

Where, y_{rj} are the positive known outputs of the DMU j; x_{ij} are the positive known inputs of the DMU j; u_r and v_i are the positive optimal weights which have been assigned to output and input variables, respectively; ε is a non-Archimedean constant that prevents the weights from vanishing.

The Equations (4.A1) and (4.A2) are fractional linear problems, but could be converted to linear programming problems: one input-oriented solution (seeks to minimize inputs with certain outputs) and an output-oriented model (outputs maximized with the same inputs). Based on the previous literature (Charnes et al., 1978; Banker et al., 1984; and Basso & Funari, 2003a), by setting $\sum_{i=1}^{m} v_i x_{ij}$ =1, we can obtain the input-oriented model, which is presented in Equations (4.A3) and (4.A4). The output-oriented model is obtained by letting $\sum_{r=1}^{s} u_r y_{rj}$ =1, and the model is expressed in Equations (4.A5) and (4.A6). Since our main goal is to increase the output (return and ESG performance) given a certain level of inputs, the output-oriented DEA is selected for our analysis.

$$max \sum_{r=1}^{s} u_r y_{rj} \qquad (4.A3)$$

Subject to

$$\Sigma_{i=1}^{m} v_i x_{ij} = 1$$

$$\sum_{r=1}^{s} u_r y_{rj} - \Sigma_{i=1}^{m} v_i x_{ij} \leq 0, j = 1,2, \dots, n \qquad (4.A4)$$

$$-u_r \leq -\varepsilon, r = 1,2, \dots, s$$

$$-v_i \leq -\varepsilon, i = 1,2, \dots, m$$

$$min \sum_{i=1}^{m} v_i x_{ij} \qquad (4.A5)$$

Subject to

$$\Sigma_{r=1}^{t} u_r y_{rj} = 1$$

$$\Sigma_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} \geq 0, j = 1,2, \dots, n \qquad (4.A6)$$

$$u_r \geq \varepsilon, r = 1,2, \dots, s$$

$$v_i \geq \varepsilon, i = 1,2, \dots, m$$

Chapter 5: Conclusions

5.1 Summary and Key Findings

The RIF market has become a significant part of the managed fund industry, driven by growing investor demand for products that not only deliver financial returns but also address significant non-financial issues. However, as the market has grown, so has the increasing concern that investors may not be getting the products advertised. To maintain and ensure continued trust in the ever-growing RIF market, it is crucial that funds fulfil their promises regarding ESG. This thesis investigates the ESG performance of US domestic equity RIFs across three dimensions: 1) the existence of window dressing based on portfolio holdings information, 2) fund management companies' commitment to responsible investment, and 3) fund management teams' previous work experience.

By conducting a comprehensive analysis of US domestic equity RIFs, my results show that some RIFs alter their investments to higher ESG score companies close to the end of each quarter, and such shifts disappear almost immediately after the reporting date. Such end-of-quarter clusters indicate the existence of window dressing in ESG performance. In manuscript 2, I find that improvement in fund ESG scores is more like the "icing on the cake" and will be promptly sacrificed if the fund suffers outflows, suggesting that financial returns are their primary concern. In addition, I observe that investors who choose fund management companies (FMCs) with the highest ESG commitment level are less sensitive to financial returns when taking ESG performance into consideration. These results may suggest that some RIFs are flow-chasers, which may be explained by the competitive nature of the industry as they fight to maximise their market share. As a result, they may sacrifice ESG performance to obtain higher fund inflows. Lastly, manuscript 3 documents evidence that funds with a higher proportion of managers with exclusive RIF work experience exhibit better overall fund efficiency (jointly consider financial and non-financial performance). I confirm past work experience shapes managers' asset selection and allocations.

5.2 Key Contributions

My thesis primarily contributes to two strands of literature: the extant literature on RIFs and on ESG (non-financial) performance of RIFs, by assessing RIFs' ESG performance from multiple angles. This section brings together the insights reported in the three empirical studies summarized above.

Contributing to the Responsible Investment Fund Literature

My first manuscript focuses on the potential "deceptive" behaviour of RIFs. Unlike extant papers that investigate window dressing in the context of risk (Morey & O'Neal, 2006), financial performance (Agarwal et al., 2014) or investment style (Meier & Schaumburg, 2006), I provide unique insights into ESG-based window dressing. The second manuscript provides insight into the FMCs' attitude and the emphasis they place on ESG performance. Instead of comparing the ESG performance at the fund level, either high ESG versus low ESG, or RIFs versus non-RIFs (Thompson et al., 2011; Lean et al., 2015; El Ghoul & Karoui, 2017), my research considers the importance of RIFs for an FMC to identify how differences at the FMC level translate into ESG performance for funds. My last manuscript (Chapter 4) investigates fund managers' impact, extending the manager characteristics literature (Chen et al., 2018; Cici et al., 2014; Deuskar et al., 2011) to the RI context by building a unique dataset of RIF managers' previous work experience. My results show that previous career path influences RIF managers' current investments and thus also contributes to the literature on the role of familiarity in investment decision-making for mutual funds (Hong et al., 2005; Pool et al., 2012; Gu et al., 2019).

Taken together, my thesis contributes to the RIF literature and supports greater transparency within the industry. In conducting my research, it became clear many RIFs do not explicitly state their ESG strategies or define them in much detail, leading to ambiguity in the implementation and intensity of funds' ESG strategies. Moreover, my findings of potential window dressing behaviour in ESG performance support similar behaviour highlighted by the SEC in 2021. There is compelling evidence for enhanced verification of how ESG strategies are applied within the RIF industry, to ensure accuracy and integrity in disclosures. Additionally, my results also reveal some characteristics at the fund manager level (i.e., past work experience and the tenure of RIF managers) and the FMC level (i.e., their ESG commitment level) may also lead to diverse ESG performance.

While retaining and protecting proprietary investment strategies is important, there is a reasonable need for more transparent and standardized policies to guide and monitor practices among fund managers and FMCs. It is important investment products offered to investors align with funds' announced strategies and meet investors' requirements on both ESG considerations and financial objectives. Such transparency would aid and enhance efforts toward a more consistent, comparable, efficient, clear and fair RIF market.

