HEC MONTRÉAL

Comparative Analysis of Mutual Fund Family's ESG Investment Strategies

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A Thesis Submitted in Partial Fulfillment of Requirements for a

Master of Science in Finance

August 2024

Résumé

Cette thèse examine comment les familles de fonds communs de placement intègrent les facteurs ESG dans leurs stratégies d'investissement, en mettant l'accent sur l'impact environnemental (le facteur "E") mesuré par les émissions de gaz à effet de serre. En utilisant un ensemble de données complet provenant de la base de données CRSP Mutual Funds et des données environnementales de Trucost, l'étude couvre les fonds d'actions nationales américaines entre 2016 et 2022. Les résultats indiquent une tendance significative à la baisse des intensités des émissions de GES des Scopes 1, 2 et 3, suggérant que les portefeuilles de fonds communs de placement deviennent moins intensifs en carbone au fil du temps. De plus, l'étude observe un changement dans les allocations sectorielles, avec une augmentation des investissements verts et une baisse correspondante des investissements bruns, tels que ceux dans les combustibles fossiles. L'analyse révèle également divers degrés de dispersion dans les stratégies d'investissement au sein des familles de fonds, certaines familles montrant des approches plus concentrées sur la durabilité tandis que d'autres présentent un éventail plus large de stratégies. En outre, l'analyse des rendements montre que les familles de fonds communs avec des émissions de GES plus faibles ne sacrifient pas nécessairement la performance financière, ces fonds surpassant parfois leurs homologues à plus fortes émissions. Ces résultats fournissent des perspectives sur la diversité de l'intégration des critères ESG au sein des familles de fonds communs de placement et ses implications pour la performance financière et environnementale.

Mots clés: Investissement ESG, Fonds Mutuel, Investissement durable, Stratégie d'investissement, Performance environnementale.

Abstract

This thesis examines how mutual fund families incorporate ESG factors into their investment strategies, with a focus on the environmental impact (the “E” factor) as measured by greenhouse gas (GHG) emissions. Using a comprehensive dataset from the CRSP Mutual Funds Database and Trucost’s environmental data, the study covers US domestic equity mutual funds between 2016 and 2022. The results indicate a significant downward trend in Scope 1, 2, and 3 GHG emissions intensities, suggesting that mutual fund portfolios are becoming less carbon-intensive over time. Additionally, the study observes a shift in sectoral allocations, with an increase in green investments and a corresponding decline in brown investments, such as those in fossil fuels. The analysis also reveals varying degrees of dispersion in investment strategies within mutual fund families, with some families showing more concentrated approaches to sustainability while others exhibit a broader mix of strategies. Furthermore, the returns analysis shows that mutual fund families with lower GHG emissions do not necessarily sacrifice financial performance, as these funds occasionally outperform their higher-emission counterparts. These findings provide insights into the diversity of ESG integration within mutual fund families and its implications for both financial and environmental performance.

Keywords: ESG Investing, Mutual Funds, Sustainable Investing, Investment Strategy, Environmental Performance.

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List of Abbreviations and Acronyms

Abbreviation/Acronym/Variable	Definition
ANOVA	Analysis of Variance
CRSP	Center for Research in Security Prices
CUSIP	Committee on Uniform Securities Identification Procedures
GHG	Greenhouse Gas
GVKEY	Global Company Key
IQR	Interquartile Range
ISIN	International Securities Identification Number
KDE	Kernel Density Estimate
NAICS	North American Industry Classification System
PACT Indices	Paris-Aligned and Climate Transition Indices
PERMNO	Permanent Number used by CRSP to identify companies
PPAs	Power Purchase Agreements
RECs	Renewable Energy Credits
TCUID	Trucost Unique Identifier
TNA	Total Net Assets
WRDS	Wharton Research Data Services

Acknowledgements

I would like to thank my supervisor, Professor Iwan Meier, for his constant guidance and support, as well as his insightful feedback. He is undoubtedly one of the best in sustainable finance, and I am fortunate to have had the opportunity to study under his mentorship. I also wish to extend my heartfelt thanks to my family for their unwavering support and encouragement throughout my academic journey and the completion of this thesis.

Introduction

Environmental, social, and governance (ESG) investing, which takes into account environmental, social, and governance factors, is becoming increasingly common among organizations, particularly as climate risks increase. About one in three dollars under professional management in the U.S. – approximately $12 trillion – is invested according to sustainable investment strategies (Cochardt, et al., 2023). ESG investing involves making decisions about investments that consider environmental factors such as the response to climate change and the conservation of nature. It also considers social factors like human rights and consumer protection, and governance factors such as standards for managing a company and the economy (Pastor et al., 2019). To meet investor demand, more and more fund companies are now offering "sustainable investment" funds, either by launching new ones or by rebranding existing ones.

In 2006, the launch of the Principles of Responsible Investment (PRI) drew widespread attention to ESG issues in investment decisions. This initiative, supported by the UN, is a network of investors who are committed to incorporating ESG considerations into their investment strategies in order to contribute to a more sustainable global financial system. According to an analysis of SEC filings, at least 10% of the US actively managed diversified equity funds had formally integrated ESG factors into their investment decisions in 2020. These funds represented a combined asset value of USD 366 billion (Li et al., 2023). Another significant development that led to the increased adoption of sustainable finance practices was the signing of the Paris Agreement in 2015. This international treaty aims to limit global warming to below 2° C and support countries in adapting to the impacts of climate change (UNFCCC, 2022).

The financial sector is essential for financing and raising awareness of sustainable issues. There has been significant growth in ESG investment by the mutual fund industry. In the United States, investments in ESG-related funds increased from around $22 trillion in 2016 to more than $40 trillion in 2020 (Curtis et al., 2021). The US mutual fund industry, representing $23.9 trillion in total net assets as of the end of 2020, has seen equity mutual funds dominate this space despite facing net outflows of $646 billion that year (ICI, 2021). Fund managers employ various long-term strategies to enhance performance and manage risk, particularly in light of unprecedented global events like the COVID-19 pandemic, which illustrated the impact of such crises on financial markets. Sustainability issues such as climate change also pose a growing risk to financial markets. Therefore, action plans are needed to reduce portfolios' exposure to threats such as climate risk (Humphrey & Li, 2021). However, there is no consensus on the definition or reporting standards for ESG investing. This leads to a wide variety of strategies, portfolios, and voting records among ESG funds (Cochardt et al., 2023). Moreover, it remains unclear whether corporate leaders genuinely prioritize the interests of broader stakeholders. One common concern is greenwashing: when companies misrepresent their ESG credentials in order to attract investors. In an attempt to meet the demands of investors, fund companies may claim to be ESG-conscious. However, their investment approach may not justify an ESG label and may mislead investors about the ESG-related benefits of their funds.

The purpose of this study is to determine whether mutual fund families truly integrate ESG considerations, with a particular focus on environmental impact as measured through GHG emissions, into their investment strategies and decision-making processes. This research has three main objectives: first, to analyze the ESG characteristics of mutual fund portfolios by evaluating their environmental impact; second, to assess whether mutual fund families consistently prioritize investments in ESG-friendly holdings or reduce their exposure to carbon-intensive sectors; and third, to evaluate the financial performance of these mutual fund families in relation to their ESG integration. By exploring these aspects, the study contributes to the literature on sustainable finance and responsible investment by offering a detailed empirical analysis of ESG integration within mutual fund families. It provides insights into how these families manage environmental risks and opportunities, and how such management practices influence their financial performance.

The research methodology involves several key steps. It begins with retrieving data from the CRSP Mutual Funds database, focusing on U.S. domestic equity mutual funds, and integrating this with TRUCOST's environmental data to analyze portfolio emissions and assess their environmental impact. Thresholds are established to determine which portfolios are included based on the coverage of environmental data. The analysis then examines how these portfolios are managed within their respective mutual fund families, particularly in relation to ESG considerations. Finally, the study evaluates the financial performance of these mutual fund families over the sample period, considering how ESG integration influences their returns.

The findings reveal that while many mutual fund families have made strides in reducing GHG emissions, the extent of these efforts varies widely. Some families, such as BlackRock and Fidelity, have demonstrated a strong commitment to lowering their carbon footprint, while others show less focused or sporadic practices. Additionally, the study indicates that families with greater investments in ESG-friendly holdings tend to perform comparably, if not better, in financial terms than those with less emphasis on sustainability. These results suggest that integrating ESG criteria into investment practices can effectively align environmental goals with financial performance, highlighting the potential for mutual fund families to contribute positively to sustainable finance.

The thesis begins with a comprehensive literature review of relevant studies on ESG investing, sustainable finance, and mutual fund performance. This section provides a theoretical basis for integrating ESG factors and empirical evidence of their impact on investment performance. The Data and Methodology chapter provides information on data sources and collection methods. It describes the CRSP Mutual Funds database, TRUCOST environmental data, and the integration process of these datasets. It explains the methodology for evaluating ESG characteristics, portfolio emissions, and return analysis. The Results and Analysis chapter presents the study's findings, including an analysis of ESG characteristics of mutual fund portfolios, trends in greenhouse gas emissions, and the investment strategies of mutual fund families. The financial performance of funds with varying degrees of ESG integration is compared. The conclusion of the thesis summarizes the main findings and discusses their implications for mutual fund families and policymakers, as well as suggesting directions for future research.

Literature review

Over the last decade, one of the biggest trends in asset management has been the growth of mutual funds that claim to be environmentally friendly or ESG-compliant (Environmental, Social and Governance). This trend reflects investors growing concern about environmental issues such as climate change and social inequalities, including those related to corporate governance. Investors now demand more from their investments than just financial returns; they want them to contribute to broader societal and environmental benefits. As a result, mutual fund companies have had to integrate ESG considerations into their investment strategies. The purpose of this literature review is to examine how far these companies go in doing so, comparing their investment behavior, performance and the risk of greenwashing.

Integration of ESG in Investment Strategies

The paper by Li, Ruan, Titman, and Xiang (2023) investigates the relationship between newly launched ESG mutual funds and their non-ESG sibling funds when the two coexist in the same family of mutual funds. The authors' findings point out that high ESG stocks, actively held by non-ESG funds, outperform and are overweighted over time. We find that, even controlling for fewer ex-ante constraints in their prospectuses, these non-ESG funds underperform their ESG counterparts, suggesting that mutual fund families have a strong incentive to shift performance towards ESG funds to attract inflows. We identify two potential channels through which this performance shift occurs: ESG funds trade illiquid stocks before the non-ESG siblings of these stocks and get preferential IPO allocations. The hypothesis is that managers of non-ESG sibling funds, with the ESG mandate acting as a supplemental requirement, spend more effort on high-ESG stocks and hence end with higher average ESG portfolio scores. This has indeed been supported by the evidence in the results with an average portfolio score for ESG among sibling funds being higher than a standalone non-ESG average, and the difference strengthening over time. Specifically, high-ESG stocks chosen by non-ESG siblings overwhelmingly dominate the choice of standalone non-ESG funds, whereas low-ESG stocks chosen by non-ESG siblings are dominated by those chosen by ESG funds. That is, while a non-ESG fund might select the best high-ESG stocks, the ESG sibling is pickier when it comes to low-ESG stocks, which ought to perform better as a group. The study also continues with this topic but takes a closer look at the discrepancies that occur between the flow-performance sensitivity for ESG and non-ESG funds. For ESG funds, positive performance results in higher inflows to be registered. The management strategies and tactics used by the mutual fund families focus on assigning priorities to the trades flowing to the ESG funds and the allocation of the IPOs taking place to be used to the benefit of ESG funds. In contrast, Baily and Gnabo (2022) found that the high-ESG funds have significantly different portfolio compositions at the outset, but their differences dissipated over time, which eventually led them to have a similar investment strategy. This means that the initial advantage of the ESG funds will slip through as the market adapts further and more funds incorporate the ESG criteria.

The research by Baily and Gnabo (2022) is crucial in examining the distinctiveness of ESG mutual funds compared with their conventional counterparts using a panel dataset of 2,042 US equity mutual funds over the period from the first quarter of 2013 to the fourth quarter of 2018. The authors verify whether ESG funds that are marketed as sustainable really differ in their investment strategies, financial performance, and capital flows. Their results indicated that high-ESG funds are different from conventional funds and from each other in portfolio composition, although these differences decrease over time because of a high convergence in the investment strategy. However, high-ESG funds were slightly more resilient to climate risks and effectively narrowed the performance gap with conventional funds in periods of heightened climate risks. Paradoxically, high-ESG funds underperform their conventional peers on average but receive increasing capital flows in times of climate risk, particularly to those that are less distinctive. This suggests investors probably see ESG funds as offering better protection against climate risk. The present study also takes into account public skepticism of ESG funds in terms of the reliability of such investments and the resulting phenomenon of greenwashing, which further points towards better defined and more open practices under ESG investments. Baily and Gnabo analyze the similarities and dissimilarities in portfolio holdings, financial returns, and fund flows to settle the debate that has been going on concerning the effectiveness and the genuineness of ESG investment strategies by providing empirical evidence in support of the potentials ESG funds have to enhance resiliency of portfolios to climate risks.

In contrast, Avramov, Cheng, and Tarelli (2022) provide an information acquisition model to study the implications of sustainable investing on active fund management. They research how the dispersion in cross-asset ESG characteristics and cross-fund ESG preferences affects mutual fund managers' information acquisition decisions and active management scope. The model predicts that sustainable investing amplifies fund heterogeneities in stock holdings and tracking errors, enhances the scope of active management, and improves price informativeness for assets with distinct sustainability profiles. Mutual funds with strong ESG preferences (ESG-perceptive funds) tend to overweight green stocks, while those with weak ESG preferences (ESG-indifferent funds) prefer brown stocks. It is found that signal precision is increasing in the divergence of an individual fund's ESG preference from aggregate, and the departure of an asset's ESG attributes from neutrality. The two sets of funds have therefore been presented as having significantly differing portfolio tilts and information acquisition strategies, with pronounced effects in low-volatility stock environments. It also shows that the utility loss is large under uniform portfolio policies for funds with heterogeneous ESG preferences, implying the importance of including ESG motives in optimal fund management strategies. The researchers validate the model with data showing that the performance measures are joint to both a fund's ESG considerations and managerial skills. They find that as funds hold assets with more extreme ESG profiles, portfolio dispersion and tracking error increase reflecting the enhanced information acquisition activities and distinct trading strategies adopted by these funds. This is in line with the finding that mutual fund families signing to the PRI significantly lower their portfolio emissions, indicating that indeed those fund families are integrating ESG criteria in their investment policies as measures to mitigate environmental risks. Unlike in the Avramov et al. study, though, what Humphrey and Li find to be of central importance is the effect of stakeholder attitudes toward the environment as a mechanism driving the reduction of portfolio emissions.