Insights on the ESG (Non-Financial) Performance of RIFs

In this thesis, I primarily use holding portfolio-based ESG scores to proxy fund-level ESG performance. However, I also employ other ESG performance metrics to generate further insights and consider stakeholders' different roles in real circumstances. For example, current regulatory trends primarily emphasize the Environmental aspect of ESG. In the second manuscript, I analyse both the overall score and its component parts, the E, S, and G scores and observe differences in the results of the E score. Further, using fund percentile rankings takes the general upward trend in raw scores over time into account, offering an advantage for comparing funds' ESG performance within the sample. In assessing the influence of FMCs on their funds' ESG performance, I use the change in score. As FMC-level strategies are policies with far-reaching goals, which tend to manifest as guiding principles and practice recommendations rather than as quantitative metrics (Evans et al., 2020), the change in RIFs' ESG performance is a relatively simple way to quantify FMCs' action on ESG performance.

In manuscript 3, I also include the percentage of holdings invested in the high and low ESG score companies and carbon emissions as alternative ESG performance metrics. Using varied approaches for different scenarios reflects the need for a multi-dimensional approach to assess RIFs' ESG performance, beyond score ratings. My results indicate that despite the growing importance of ESG factors, financial returns remain a primary concern for fund managers and FMCs, suggesting a comprehensive assessment framework measuring the joint financial return and ESG performance would be useful for investors. This approach should not only reflect the funds' ESG intensity but could also benchmark against current market trends and regulatory focuses. Furthermore, it should be adaptable to reflect the preferences of various stakeholders within the industry. This measure would provide a more holistic understanding of RIFs' ESG performance and decrease reliance on vague statements of investment policy intention.

5.3 Implications for Practice and Research

As an increasingly popular investment vehicle, RIFs require more transparency and governance, especially regarding how funds pursue their non-financial goals. There is often opacity with regard to disclosures for investors regarding ESG-related processes and insufficient internal ESG procedures (Bloomberg Law, 2021). For instance, only 7% of fund manager bonus structures made reference to responsible investment in 2020 (Vrublevskis & Zorila, 2023), suggesting managerial incentives likely still emphasise financial performance for many. Addressing these issues is essential not only for the integrity of the entire responsible investment industry, but also vital for various stakeholders. The results of my thesis may be useful for stakeholders, such as investors, regulators, fund managers, and fund families. Specifically:

1. In recent years, investors have raised concerns in the RIF field regarding the lack of clear classification criteria, precise investment standards, and high-quality ESG rating data (Avetisyan & Hockerts, 2017; Friede, 2019). They are demanding more information about the ESG impact generated from their investments. My results suggest that self-identified RIFs may engage in misleading behaviours, which implies investors ought to scrutinise funds closely when making investment decisions. Further, information regarding the fund's management team's past work experience and FMCs' ESG commitment level are also worth considering when making decisions around which fund to invest with.
2. Regulators (i.e., the SEC) have already noticed potential deceptive or misleading marketing practices within environmentally friendly policies (so-called greenwashing) in the US RIF market (SEC, 2021). My findings suggest stricter disclosure and reporting standards are needed in the US RIF industry. In addition, to enhance the transparency and accountability of RIFs, regulators should also monitor the capacity and quality of fund managers and fund management companies.
3. In regard to fund managers, my findings suggest that some funds may need to provide more precise and accurate information to investors to help them make informed investment decisions. While the trade-off between improving financial return and ESG performance is not purely determined by the

manager, their choices around portfolio holdings impact ESG performance. Further, past work experience may shape the understanding and implementation of ESG principles and practices.

4. For fund families, my results imply that for RIFs prioritising ESG objectives over financial returns (i.e., those funds targeting the 'true believer' investors), it is better to be more transparent in ESG policy and practice to enhance investors' trust and attract those pursuing ESG benefits in their investments. Additionally, incentives that encourage managers' emphasis on ESG considerations may impact managers' behaviour and lead to higher ESG performance.

5.4 Limitations and Future Research

5.4.1 Limitations

Every research study has limitations, and my thesis is no exception. The main limitation of the work is that I used only ESG data from Refinitiv, encompassing ESG, E, S, and G scores as well as carbon emission information for individual firms. There are several recent papers that argue ESG rating disagreements are driven by variations in data collection and methodologies across the different rating agencies (Downar et al., 2021; Christensen et al., 2022; and Berg et al., 2022). Like many researchers before me, my research faced data access limitations. I rely on Morningstar Direct and Refinitiv as data sources. Morningstar provides the fund-level Morningstar Sustainability Rating, which was launched in March 2016. Unfortunately, the oldest available data for my sample of RIFs is from September 2018, providing too few years of data. Therefore, I did not use this rating in my thesis.

5.4.2 Future Research

There are potential issues relating to RIFs' ESG performance that could be explored in future work. For instance, I find evidence suggesting that fund managers window dress to enhance their ESG performance before the portfolio disclosure date, and that the characteristics of RIF managers play a role in overall performance (jointly considering the ESG and financial return). Given these results, it may be interesting to investigate how fund managers balance pursuing financial returns and adhering to their stated ESG objectives.

This question sheds light on industry practices and may provide guidance for improving the efficiency and effectiveness of the RIF market.

Furthermore, future research could also explore the investors' perspective. Every participant plays an important role in the RIF market. My thesis conducts a comprehensive analysis from three angles: fund holdings, the fund management company, and fund managers, but it does not consider the perspective of investors. Several papers address investors' interest by measuring fund flows (Benson & Humphrey, 2008; Renneboog et al., 2011), and some papers investigate RIF investors' motivation or investment patterns (Fernandez-Perez et al., 2022; Gibson Brandon et al., 2020; Hartzmark & Sussman, 2019a; Ilhan et al., 2021), but less is known about how investors balance financial returns and ESG considerations. Some survey data have investigated investors' perspectives on ESG (PricewaterhouseCoopers LLP, 2020; Morgan Stanley, 2019). However, survey responses may differ from actual investment behaviour or may not be representative of all investors.

In addition, RIFs are trading in the same market as conventional funds, making it difficult to distinguish whether investors choose RIFs to contribute to ESG or to pursue better financial returns. It may be interesting to investigate investors' reactions to the change in ESG performance with experiment-based methodologies that could link the gap between stated preferences and real-world investment decisions. For instance, tracking investment behaviours via demo investment accounts could provide valuable insights into how investors respond when facing the actual movement of returns and ESG performance, and thereby enhancing our understanding of RIF investors.

References

Abdelsalam, O., Fethi, M. D., Matallín, J. C., & Tortosa-Ausina, E. (2014). On the comparative performance of socially responsible and Islamic mutual funds. *Journal of Economic Behavior and Organization*, *103*.

Adrianto, F., Chen, E.-T. (John), & How, J. C. Y. (2018). Cross-Subsidization in SRI Fund Families. *SSRN Electronic Journal*.

Agarwal, V., Gay, G. D., & Ling, L. (2014). Window dressing in mutual funds. *Review of Financial Studies*, *27*(11), 3133–3170.

Ahrens, Dan. (2004). *Investing in vice: the recession-proof portfolio of booze, bets, bombs, and butts*. St. Martin's Press.

Alda, M. (2020). ESG fund scores in UK SRI and conventional pension funds: Are the ESG concerns of the SRI niche affecting the conventional mainstream? *Finance research letters, 36*, 101313.

Alda, M. (2021). The environmental, social, and governance (ESG) dimension of firms in which social responsible investment (SRI) and conventional pension funds invest: The mainstream SRI and the ESG inclusion. *Journal of Cleaner Production*, *298*, 126812.

Alda, M., Muñoz, F., & Vargas, M. (2020). Socially responsible mutual fund exit decisions. *Business Ethics: A European Review, 29*(1), 82-97.

Amel-Zadeh, A., & Serafeim, G. (2018). Why and how investors use ESG information: Evidence from a global survey. *Financial Analysts Journal, 74*(3), 87-103.

Ammann, M., Bauer, C., Fischer, S., & Müller, P. (2019). The impact of the Morningstar Sustainability Rating on mutual fund flows. *European Financial Management*, *25*(3), 520-553.

Arjaliès, D. L. (2010). A social movement perspective on finance: How socially responsible investment mattered. *Journal of Business Ethics*, *92*(SUPPL 1), 57–78.

Armstrong, J. S., & Green, K. C. (2013). Effects of corporate social responsibility and irresponsibility policies. *Journal of Business Research*, *66*(10), 1922–1927.

Avetisyan, E., & Hockerts, K. (2017). The Consolidation of the ESG Rating Industry as an Enactment of Institutional Retrogression. *Business Strategy and the Environment*, *26*(3), 316–330.

Azmi, W., Mohamad, S., & Shah, M. E. (2020). Ethical investments and financial performance: An international evidence. *Pacific Basin Finance Journal*, *62*.

Bai, J. J., Ma, L., Mullally, K. A., & Solomon, D. H. (2019). What a difference a (birth) month makes: The relative age effect and fund manager performance. *Journal of financial economics*, *132*(1), 200-221.

Baker, M., Litov, L., Wachter, J. A., & Wurgler, J. (2010). Can mutual fund managers pick stocks? Evidence from their trades prior to earnings announcements. *Journal of Financial and Quantitative Analysis*, *45*(5), 1111–1131.

Bani Atta, A. A., & Marzuki, A. (2019). The Impact of Funds and Fund Family Characteristics on Fund Performance: Evidence from Malaysia. *Journal of Wealth Management & Financial Planning*, 6, 3-23.

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management science*, *30*(9), 1078-1092.

Basso, A., & Funari, S. (2001). Theory and Methodology A data envelopment analysis approach to measure the mutual fund performance. *European Journal of Operational Research*, *135*(3), 477–492.

Basso, A., & Funari, S. (2003a). Measuring the performance of ethical mutual funds: A DEA approach. *Journal of the Operational Research Society*, *54*(5), 521–531.

Basso, A., & Funari, S. (2003b). Measuring the performance of museums: classical and FDH DEA models. In *Rendiconti per gli studi economici quantitativi* (pp. 1–16).

Basso, A., & Funari, S. (2007). DEA models for ethical and non ethical mutual funds. *Mathematical Methods in Economics and Finance*, *2*(1), 21–40.

Basso, A., & Funari, S. (2014). Constant and variable returns to scale DEA models for socially responsible investment funds. *European Journal of Operational Research*, *235*(3), 775–783.

Belghitar, Y., Clark, E., & Deshmukh, N. (2017). Importance of the Fund Management Company in the Performance of Socially Responsible Mutual Funds. *Journal of Financial Research*, *40*(3), 349–367.

Bello, Z. (2005). Socially responsible investing and portfolio diversification. *Journal of Financial Research, 28*(1), 41-57.

Benson, K. L., & Humphrey, J. E. (2008). Socially responsible investment funds: Investor reaction to current and past returns. *Journal of Banking & Finance, 32*(9), 1850-1859.

Berg, F., Fabisik, K., & Sautner, Z. (2021). Is History Repeating Itself? The (Un)Predictable Past of ESG Ratings. *SSRN Electronic Journal*.

Berg, F., Kölbel, J. F., & Rigobon, R. (2022). Aggregate Confusion: The Divergence of ESG Ratings. *Review of Finance*, *26*(6), 1315–1344.

Berk, J. B., & Green, R. C. (2004). Mutual Fund Flows and Performance in Rational Markets. *Journal of Political Economy*, 112(6), 1269-1295.

Berry, T. C., & Junkus, J. C. (2013). Socially Responsible Investing: An Investor Perspective. *Journal of Business Ethics*, *112*(4), 707–720.

Bialkowski, J., & Starks, L. T. (2016). SRI funds: Investor demand, exogenous shocks and ESG profiles. Working Paper, University of Texas.

Bloomberg Law. (2021). *Growth of ESG-Related Investments & Regulatory Action.* https://www.bloomberglaw.com/external/document/X414T0OG000000/esg-professional-perspective-growth-of-esg-related-investments-r

Boffo, R., & Patalano, R. (2020), *ESG Investing: Practices, Progress and Challenges*. OECD Paris. www.oecd.org/finance/ESG-Investing-Practices-Progress-and-Challenges.pdf

Bollen, N. P. B. (2007). Mutual Fund Attributes and Investor Behavior. *Journal of Financial and Quantitative Analysis*, *42*(3), 683–708.

Borgers, A., Derwall, J., Koedijk, K., & ter Horst, J. (2015). Do social factors influence investment behavior and performance? Evidence from mutual fund holdings. *Journal of Banking & Finance, 60*, 112-126.