Peng, Zhang, Goodell, and Li (2023) critically test if the mutual funds that claim to bind to the ESG principle really do so or just claim to practice it for marketing purposes. Their work indicates that SRI mutual funds do favor companies with better ESG performance and help the ESG outcomes of investee firms. Estimating the effect of the ESG score on the likelihood of firms receiving investments from SRI mutual funds among A-share companies in China from 2010 to 2020 shows that this firm-level indicator works positively. Most importantly, by going further to control for several other factors, such as firm characteristics and potential endogeneity, they show that the investment of SRI mutual funds has a positive impact on firms' ESG performance in subsequent years. In addition, other important avenues through which SRI mutual funds work include ownership structure, international experience of the board members, and attention on social media. For example, the positive effect of SRI funds on ESG performance is stronger for state-owned enterprises (SOEs) and firms with higher media attention, which in turn indicates that those avenues boost the efficacy of ESG engagement. Besides, this paper has also focused on the motivations of SRI investment. It is worth pointing out that there are some doubts about the SRI as a marketing tool. But the truth is proven by empirical evidence to be commitment to real ESG issues. The broad contribution of these findings to literature is that they showed that the role of SRI mutual funds in enhancing corporate ESG was paramount and unchallenged, contrary to the fact that they were just similar to ordinary funds. The strength of the findings across measures and methodologies—be it propensity score matching or instrumental variable regressions—affords even more confidence about a positive effect from SRI investment onto ESG outcomes. On the whole, this is valuable research offering insight into mechanisms and effectiveness by which mutual funds focusing on SRI are empowered to have a greater influence over sustainable corporate practices and, at last, long-term ESG performance.

The research by Curtis, Fisch, and Robertson (2021) provides an in-depth empirical analysis of whether ESG mutual funds live up to their claims of prioritizing environmental, social, and governance (ESG) issues in their investment strategies. Amidst growing public and regulatory scrutiny, this study evaluates the performance and practices of ESG funds by leveraging comprehensive data from mutual funds and proprietary ESG ratings. The authors find that ESG funds do indeed offer increased exposure to ESG factors compared to non-ESG funds and tend to vote more in favor of ESG-related shareholder proposals. This behavior aligns with the funds' stated objectives and suggests that these funds are generally delivering on their promises. Furthermore, the paper addresses regulatory concerns, noting that despite rapid growth and significant inflows into ESG funds, there is no compelling reason for these funds to be subject to special regulatory measures. The study's findings challenge several criticisms made by academics and policymakers, providing evidence that ESG funds represent a differentiated and competitive investment product. The authors argue that ESG funds' integration of sustainability criteria is both effective and beneficial for investors, supporting the view that ESG investments can align with broader environmental and social goals while still adhering to fiduciary responsibilities.

Greenwashing Concerns

The issue of greenwashing is critically examined in several studies. Nitsche and Schroder (2015) explore whether socially responsible investment (SRI) mutual funds invest according to their ESG objectives. They identify SRI funds by filtering on relevant keywords in the fund names that would suggest ESG objectives in a fund's investment strategy. In addition, instead of applying a specific measure such as GHG emissions, the authors evaluate a fund's social responsibility by comparing SRI funds to conventional funds based on ESG corporate ratings from different rating agencies. Their results from the rating analysis and cross-sectional regressions demonstrate that SRI fund holdings have higher average ESG ratings than non-SRI funds and that the absolute rating differences between the funds are statistically significant. They conclude that SRI funds are not conventional funds in disguise and they invest in line with their ESG objectives since they place significantly greater weight on firms with a relatively high ESG rating. However, the study by Przychodzen, Gómez-Bezares, Przychodzen, and Larreina (2016) highlights that risk aversion and herding behavior are primary drivers behind ESG investment strategies, suggesting that some ESG funds may still engage in greenwashing by focusing more on risk management than on true ESG commitment. Przychodzen et al. investigates the motives, behavior, and characteristics shaping mutual fund managers' willingness to incorporate Environmental, Social, and Governance (ESG) issues into their investment decision-making processes. The study contributes to the literature by analyzing both "objective" (e.g., professional experience, type of fund managed, and major investment segment) and "subjective" (e.g., personal points of view, attitudes, and perceptions) manager characteristics, providing empirical evidence on factors not extensively covered in existing studies. These factors include experience in the current fund, working hours, major investment segment, type of fund managed, assets under management, forecasting horizon, tendency to herd, loss aversion, performance-based remuneration characteristics, and work motivators. Using survey evidence from fund managers across five countries, US, Canada, the UK, Spain, and Poland, the study demonstrates that the predisposition to incorporate ESG factors is stronger among managers with shorter forecasting horizons and higher reliance on business risk in portfolio management. The findings highlight that risk aversion and herding behavior are the primary drivers behind ESG investment strategies, contrasting with the notion of ESG investments being solely for value creation.

Kaustia and Yu (2021) further investigate the phenomenon of greenwashing: does the fund with an ESG—Environmental, Social, and Governance—label actually follow sustainable investing principles or rather engage in greenwashing to attract inflows? The authors use a sample of U.S. equity mutual funds, while the dependent variable in the study is the relationship of the ESG label with actual ESG performance, proxied by Morningstar's sustainability ratings (Globe ratings). The study finds that mutual funds labeled as ESG receive significantly higher inflows compared to non-ESG funds, even when their objective ESG profiles are lower. This gap suggests that lots of the ESG labelled funds may not be so devoted to sustainability in practice; they only lead to an incorrect impression for the investors. The authors also examine the conduct of mutual funds that rebrand themselves with ESG-related terms. They find that funds that are especially unsuccessful in attracting flows are more likely to rebrand and attract investor interest in their ESG-friendly fund, which is more successful in raising capital inflows. The poor performers, the underdog funds, even post-rebranding, can scarcely claim an astonishing improvement in their ESG behavior, especially when it comes to ESG proposal vote changes, which indeed remains unchanged. The greenwashing hypothesis is further fueled by this kind of noncommittal attitude toward actually improving the sustainability practices of firms by gaining a stake in them. Also, this is consistent with what Guidolin and Magnani (2024) find when they show that while ESG funds invest more in companies with higher ESG ratings and avoid sin stocks, the difference between ESG and non-ESG funds has significantly dropped over the last years.

Similarly, the research by Curtis, Fisch, and Robertson (2021) addresses regulatory concerns, noting that despite rapid growth and significant inflows into ESG funds, there is no compelling reason for these funds to be subject to special regulatory measures. The study's findings challenge several criticisms made by academics and policymakers, providing evidence that ESG funds represent a differentiated and competitive investment product. The authors argue that ESG funds' integration of sustainability criteria is both effective and beneficial for investors, supporting the view that ESG investments can align with broader environmental and social goals while still adhering to fiduciary responsibilities.

Also, the paper by Candelon, Hasse, and Lajaunie (2021) explores the prevalence of ESG-washing in the mutual fund industry, providing empirical evidence of significant information asymmetry between asset managers and investors. This study highlights the need for regulatory frameworks to enhance transparency and accountability, which aligns with the findings of Cochardt, Heller, and Orlov (2023). They demonstrate that while ESG-related name changes attract significant capital inflows, actual commitment to ESG principles varies, suggesting the need for regulatory measures to ensure authenticity in ESG investing.

Commitment and Authenticity

The commitment to ESG principles is examined in various studies. Dikolli, Frank, Guo, and Lynch (2021) investigate whether U.S. mutual funds labeled as "Sustainable Investment Overall" by Morningstar align their voting behavior with their stated ESG objectives. They find that ESG funds are significantly more likely to support ES and G proposals compared to non-ESG funds, particularly in index funds. This suggests a genuine commitment to ESG principles, contrasting with the findings of Kim and Yoon (2022), who argue that most asset managers perceive ESG issues as financially irrelevant and thus do not improve their fund-level ESG scores post-signing the UN PRI. The study by Peng, Zhang, Goodell, and Li (2023) critically examines whether SRI mutual funds genuinely commit to ESG principles or merely use them for marketing purposes. Their study finds that SRI mutual funds do prioritize companies with better ESG performance and positively influence their investee firms' ESG outcomes. This contrasts with Curtis, Fisch, and Robertson (2021), who provide evidence that while ESG funds offer increased exposure to ESG factors, there is no need for special regulatory measures as these funds generally deliver on their promises.

Furthermore, the paper by Avramov, Cheng, and Tarelli (2022) develops an information acquisition model to analyze the effects of sustainable investing on active fund management. They investigate how the dispersion in cross-asset ESG attributes and cross-fund ESG preferences influences mutual fund managers' information acquisition decisions and active management scope. The model predicts that sustainable investing amplifies fund heterogeneities in stock holdings and tracking errors, enhances the scope of active management, and improves price informativeness for assets with distinct sustainability profiles. This finding aligns with the study by Humphrey and Li (2021), which shows that mutual fund families that sign the PRI significantly lower their portfolio emissions, suggesting that these families are indeed integrating ESG criteria in their investment policies to mitigate environmental risks. However, unlike Avramov et al., Humphrey and Li emphasize the importance of stakeholder attitudes towards the environment as a mechanism driving the reduction of portfolio emissions.

The commitment to ESG principles is further highlighted by Nitsche and Schroder (2015), who explore whether socially responsible investment (SRI) mutual funds invest according to their ESG objectives. They identify SRI funds by filtering on relevant keywords in the fund names that would suggest ESG objectives in a fund’s investment strategy. In addition, instead of applying a specific measure such as GHG emissions, the authors evaluate a fund’s social responsibility by comparing SRI funds to conventional funds based on ESG corporate ratings from different rating agencies. Their results from the rating analysis and cross-sectional regressions demonstrate that SRI fund holdings have higher average ESG ratings than non-SRI funds and that the absolute rating differences between the funds are statistically significant. They conclude that SRI funds are not conventional funds in disguise and they invest in line with their ESG objectives since they place significantly greater weight on firms with a relatively high ESG rating. However, SRI funds may be taking a best-in-class approach by which they invest in the best-rated company of an industry that has poor sustainability characteristics. This gives motivation for studying the industry composition of fund portfolio holdings in order to address this limitation.

Investment Behaviors

Investment behavior in ESG funds is critically examined in various studies. The paper by Guidolin and Magnani (2024) investigates the investment behaviors of U.S. mutual funds that self-declare as ESG-driven, using panel regression methods to compare these funds with non-ESG counterparts. The authors focus on two key aspects: the implied average ESG ratings of the stocks within a fund's portfolio and the share of investments in sin stocks (e.g., tobacco, alcohol, gambling). The study reveals that ESG funds tend to invest more in companies with higher ESG ratings and avoid sin stocks more than non-ESG funds, indicating that these funds generally adhere to their stated ESG motives. This finding counters the hypothesis of widespread greenwashing. However, over time, the distinction between ESG and non-ESG funds in these behaviors has diminished, suggesting that the incidence of greenwashing may be decreasing as market practices evolve. This aligns with the findings of Curtis, Fisch, and Robertson (2021), who argue that ESG funds' integration of sustainability criteria is both effective and beneficial for investors.

The study by Dikolli et al. (2021) further supports the commitment of ESG funds by showing that they are significantly more likely to support ES and G proposals compared to non-ESG funds. This suggests that ESG funds "walk the talk" by voting in line with their sustainability objectives, although the degree of support is influenced by the type of fund and its family affiliation. This finding is consistent with the results of Kim and Yoon (2022), who argue that while PRI signatories exhibit a slight decrease in fund returns post-signing, there is a notable spike in inflows, indicating that investors view PRI affiliation as a positive signal.

Peng, Zhang, Goodell, and Li (2023) critically examine whether socially responsible investment (SRI) mutual funds genuinely commit to ESG principles or merely use them for marketing purposes. Their study finds that SRI mutual funds do indeed prioritize companies with better ESG performance and positively influence their investee firms' ESG outcomes. The analysis, covering A-share companies in China from 2010 to 2020, shows that a firm's ESG score significantly increases the likelihood of receiving investment from SRI mutual funds. More importantly, after controlling for various factors, including firm characteristics and potential endogeneity, the authors find that SRI mutual fund investment positively impacts firms' ESG performance in subsequent years. The study further identifies ownership structure, board members' international experience, and social media attention as critical channels through which SRI mutual funds exert their influence. For example, the positive impact of SRI funds on ESG performance is more pronounced in state-owned enterprises (SOEs) and firms with greater media attention, suggesting that these factors enhance the effectiveness of ESG engagement.

The literature reviewed provides a comprehensive overview of the extent to which mutual fund families incorporate ESG regulations in their investment strategies. While many studies demonstrate genuine ESG integration and positive impacts on portfolio performance and risk management, concerns about greenwashing persist. The findings underscore the importance of transparency, objective measurement, and regulatory frameworks to ensure that ESG commitments are not merely rhetorical but translate into meaningful investment practices. By comparing the results across various studies, it becomes evident that while there are significant efforts towards integrating ESG criteria, the effectiveness and authenticity of these efforts vary, necessitating continued scrutiny and regulation in the ESG investment space.

Chapter 1:
Data and Methodology

1.1 Data Sources and Collection

The primary data sources for this study include the Center for Research in Security Prices (CRSP) Mutual Fund Database and Trucost Environmental Data. The CRSP Mutual Fund Database, accessed via Wharton Research Data Services (WRDS), provides comprehensive data on mutual funds, including fund characteristics, returns, and holdings. The Trucost dataset offers detailed information on greenhouse gas (GHG) emissions, including Scope 1, Scope 2, and Scope 3[1]. Greenhouse Gas emissions are categorized into three scopes by the GHG Protocol to help businesses understand and manage their emissions comprehensively. Below is a detailed description of Scope 1, Scope 2, and Scope 3 emissions.

Scope 1: Direct GHG Emissions

Scope 1 emissions are direct emissions from sources that are owned or controlled by the company. These emissions are the result of activities that the company has direct operational control over. Key sources of Scope 1 emissions include:

1. Stationary Combustion: Emissions from the combustion of fuels in stationary sources such as boilers, furnaces, and generators.
2. Mobile Combustion: Emissions from the combustion of fuels in company-owned or controlled vehicles.
3. Process Emissions: Emissions from physical or chemical processes, such as those from cement manufacturing, steel production, and chemical manufacturing.
4. Fugitive Emissions: Emissions that are not physically controlled but result from the intentional or unintentional releases of GHGs. This can include leaks from equipment, refrigerant losses, and emissions from the handling of gases.