Brandon, R. G., Glossner, S., Krueger, P., Matos, P., & Steffen, T. (2021). *Do Responsible Investors Invest Responsibly?*. ECGI Working Paper Series in Finance.

Busch, T., Johnson, M., & Pioch, T. (2022). Corporate carbon performance data: Quo vadis?. *Journal of Industrial Ecology*, *26*(1), 350-363.

Capelle-Blancard, G., & Monjon, S. (2012). Trends in the literature on socially responsible investment: looking for the keys under the lamppost. *Business Ethics: A European Review, 21*(3), 239-250.

Capelle-Blancard, G., & Monjon, S. (2014). The Performance of Socially Responsible Funds: Does the Screening Process Matter? *European Financial Management*, *20*(3), 494–520.

Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance*, *52*(1), 57–82.

Ceccarelli, M., Ramelli, S., & Wagner, A. F. (2022). Low-carbon Mutual Funds. *SSRN Electronic Journal*.

Charnes, A., Cooper, W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, *2*(6), 429–444.

Chen, R., Gao, Z., Zhang, X., & Zhu, M. (2018). Mutual Fund Managers' Prior Work Experience and Their Investment Skill. *Financial Management*, *47*(1), 3–24.

Chevalier, J., & Ellison, G. (1997). Risk taking by mutual funds as a response to incentives. *Journal of political economy, 105*(6), 1167-1200.

Chevalier, J., & Ellison, G. (1999). Are some mutual fund managers better than others? Cross-sectional patterns in behavior and performance. *Journal of Finance*, *54*(3), 875–899.

Chieffe, N., & Lahey, K. E. (2009). Helping clients select SRI mutual funds and firms. *Journal of Financial Planning, 22*(2).

Chin, K. (2021). *SEC Review Highlights Potentially Misleading ESG Practices Among Funds.* Wall Street Journal. https://www.wsj.com/articles/secreview-highlights-potentially-misleading-esg-practices-among-funds-116180195

Christensen, D. M., Serafeim, G., & Sikochi, A. (2022). Why is Corporate Virtue in the Eye of The Beholder? The Case of ESG Ratings. *Accounting Review*, *97*(1), 147–175.

Christiansen, C., Jansson, T., Kallestrup Lamb, M., & Noren, V. (2020). Households' Investments in Socially Responsible Mutual Funds. *SSRN Electronic Journal*.

Cici, G., Gehde-Trapp, M., Göricke, M.-A., & Kempf, A. (2014). *The Investment Value of Mutual Fund Managers' Experience outside the Financial Sector*.

Cici, G., Hendriock, M., & Kempf, A. (2021). The impact of labor mobility restrictions on managerial actions: Evidence from the mutual fund industry. *Journal of Banking & Finance*, *122*, 105994.

Clare, A. (2017). The performance of long-serving fund managers. *International Review of Financial Analysis*, *52*, 152–159.

Clare, A., Sherman, M., O'Sullivan, N., Gao, J., & Zhu, S. (2022). Manager characteristics: Predicting fund performance. *International Review of Financial Analysis*, *80*.

Climent, F., & Soriano, P. (2011). Green and Good? The Investment Performance of US Environmental Mutual Funds. *Journal of Business Ethics. 103*(2), 275–287.

Coval, J. D., & Stafford, E. (2007). Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics.* 86(2), 479-512.

Crifo, P., & Mottis, N. (2016). Socially Responsible Investment in France. *Business and Society*, *55*(4), 576–593.

D'Apice, V., Ferri, G., & Intonti, M. (2021). Sustainable disclosure versus ESG intensity: Is there a cross effect between holding and SRI funds? *Corporate Social Responsibility and Environmental Management*, *28*(5), 1496–1510.

Del Guercio, D., Dann, L. Y., & Partch, M. M. (2003). Governance and boards of directors in closed-end investment companies. *Journal of Financial Economics*, *69*(1), 111–152.

Delmas, M. A., & Burbano, V. C. (2011). The drivers of greenwashing. *California management review, 54*(1), 64-87.

Deuskar, P., Pollet, J. M., Wang, Z. J., & Zheng, L. (2011). The good or the bad? Which Mutual fund managers join hedge funds? *Review of Financial Studies*, *24*(9), 3008–3024.

Dorfleitner, G., Kreuzer, C., & Laschinger, R. (2021). How socially irresponsible are socially responsible mutual funds? A persistence analysis. *Finance Research Letters*, *43*, 101990.

Dorfleitner, G., Kreuzer, C., & Sparrer, C. (2020). ESG controversies and controversial ESG: about silent saints and small sinners. *Journal of Asset Management*, *21*(5), 393-412.

Dorfleitner, G., Leidl, M., & Reeder, J. (2012). Theory of social returns in portfolio choice with application to microfinance. *Journal of Asset Management*, *13*(6), 384-400.

Doshi, H., Elkamhi, R., & Simutin, M. (2015). Managerial activeness and mutual fund performance. *Review of Asset Pricing Studies, 5*(2), 156-184.

Døskeland, T., & Pedersen, L. J. T. (2016). Investing with brain or heart? A field experiment on responsible investment. *Management Science, 62*(6), 1632-1644.

Douglas, G. & Michelle, P. (2021). *US SEC cracks down on funds "greenwashing" with new investment requirement*. Thomson Reuters. https://www.reuters.com/sustainability/us-sec-poised-ban-deceptive-esg-growth-fund-labels-2023-09-20/

Downar, B., Ernstberger, J., Reichelstein, S., Schwenen, S., & Zaklan, A. (2021). The impact of carbon disclosure mandates on emissions and financial operating performance. *Review of Accounting Studies*, *26*(3), 1137–1175.

Drempetic, S., Klein, C., & Zwergel, B. (2020). The influence of firm size on the ESG score: Corporate sustainability ratings under review. *Journal of Business Ethics*, *167*(2), 333-360.

Eccles, R. G., Lee, L. E., & Stroehle, J. C. (2020). The social origins of ESG: An analysis of Innovest and KLD. *Organization & Environment*, *33*(4), 575-596.

El Ghoul, S., & Karoui, A. (2017). Does corporate social responsibility affect mutual fund performance and flows? *Journal of Banking & Finance, 77*, 53-63.