[1] In this study we focus on Upstream Scope 3.

Scope 2: Indirect GHG Emissions from Energy

Scope 2 emissions are indirect emissions from the consumption of purchased electricity, steam, heating, and cooling. These emissions are a consequence of the company's energy use but occur at sources owned or controlled by another entity, typically an energy producer. Scope 2 emissions are categorized into two main types:

1. Location-Based: This method reflects the average emissions intensity of the grids on which energy consumption occurs (using average emission factors specific to the location).
2. Market-Based: This method reflects emissions from electricity that companies have purposefully chosen (or their lack thereof), through instruments like renewable energy credits (RECs) and power purchase agreements (PPAs).

Scope 3: Indirect GHG Emissions

Scope 3 emissions are all indirect emissions (not included in Scope 2) that occur in the value chain of the reporting company, including both upstream and downstream emissions. These emissions are a consequence of the company's activities but occur from sources not owned or controlled by the company. Scope 3 emissions typically represent the largest portion of a company's total GHG emissions, and they offer significant opportunities for GHG reduction.

The GHG Protocol Corporate Value Chain (Scope 3) Accounting and Reporting Standard identifies 15 distinct categories of Scope 3 emissions, organized into upstream and downstream activities.

Upstream Scope 3 Emissions:

1. Purchased Goods and Services: Emissions from the production of goods and services that the company purchases.
2. Capital Goods: Emissions from the production of capital goods, such as buildings, machinery, and vehicles.
3. Fuel- and Energy-Related Activities (not included in Scope 1 or Scope 2): Emissions from the production and transportation of fuels and energy purchased and consumed by the company.

4. Upstream Transportation and Distribution: Emissions from the transportation and distribution of goods in vehicles not owned or controlled by the company, including inbound and outbound logistics.
5. Waste Generated in Operations: Emissions from the disposal and treatment of waste generated by the company's operations.
6. Business Travel: Emissions from employee business travel in vehicles not owned or controlled by the company.
7. Employee Commuting: Emissions from employees commuting to and from work in vehicles not owned or controlled by the company.
8. Upstream Leased Assets: Emissions from the operation of assets leased by the company (lessee) not included in Scope 1 or Scope 2.

Downstream Scope 3 Emissions:

1. Downstream Transportation and Distribution: Emissions from the transportation and distribution of sold products in vehicles not owned or controlled by the company.
2. Processing of Sold Products: Emissions from the processing of intermediate products sold by the company by downstream companies.
3. Use of Sold Products: Emissions from the use of goods and services sold by the company.
4. End-of-Life Treatment of Sold Products: Emissions from the disposal and treatment of products sold by the company at the end of their life.
5. Downstream Leased Assets: Emissions from the operation of assets owned by the company (lessor) and leased to other entities.
6. Franchises: Emissions from the operation of franchises.
7. Investments: Emissions from the operation of investments not included in Scope 1 or Scope 2.

Understanding and managing these emissions scopes are crucial for companies aiming to reduce their overall GHG footprint and make informed decisions regarding their environmental impact (Scope 3 FAQs, 2022).

Trucost's standard intensity metrics denominate environmental impacts by a company's annual consolidated revenues in millions of US dollars. For example, carbon intensity is measured in units of tCO2e/US$ mn Revenues. These environmental intensities are useful in comparing companies both within and across different sectors, as they control for various company characteristics, such as size. This normalization makes it possible to assess the environmental efficiency of a company, providing a standardized means to evaluate and compare the sustainability performance of different companies (Trucost ESG Analysis, 2019).

1.2 Mutual Fund Family Selection

Fund and Portfolio Identification

The focus of this study is on actively-managed U.S. domestic equity mutual funds. Following the methodology employed by Doshi et al. (2015), we filtered funds using specific CRSP Style Codes, focusing on Equity (E), Domestic (D), Cap-based (C), and Style (Y) classifications. To maintain the emphasis on actively-managed funds, index and sector funds were excluded. The filtering process involved selecting funds based on relevant Lipper and Wiesenberger objective codes, Lipper classifications, and SI objective codes, while excluding certain policy categories such as bonds and balanced funds. Additionally, CRSP objective codes indicative of actively-managed equity funds were used, with further exclusions applied to other fund types. The methodology also included an analysis of "flippers," or funds that changed their CRSP style code, to distinguish them from non-flippers. Finally, to ensure the accuracy of the actively-managed fund list, text-based filters were applied to fund names to exclude index and target date funds.

Each mutual fund in the CRSP database is uniquely identified by a Fund Identifier. These funds are aggregated to the portfolio level using the CRSP Fund-Portfolio map, which links the Fund Identifier to the Portfolio Identifier and includes the report date representing the period end date. Further aggregation occurs at the holdings level using the CRSP Portfolio Holdings table, which is reported quarterly. This allows for the extraction of key details such as the security name, primary permanent identifier (PERMNO), CUSIP, number of shares, and the security's percentage of the portfolio's total net assets. Following the methodology of Doshi et al. (2015), portfolios with fewer than 10 holdings are considered outliers and are excluded from all analyses, as low coverage in these portfolios can skew results.

Data Matching and Trucost Coverage

In order to perform analysis on the carbon footprint within and across fund families, we utilized the Trucost dataset, which provides detailed annual data on Scope 1, 2, and 3 (Upstream) Greenhouse Gas (GHG) Intensities for each institution. This dataset spans from 2016 to 2022 and includes key information such as institution ID, company ID, fiscal year, period end date, and the specific intensities of GHG emissions. The period beginning in 2016 was chosen due to the increased availability of environmental data following the Paris Agreement in 2015, which likely prompted mutual fund families to incorporate regulatory considerations into their investment strategies.

The matching process involves several steps to ensure accurate alignment of data across multiple sources. Holdings data from CRSP, originally based on calendar dates, was first converted to fiscal period end dates to align with the fiscal periods used in Compustat and Trucost datasets. We then matched the CRSP PERMNO with the Compustat GVKEY using CUSIP and fiscal year-end dates, creating a PERMNO-GVKEY link that facilitated the integration of CRSP fund holdings with Compustat's firm-level data. Next, the GVKEY was linked to the Trucost TCUID using ISIN and fiscal year-end dates, establishing a GVKEY-TCUID connection that allowed us to map the emissions data directly to portfolio holdings. The final dataset includes PERMNO, GVKEY, and TCUID for each company in each portfolio covering the period from 2016 to 2022.

Figure 1: Trucost coverage (2016-2022)

The bar plot illustrates the annual Total Net Assets (TNA) coverage of portfolio holdings within our sample of actively managed U.S. domestic equity mutual funds, matched with Trucost emissions data from 2016 to 2022. Each bar represents the percentage of TNA in our sample that is covered by Trucost emissions data, with the green portion indicating the coverage percentage and the red portion representing the portion of TNA for which emissions data is missing.

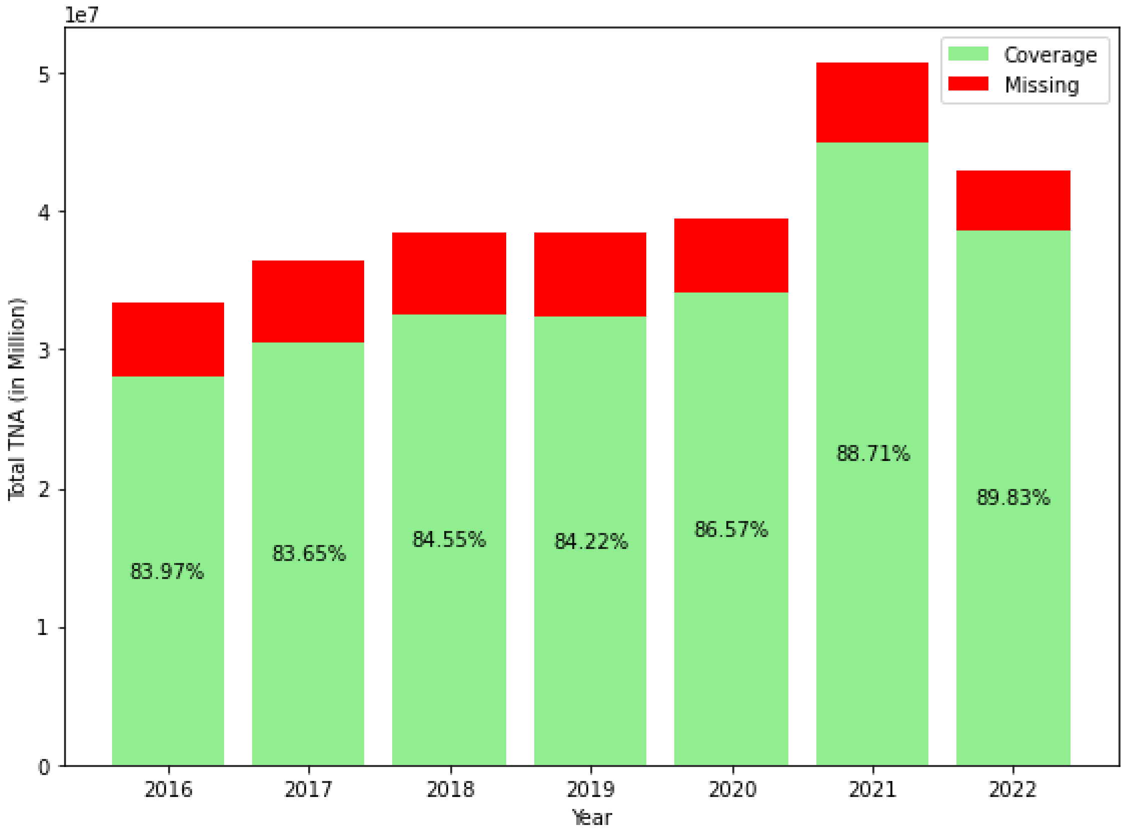


Figure 1 shows a steady improvement in Trucost coverage over the years, beginning at 83.97% in 2016 and increasing to 89.83% by 2022. This trend reflects the enhanced alignment of emissions data with the financial assets in our sample.

Portfolio Qualification and Family Selection

The coverage for each portfolio was determined by calculating the percentage of Total Net Assets (TNA) matched to Trucost data. To qualify for further analysis, portfolios needed to maintain an average of 75% TNA coverage matched with Trucost data over the years 2016 to 2022, with a minimum threshold of 70% in any given year. Identifying the correct fund family names involved a meticulous process using the fund_name table, which includes details such as the fund management name, advisor name, and manager name. Since the fund management name often differs from the family name—such as "FIDELITY DISTRIBUTORS CORPORATION" or "FIDELITY MANAGEMENT RESEARCH" corresponding to the family name "Fidelity"—we employed additional steps to ensure accuracy. When the fund management name was unclear or unavailable, we used the advisor or manager name to infer the family name, verifying these inferences with external sources like company websites, fund prospectuses, and other relevant materials. This thorough process was essential for accurately filtering and analyzing fund families that manage a substantial number of portfolios.

Figure 2: Distribution of portfolio counts among mutual fund families

The histogram displays the distribution of 2966 qualified portfolio counts across 462 mutual fund families for actively managed U.S. domestic equity mutual funds. These qualified portfolios meet the criteria of having at least 75% average coverage of Total Net Assets (TNA) matched with Trucost emissions data from 2016 to 2022, with a minimum of 70% coverage in any given year.

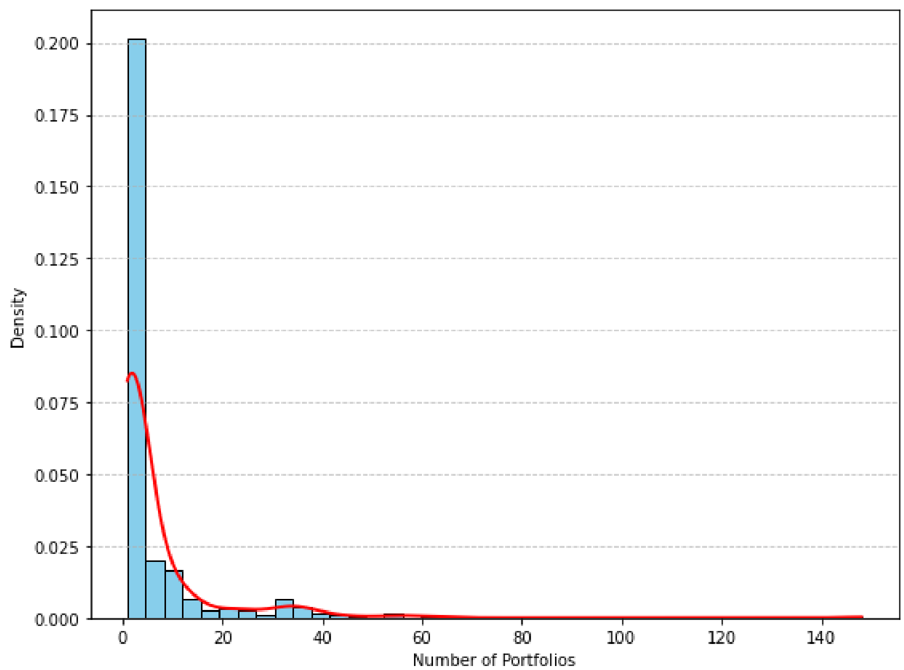


Figure 2 indicates that most mutual fund families manage a relatively small number of these qualified portfolios, with a sharp decline in frequency as the number of portfolios increases. The red line represents the density curve, emphasizing the concentration of families with fewer qualified portfolios and the extended tail of families managing a larger number of portfolios. These families may have more resources, expertise, or strategic approaches to managing multiple portfolios, which could impact their investment practices and performance.

Therefore, an additional filtration step was applied to identify families that represent a major portion of portfolios, defined as those within the 90th percentile in terms of the number of portfolios managed by their respective mutual fund families. Specifically, only families managing more than 11 portfolios were retained. This final step ensures that the analysis focuses on the most substantial and impactful mutual fund families. As a result, the process concluded with 47 mutual fund families managing a total of 1,671 portfolios over the period from 2016 to 2022.

Figure 3: Number of total, qualified, and filtered portfolios by year.