El Ghoul, S., & Karoui, A. (2021). What's in a (Green) Name? The Consequences of Greening Fund Names on Fund Flows, Turnover, and Performance. *Finance Research Letters*, *39*, 101620.

Elaut, G., Frömmel, M., & Verbeeck, B. (2015). What is the price of a clear conscience? The performance of socially responsible investments in the BRICS countries.

Elton, E. J., Gruber, M. J., Blake, C. R., Krasny, Y., & Ozelge, S. O. (2011). The effect of holdings data frequency on conclusions about mutual fund behavior. In *Investments And Portfolio Performance* (pp. 195-205). World Scientific.

Evans, R. B., Prado, M. P., & Zambrana, R. (2020). Competition and cooperation in mutual fund families. *Journal of Financial Economics*, *136*(1), 168–188.

Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium Empirical tests. *Journal of Political Economy*, *81*(3), 607–636.

Fama, E., & French, K. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*(1), 3–56.

Fang, Y., & Wang, H. (2015). Fund manager characteristics and performance. *Investment Analysts Journal*, *44*(1), 102–116.

Fernandez-Perez, A., Garel, A., & Indriawan, I. (2022). In the mood for sustainable funds? *SSRN Electronic Journal*.

Ferriani, F., & Natoli, F. (2021). ESG risks in times of Covid-19. *Applied Economics Letters*, *28*(18), 1537–1541.

Ferruz, L., Muñoz, F., & Vargas, M. (2010). Stock picking, market timing and style differences between socially responsible and conventional pension funds: evidence from the United Kingdom. *Business Ethics: A European Review*, *19*(4), 408-422.

Financial Markets Authority. (2018). *Product disclosure statements: understanding investors' information needs*. https://www.fma.govt.nz/news-and-resources/reports-and-papers/pds/

Findlay, S., & Moran, M. (2018). Purpose-washing of impact investing funds: motivations, occurrence and prevention. *Social Responsibility Journal*.

Fisch, J. E., & Robertson, A. Z. (2023). What's in a Name? ESG Mutual Funds and the SEC's Names Rule. *Southern California Law Review, 96*(6), 1417–1451.

Forum for Sustainable and Responsible Investment. (2020). *US SIF Trends Report 2020 Executive Summary*.

Franch, M. R. B., Izquierdo, M. Á. F., & Torres, M. J. M. (2008). The role of fund management institutions in the development of socially responsible investments: An analysis of the Spanish case. *International Journal of Electronic Finance*, *2*(3), 314–329.

Frank, M. M., Poterba, J. M., Shackelford, D. A., & Shoven, J. B. (2004). Copycat funds: Information disclosure regulation and the returns to active management in the mutual fund industry. *The Journal of Law and Economics*, *47*(2), 515-541.

Friede, G. (2019). Why don't we see more action? A metasynthesis of the investor impediments to integrate environmental, social, and governance factors. *Business Strategy and the Environment*, *28*(6), 1260–1282.

Friede, G., Busch, T., & Bassen, A. (2015). ESG and financial performance: aggregated evidence from more than 2000 empirical studies. *Journal of Sustainable Finance & Investment*, *5*(4), 210-233.

Frijns, B., Gilbert, A., & Zwinkels, R. C. (2016). On the style-based feedback trading of mutual fund managers. Journal of Financial and Quantitative Analysis, 51(3), 771-800.

Fu, Y., Hua, P., & Chen, Q. (2021). Information Sharing and Sustainable Growth: Evidence from the US Mutual Fund Family. *SSRN Electronic Journal*.

Galagedera, D. U. A. (2019). Modelling social responsibility in mutual fund performance appraisal: A two-stage data envelopment analysis model with non-discretionary first stage output. *European Journal of Operational Research*, *273*(1), 376–389.

Garvey, G. T., Iyer, M., & Nash, J. (2018). Carbon footprint and productivity: does the "E" in ESG capture efficiency as well as environment. *Journal of Investment Management*, *16*(1), 59–69.

Gibson Brandon, R., Glossner, S., Krueger, P., Matos, P., & Steffen, T. (2020). *Responsible Institutional Investing Around the World*. (No. 20-13). Swiss Finance Institute.

Gibson Brandon, R., Krueger, P., & Schmidt, P. S. (2021). ESG rating disagreement and stock returns. *Financial Analysts Journal*, *77*(4), 104-127.

Gil-Bazo, J., & Ruiz-Verdú, P. (2009). The relation between price and performance in the mutual fund industry. *The Journal of Finance*, *64*(5), 2153–2183.

Gil-Bazo, J., Ruiz-Verdú, P., & Santos, A. A. P. (2010). The performance of socially responsible mutual funds: The role of fees and management companies. *Journal of Business Ethics*, *94*(2), 243–263.

Glawischnig, M., & Sommersguter-Reichmann, M. (2010). Assessing the performance of alternative investments using non-parametric efficiency measurement approaches: Is it convincing? *Journal of Banking and Finance*, *34*(2), 295–303.

Global Sustainable Investment Alliance. (2021). *2020 Global Sustainable Investment Review*.

Global Sustainable Investment Alliance. (2023). *Global Sustainable Investment Review 2022*.

Golec, J. H. (1996). The effects of mutual fund managers' characteristics on their portfolio performance, risk and fees. *Financial Services Review*, *5*(2), 133-147.

Gormley, T., Kaplan, Z., & Verma, A. (2019). *Can disclosure decrease price efficiency? Evidence from mutual fund disclosures*. Working paper.

Gottesman, A. A., & Morey, M. R. (2006). Manager education and mutual fund performance. *Journal of Empirical Finance*, *13*(2), 145–182.

Graham, J. E., Lassala, C., & Ribeiro-Navarrete, B. (2019). A fuzzy-set analysis of conditions influencing mutual fund performance. *International Review of Economics and Finance*, *61*, 324–336.

Greenwood, R., & Nagel, S. (2009). Inexperienced investors and bubbles. *Journal of Financial Economics*, *93*(2), 239–258.

Gu, Z., Li, Z., Yang, Y. G., & Li, G. (2019). Friends in need are friends indeed: An analysis of social ties between financial analysts and mutual fund managers. *Accounting Review*, *94*(1), 153–181.