The bar chart illustrates the annual progression of portfolio qualification and filtration for actively managed U.S. domestic equity mutual funds from 2016 to 2022. The red bars represent the total number of portfolios identified each year. The blue bars show the number of portfolios that met the qualification criteria, which included achieving an average of at least 75% coverage of Total Net Assets (TNA) matched with Trucost emissions data over the period from 2016 to 2022, with a minimum of 70% coverage in any given year. This qualification specifically ensured the inclusion of upstream Scope 3 data, which also guarantees coverage of Scope 1 and Scope 2 emissions. The green bars represent the portfolios that were further filtered through an additional step, retaining only those managed by mutual fund families within the 90th percentile in terms of portfolio count.

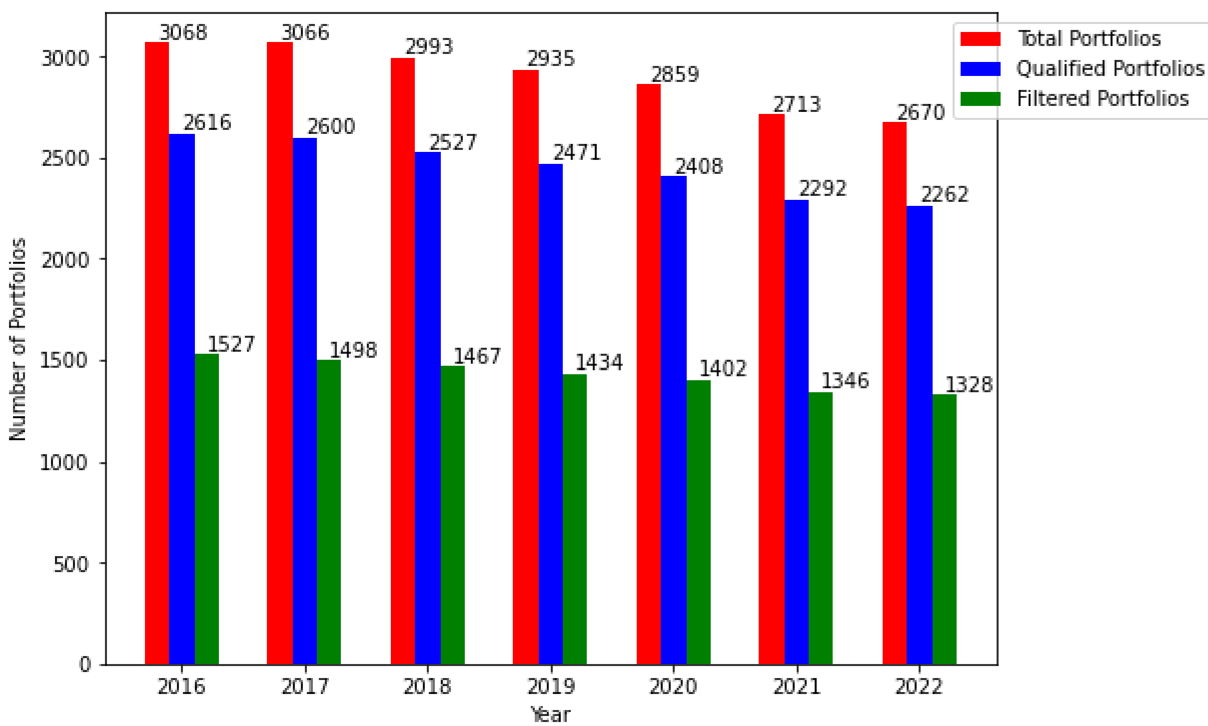


Figure 3 illustrates the qualification and filtration process applied to portfolios of actively managed U.S. domestic equity mutual funds from 2016 to 2022. The qualified portfolios were required to have an average of at least 75% coverage of Total Net Assets (TNA) matched with Trucost emissions data, with a minimum of 70% coverage in any given year, specifically focusing on the inclusion of upstream Scope 3 data, which also ensures coverage of Scope 1 and Scope 2 emissions. The green bars represent the further filtered portfolios, where additional criteria were applied to focus on the most impactful mutual fund families. This filtration process retained only those families within the 90th percentile in terms of portfolio count, specifically those managing more than 11 portfolios. The reduction in numbers from the blue bars to the green bars highlights the narrowing of the sample, which was done to concentrate the analysis on the largest and potentially most influential mutual fund families.

Figure 4: Percentage of market value by year for filtered portfolios.

This bar plot shows the percentage of market value represented by the filtered portfolios each year from 2016 to 2022. The green bars represent the percentage of the total market value associated with the filtered portfolios, which were required to have at least 75% average coverage of Total Net Assets (TNA) matched with Trucost emissions data, with a minimum of 70% coverage in any given year, and to belong to mutual fund families within the 90th percentile in terms of portfolio count, managing more than 11 portfolios. The grey portion of each bar indicates the market value of the portfolios that met the initial qualification criteria but were not included in the final filtered set.

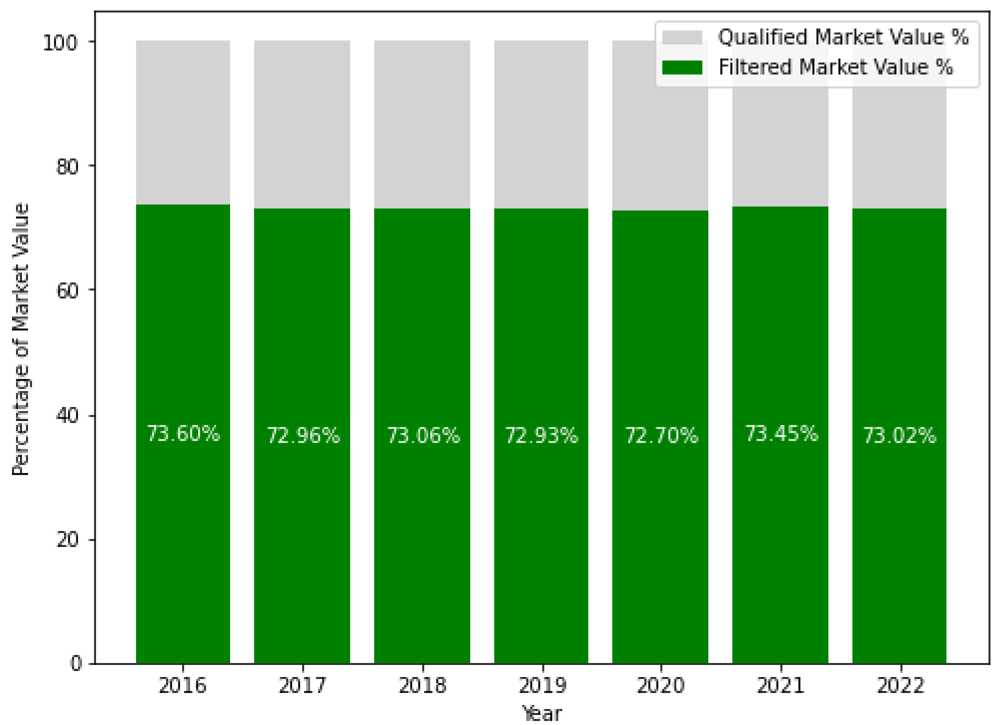


Figure 4 illustrates the proportion of filtered market value as a percentage of the qualified market value from 2016 to 2022. The percentages of the filtered market value consistently remain around

73%. This stability suggests that the filtering criteria effectively identify the substantial portion of market value within the qualified portfolios.