Hale, J. (2021, January 28). *A Broken Record: Flows for U.S. Sustainable Funds Again Reach New Heights*. https://www.morningstar.com/articles/1019195/a-broken-record-flows-for-us-sustainable-funds-again-reach-new-heights

Hartzmark, S. M., & Sussman, A. B. (2019). Do Investors Value Sustainability? A Natural Experiment Examining Ranking and Fund Flows. *The Journal of Finance*, *74*(6), 2789–2837.

Hasford, J., & Farmer, A. (2016). Responsible you, despicable me: Contrasting competitor inferences from socially responsible behavior. *Journal of Business Research*, *69*(3), 1234–1241.

Haugen, R. A., & Lakonishok, J. (1987). *The incredible January effect: The stock market's unsolved mystery*. Irwin Professional Pub.

Hong, H., & Kacperczyk, M. (2009). The price of sin: The effects of social norms on markets. *Journal of Financial Economics*, *93*(1), 15–36.

Hong, H., Kubik, J. D., & Stein, J. C. (2005). Thy neighbor's portfolio: Word-of-mouth effects in the holdings and trades of money managers. *Journal of Finance*, *60*(6), 2801–2824.

Hu, J.L., Yu, H.E., & Wang, Y.T. (2012). Manager Attributes and Fund Performance: Evidence from Taiwan. In *Journal of Applied Finance & Banking* (Vol. 2, Issue 4). online) Scienpress Ltd.

Huang, J., Wei, K. D., & Yan, H. (2007). Participation Costs and the Sensitivity of Fund Flows to Past Performance. *The Journal of Finance*, *62*(3), 1273–1311.

Huang, S., Shi, J., Zheng, L., & Zhu, Q. (2015). *Work Experience and Managerial Performance: Evidence from Mutual Fund Mangers*.

Humphrey, J. E., & Lee, D. D. (2011). Australian Socially Responsible Funds: Performance, Risk and Screening Intensity. *Journal of Business Ethics 2011 102:4*, *102*(4), 519–535.

Humphrey, J. E., Warren, G. J., & Boon, J. (2016). What is Different about Socially Responsible Funds? A Holdings-Based Analysis. *Journal of Business Ethics*, *138*(2), 263–277.

Hung, P.H., Lien, D., & Kuo, M.S. (2020). Window dressing in equity mutual funds. *The Quarterly Review of Economics and Finance, 78*, 338-354.

Hunter, D., Sun, Z., & Benson, K. (2020). The Exclusive Role of Centralized Fund Family Management. *Journal of Financial Services Research*, *58*(2–3), 199–236.

Ibikunle, G., & Steffen, T. (2017). European green mutual fund performance: A comparative analysis with their conventional and black peers. *Journal of Business Ethics, 145*(2), 337-355.

Ilhan, E., Krueger, P., Sautner, Z., & Starks, L. T. (2021). Climate Risk Disclosure and Institutional Investors. *SSRN Electronic Journal*.

In, F., Kim, M., Park, R. J., Kim, S., & Kim, T. S. (2014). Competition of socially responsible and conventional mutual funds and its impact on fund performance. *Journal of Banking & Finance, 44*, 160-176.

Ivanisevic Hernaus, A. (2019). Exploring the strategic variety of socially responsible investment: Financial performance insights about SRI strategy portfolios. *Sustainability Accounting, Management and Policy Journal, 10*(3), 545-569.

Jiang, G. J., & Yüksel, H. Z. (2019). Sentimental mutual fund flows. *Financial Review*, *54*(4), 709–738.

Jitmaneeroj, B. (2023). Time-varying fund manager skills of socially responsible investing (SRI) funds in developed and emerging markets. *Research in International Business and Finance*, *64*, 101877.

Joliet, R., & Titova, Y. (2018). Equity SRI funds vacillate between ethics and money: An analysis of the funds' stock holding decisions. *Journal of Banking & Finance, 97*, 70-86.

Kalman, R. E. (1960). A new approach to linear filtering and prediction problems.

Kempf, A., & Osthoff, P. (2008). SRI Funds: Nomen est omen. *Journal of Business Finance & Accounting, 35*(9-10), 1276-1294.

Kempf, E., Manconi, A., & Spalt, O. (2017). Learning By Doing: The Value Of Experience And The Origins Of Skill For Mutual Fund Managers. *Available at SSRN 2124896*.

Khorana, A., Servaes, H., & Wedge, L. (2007). Portfolio manager ownership and fund performance. *Journal of Financial Economics*, *85*(1), 179–204.

Kim, S., & Yoon, A. (2020). *Analyzing Active Managers' Commitment to ESG: Evidence from United Nations Principles for Responsible Investment*.

Kim, S., & Yoon, A. S. (2022). United Nations Principles for Responsible Investment Signatories: Evangelists or Hypocrites?. *The Journal of Impact and ESG Investing*.

Kiymaz, H. (2019). Factors influencing SRI fund performance. *Journal of Capital Markets Studies*, *3*(1), 68–81.

Kurniawan, M., How, J., & Verhoeven, P. (2016). Fund governance and style drift. *Pacific-Basin Finance Journal, 40*, 59-72.

Lean, H. H., Ang, W. R., & Smyth, R. (2015). Performance and performance persistence of socially responsible investment funds in Europe and North America. *The North American Journal of Economics and Finance, 34*, 254-266.

Leite, P., & Cortez, M. C. (2015). Performance of European socially responsible funds during market crises: Evidence from France. *International Review of Financial Analysis*, *40*, 132–141.

Levitt, S. D., & List, J. A. (2007). What do laboratory experiments measuring social preferences reveal about the real world? *Journal of Economic perspectives, 21*(2), 153-174.

Liang, H., Sun, L., & Teo, M. (2022). Responsible hedge funds. *Review of Finance*, *26*(6), 1585-1633.

Lin, J.H., Yen, M.F., & Hsieh, W.C. (2023). Do manager characteristics matter in equity mutual fund performance? New evidence based on the double-adjusted alpha. *Pacific Basin Finance Journal*, *77*.

Lin, R., & Li, Z. (2020). Directional distance based diversification super-efficiency DEA models for mutual funds. *Omega*, *97*, 102096.

Livingston, M., Yao, P., & Zhou, L. (2019). The volatility of mutual fund performance. *Journal of Economics and Business*, *104*, 105835.

Lobe, S., & Walkshäusl, C. (2011). Vice vs. Virtue Investing Around the World. *SSRN Electronic Journal*.

Lyon, T. P., & Maxwell, J. W. (2011). Greenwash: Corporate environmental disclosure under threat of audit. *Journal of Economics & Management Strategy, 20*(1), 3-41.

Ma, L., Tang, Y., & Gómez, J. P. (2019). Portfolio Manager Compensation in the U.S. Mutual Fund Industry. *Journal of Finance*, *74*(2), 587–638.

Mallin, C. A., Saadouni, B., & Briston, R. J. (1995). The financial performance of ethical investment funds. *Journal of Business Finance & Accounting, 22*(4), 483-496.

Marques, M. R., Sampaio, J. O., & Silva, V. A. B. (2020). Window dressing in Brazilian investment funds. *Revista Contabilidade & Finanças, 31*(82), 116-128.

Marzuki, A., & Worthington, A. (2015). Comparative performance-related fund flows for Malaysian Islamic and conventional equity funds. *International Journal of Islamic and Middle Eastern Finance and Management*, *8*(3), 380–394.

Meier, I., & Schaumberg, E. (2006). Do funds window dress? Evidence for US domestic equity mutual funds, HEC Montreal, Working Paper.

Morey, M. R., & O'Neal, E. S. (2006). Window dressing in bond mutual funds. *Journal of Financial Research, 29*(3), 325-347.

Morgan Stanley. (2019). *Sustainable Signals: Individual Investor Interest Driven by Impact, Conviction and Choice Executive Summary.* https://www.morganstanley.com/content/dam/msdotcom/infographics/sustainable-investing/Sustainable_Signals_Individual_Investor_White_Paper_Final.pdf

Moskowitz, M. (1972). Choosing socially responsible stocks. *Business and society review*, *1*(1), 71-75.

Muñoz, F., Vicente, R., & Ferruz, L. (2015). Stock-picking and style-timing abilities: a comparative analysis of conventional and socially responsible mutual funds in the US market. *Quantitative Finance, 15*(2), 345-358.

Murthi, B. P. S., Choi, Y. K., & Desai, P. (1997). Efficiency of mutual funds and portfolio performance measurement: A non-parametric approach. *European Journal of Operational Research*, *98*(2), 408–418.

Nakai, M., Yamaguchi, K., & Takeuchi, K. (2016). Can SRI funds better resist global financial crisis? Evidence from Japan. *International Review of Financial Analysis*, *48*, 12–20.

Nasdaq Inc. (2022). *FINANCIAL TERMS Fund family*. https://www.nasdaq.com/glossary/f/fund-family

Niessen-Ruenzi, A., & Ruenzia, S. (2019). Sex matters: Gender bias in the mutual fund industry. *Management Science*, *65*(7), 3001–3025.

Nitsche, C., & Schröder, M. (2018). Are SRI funds conventional funds in disguise or do they live up to their name? In *Research handbook of investing in the triple bottom line*. Edward Elgar Publishing.

Nofsinger, J., & Varma, A. (2014). Socially responsible funds and market crises. *Journal of Banking & Finance, 48*, 180-193.

O'Neal, E. S. (2001). Window dressing and equity mutual funds. *Babcock Graduate School of Management Working Paper*.

Ortas, E., Moneva, J. M., & Salvador, M. (2012). Does socially responsible investment equity indexes in emerging markets pay off? Evidence from Brazil. *Emerging Markets Review*, *13*(4), 581-597.

Ortiz, C., Ramírez, G., & Vicente, L. (2015). Mutual fund trading and portfolio disclosures. *Journal of Financial Services Research, 48*(1), 83-102.

Özerol, H., Metin Camgöz, S., Baha Karan, M., & Ergeneli, A. (2011). Determining the performance of individual investors: the predictive roles of demographic variables and trading strategies. *In International Journal of Business and Social Science*, 2 (18).

Parida, S. (2017). Impact of reporting delays on profitability of front-running strategies against mutual funds. *Managerial Finance*.

Parida, S., & Teo, T. (2018). The impact of more frequent portfolio disclosure on mutual fund performance. *Journal of Banking & Finance*, *87*, 427-445.

Patel, S., & Sarkissian, S. (2017). To Group or Not to Group? Evidence from Mutual Fund Databases. *Journal of Financial and Quantitative Analysis*, *52*(5), 1989–2021.

Patton, A. J., & Ramadorai, T. (2013). On the high-frequency dynamics of hedge fund risk exposures. *The Journal of Finance, 68*(2), 597-635.

Pavlova, I., & de Boyrie, M. E. (2022). ESG ETFs and the COVID-19 stock market crash of 2020: Did clean funds fare better? *Finance Research Letters*, *44*.

Pedersen, L. H., Fitzgibbons, S., & Pomorski, L. (2021). Responsible investing: The ESG-efficient frontier. *Journal of Financial Economics*, *142*(2), 572–597.

Pérez-Gladish, B., Rodríguez, P. M., M'zali, B., & Lang, P. (2013). Mutual funds efficiency measurement under financial and social responsibility criteria. *Journal of Multi-Criteria Decision Analysis*, *20*(3–4), 109–125.

Philpot, J., & Peterson, C. A. (2006). Manager characteristics and real estate mutual fund returns, risk and fees. *Managerial Finance*, *32*(12), 988-996.

Pool, V. K., Stoffman, N., & Yonker, S. E. (2012). No place like home: Familiarity in mutual fund manager portfolio choice. In *Review of Financial Studies* (Vol. 25, Issue 8, pp. 2563–2599).

Popescu, I. S., Hitaj, C., & Benetto, E. (2021). Measuring the sustainability of investment funds: A critical review of methods and frameworks in sustainable finance. In *Journal of Cleaner Production* (Vol. 314). Elsevier Ltd.

Prather, L., Bertin, W. J., & Henker, T. (2004). Mutual fund characteristics, managerial attributes, and fund performance. *Review of Financial Economics*, *13*(4), 305–326.

PricewaterhouseCoopers LLP. (2020). *Mind the gap: The continued divide between investors and corporates on ESG*. https://www.pwc.com/us/en/services/assets/pwc-esg-divide-investors-corporates.pdf

Przychodzen, J., Gómez-Bezares, F., Przychodzen, W., & Larreina, M. (2016). ESG issues among fund managers-factors and motives. *Sustainability (Switzerland)*, *8*(10).

Raghunandan, A., & Rajgopal, S. (2022). Do ESG funds make stakeholder-friendly investments?. *Review of Accounting Studies*, *27*(3), 822-863.

Refinitiv. (2021). *Refinitiv ESG Company Scores*. https://www.refinitiv.com/en/sustainable-finance/esg-scores

Refinitiv. (2022). *Environmental, Social and Governance Scores from Refinitiv - May 2022.* https://www.refinitiv.com/content/dam/marketing/en_us/documents/methodology/refinitiv-esg-scores-methodology.pdf

Ren, T., Zhou, Z., & Xiao, H. (2021). Estimation of portfolio efficiency considering social responsibility: Evidence from the multi-horizon diversification DEA. *RAIRO - Operations Research*, *55*(2), 611–637.

Renneboog, L., Ter Horst, J., & Zhang, C. (2008). Socially responsible investments: Institutional aspects, performance, and investor behavior. *Journal of Banking and Finance*, *32*(9), 1723–1742.

Renneboog, L., Ter Horst, J., & Zhang, C. (2011). Is ethical money financially smart? Nonfinancial attributes and money flows of socially responsible investment funds. *Journal of Financial Intermediation*, *20*(4), 562–588.

Revelli, C. (2017). Socially responsible investing (SRI): From mainstream to margin? *Research in International Business and Finance*, *39*, 711–717.

Revelli, C., & Viviani, J. L. (2015). Financial performance of socially responsible investing (SRI): What have we learned? A meta-analysis. *Business Ethics*, *24*(2), 158–185.

Riedl, A., & Smeets, P. (2017). Why do investors hold socially responsible mutual funds? *The Journal of Finance, 72*(6), 2505-2550.

Rohleder, M., Wilkens, M., & Zink, J. (2022). The effects of mutual fund decarbonization on stock prices and carbon emissions. *Journal of Banking and Finance*, *134*.

Salaber, J. M. (2009). *Sin Stock Returns over the Business Cycle*. Salaber, Julie M., Sin Stock Returns Over the Business Cycle (April 24, 2009). Available at SSRN: *1443188*

Schwarz, C. G., & Potter, M. E. (2016). Revisiting mutual fund portfolio disclosure. *The Review of Financial Studies*, *29*(12), 3519-3544.

Securities and Exchange Commission. (2004). *Shareholder Reports and Quarterly Portfolio Disclosure of Registered Management Investment Companies.* https://www.sec.gov/rules/2004/02/shareholder-reports-and-quarterly-portfolio-disclosure-registered-management

Securities and Exchange Commission. (2021). *The Division of Examinations' Review of ESG Investing.* https://www.sec.gov/files/esg-risk-alert.pdf

Shahrour, M. H. (2022). Measuring the financial and social performance of French mutual funds: A data envelopment analysis approach. *Business Ethics, Environment and Responsibility*, *31*(2), 398–418.

Sirri, E. R., & Tufano, P. (1998). Costly Search and Mutual Fund Flows. *The Journal of Finance*, *53*(5), 1589–1622.

Solomon, D. H., Soltes, E., & Sosyura, D. (2014). Winners in the spotlight: Media coverage of fund holdings as a driver of flows. *Journal of Financial Economics, 113*(1), 53-72.

Solórzano-Taborga, P., Alonso-Conde, A. B., & Rojo-Suárez, J. (2020). Data envelopment analysis and multifactor asset pricing models. *International Journal of Financial Studies*, *8*(2).

Sparks, R. (2002). *Socially responsible investment: A global revolution*. John Wiley & Sons.

Sustainalytics. (2020). *ESG Risk Ratings Methodology*. https://connect.sustainalytics.com/esg-risk-ratings-methodology

Swinkels, L., & Van Der Sluis, P. J. (2006). Return-based style analysis with time-varying exposures. *The European Journal of Finance, 12*(6-7), 529-552.

Tavakoli Baghdadabad, M. R., & Houshyar, A. N. (2014). Productivity and Efficiency Evaluation of US Mutual Funds. *Finance a Uver: Czech Journal of Economics & Finance*, *64*(2).

Thomä, J., Dupré, S., & Hayne, M. (2018). A taxonomy of climate accounting principles for financial portfolios. *Sustainability (Switzerland)*, *10*(2).

Thompson, J. C., Engle, A. D., & Spain, J. W. (2011). “A Rose by Any Other Name”: Models of Social Responsibility as Predictors of Financial Performance. *Journal of Financial and Economic Practice*, *11*(1), 37–51.

Trinks, P. J., & Scholtens, B. (2017). The opportunity cost of negative screening in socially responsible investing. *Journal of Business Ethics, 140*(2), 193-208.

United Nations Principles of Responsible Investment. (2023). *What are the Principles for Responsible Investment?*. https://www.unpri.org/about-us/what-are-the-principles-for-responsible-investment

Utz, S., & Wimmer, M. (2014). Are they any good at all? A financial and ethical analysis of socially responsible mutual funds. *Journal of Asset Management, 15*(1), 72-82.

van Dijk-de Groot, M., & Nijhof, A. H. J. (2015). Socially responsible investment funds: a review of research priorities and strategic options. *Journal of Sustainable Finance & Investment, 5*(3), 178-204.

Van Duuren, E., Plantinga, A., & Scholtens, B. (2016). ESG Integration and the Investment Management Process: Fundamental Investing Reinvented. *Journal of Business Ethics*, *138*, 525-533.

Vrublevskis, D., & Zorila, M. (2023). *Point of No Returns 2023 Part II: Stewardship and Governance.* ShareAction.

Whelan, T., Atz, U., Van Holt, T., & Clark, C. (2021). *ESG and financial performance: Uncovering the relationship by aggregating evidence from 1,000 plus studies published between 2015 – 2020*. Working paper, New York University.

White, H. 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica: journal of the Econometric Society*, 817–838.

Xiao, H., Liu, X., Ren, T., & Zhou, Z. (2022). Measuring the dynamic efficiency of socially responsible investment funds: evidence from dynamic network DEA with diversification. *INFOR*, *60*(4), 531–557.