1.3 GHG Emission Analysis

The analysis of GHG emissions profiles for mutual fund families involved a multi-step process, beginning with the calculation of the Weighted Average Carbon Intensity for each year. This metric measures a portfolio's exposure to carbon-intensive companies, serving as a proxy for potential climate change-related risks (Frankel, Shakdwipee, and Nishikawa, 2015). This metric was calculated by aggregating the carbon intensities of each company within a portfolio and then computing the weighted average based on each company's portfolio weight.

To provide a more detailed assessment, we distinguished between Scope 1+2 and Scope 1+2+3 (Upstream) emission intensities. Scope 1+2 emissions cover direct and energy-related impacts, while the inclusion of Scope 3 emissions offers a broader perspective on the full value chain impact of investments. This distinction allowed for the evaluation of both direct operational emissions and indirect emissions from the entire supply chain. Data from Trucost was used to obtain annual GHG emission intensities for each portfolio holding, covering Scope 1, Scope 2, and Scope 3 emissions. This data included detailed information on each institution, such as institution ID, company ID, fiscal year, period end date, and the intensities of GHG emissions.

The study further involved calculating the weighted average GHG emission intensity for each portfolio within a mutual fund family. This involved weighting the aggregated GHG emission intensities (Scope 1+2+3_Upstream) by the market value of each portfolio to reflect its relative size and potential impact on the overall family emissions. The weighted emissions were then aggregated at the family level, where the total weighted emissions were divided by the total market value for each family.

To evaluate trends and identify patterns, mutual fund families were categorized into high, medium, and low emitters based on their weighted average aggregated GHG emission intensities (Scope 1+2+3_Upstream) levels in 2016. High emitters were those at or above the 75th percentile, medium emitters fell between the 25th and 75th percentiles, and low emitters were at or below the 25th percentile. By comparing the trends in GHG emissions reduction among these groups over the period from 2016 to 2022, the study aimed to identify which groups demonstrated greater reductions and the effectiveness of various investment approaches in mitigating climate-related risks.

1.4 Sector Analysis

The sector analysis aimed to evaluate the investment strategies of mutual fund families in high and low climate impact sectors, as well as the variability in their efforts to reduce brown holdings from 2016 to 2022. The analysis focuses on understanding how mutual fund families adapt their portfolios to align with sustainability goals and mitigate climate-related risks. This analysis was grounded in the detailed sector definitions provided by S&P Global Trucost, which align with the North American Industry Classification System (NAICS). These sectors are categorized into Brown (high climate impact) and Green (low climate impact) based on the S&P PACT Indices Methodology. This methodology utilizes Trucost’s sector revenues dataset to classify sectors as high or low climate impact, ensuring the index-level proportion of revenues from high-impact sectors is not less than in the benchmark index (Eurostat, 2008).

Table 1: High climate impact sectors (brown)

The table lists some of the high climate impact sectors as classified by S&P Global Trucost. The full list, consisting of 384 sectors, is provided in Appendix A.

High Climate Impact Sectors	
Abrasive product manufacturing	Biomass Power Generation
Adhesive manufacturing	Bituminous Coal and Lignite Surface Mining
Air and gas compressor manufacturing	Bituminous Coal and Lignite Surface Mining - Thermal Coal
Air conditioning, refrigeration, and warm air heating equipment manufacturing	Bituminous Coal and Lignite Surface Mining - Metallurgical Coal
…	…

Table 2: Low climate impact sectors (green)

The table lists some of the low climate impact sectors as classified by S&P Global Trucost. The full list, consisting of 88 sectors, is provided in Appendix B.

Low Climate Impact Sectors	
Accounting, tax preparation, bookkeeping, and payroll services	Insurance agencies, brokerages, and related activities
Advertising and related services	Insurance carriers
All other miscellaneous professional, scientific, and technical services	Internet publishing and broadcasting
Amusement parks, arcades, and gambling industries	Internet service providers and web search portals
…	…

The analysis involves retrieving sector data for each portfolio holding from the Trucost database, specifically using the "revenue" table. The "revenue" table provides detailed information about the sectoral composition of companies based on their revenue sources. For each company, the table includes the institution ID (institutionid), the sector ID (tcprimarysectorid), the name of the sector (primarysectorname), and the fiscal year (fiscalyear). This information allows us to accurately classify companies into sectors and assess their environmental impact. The sectoral classification is then merged with the qualified portfolio holdings table, which contains detailed information on each portfolio's holdings, using the institutionid and fiscalyear columns. This merging process ensures that each portfolio's holdings are accurately matched with their corresponding sector classifications, enabling a clear assessment of how much of each portfolio's market value is invested in a specific sector. Sectors are then categorized into Brown and Green based on their climate impact using the classification method by S&P Global Trucost (Appendix A and B). This categorization allows us to determine whether mutual fund families are divesting from Brown holdings over time and increasing their Green investments. The analysis involved examining the percentage breakdown of Green, Brown, and other investments for each year. This approach of categorizing companies based on their sectors has been used in previous studies to assess the environmental impact of investment portfolios (e.g., Hartzmark and Shue, 2022).

To assess the variability of divestment from Brown holdings, we calculated key dispersion metrics for each mutual fund family. These metrics included standard deviation, range (max-min), and percentiles (25th, 50th, 75th) of the percentage of Brown stocks. The standard deviation served as a measure of variability in the reduction efforts of a fund family over time. The analysis also involved evaluating whether mutual fund families systematically divested from Brown holdings. By calculating the average annual change in Brown holdings for each fund family, the study identified trends in managing carbon-intensive assets. To facilitate a more detailed analysis, mutual fund families were categorized into High, Moderate, and Low Brown groups based on their initial levels of Brown holdings in 2016. This categorization was determined by first calculating the weighted average percentage of Brown holdings for each mutual fund family in 2016. The High Brown group included families with Brown holdings at or above the 75th percentile, indicating a high concentration of investments in carbon-intensive sectors. The Low Brown group consisted of families with Brown holdings at or below the 25th percentile, reflecting lower exposure to these sectors. Those in between were classified as Moderate Brown families, with a balanced level of exposure to Brown sectors. This categorization enabled a comparative analysis of divestment trends across families with varying starting points over the study period.

Table 3: Sector names table

Using the revenue table, we retrieve the sector names and their corresponding IDs for each year.

institutionid	tcprimarysectorid	primarysectorname	fiscalyear
11485	524100	Insurance carriers	2019
11489	524100	Insurance carriers	2022
11534	524100	Insurance carriers	2019
11554	524100	Insurance carriers	2018
11620	524100	Insurance carriers	2019
…	…	…	…
117314764	611800	Other educational services	2019
117334353	31122A	Soybean and other oilseed processing	2020
117334353	31122A	Soybean and other oilseed processing	2022
117370536	550000	Management of companies and enterprises	2022
117667202	333511	Industrial mold manufacturing	2018

1.5 Return Analysis

The return analysis of mutual fund families from 2016 to 2022 focuses on evaluating the relationship between greenhouse gas (GHG) emission intensities and financial performance. The study begins by calculating annual returns for each mutual fund by aggregating monthly returns over each fiscal year. To provide an accurate picture of each fund's financial performance, the expense ratio was added back to these annual returns, offering insights into the gross performance before fees. These returns were then integrated with portfolio holdings data, linking each fund's financial performance to its parent fund family and their corresponding holdings through unique identifiers. Humphrey and Li (2021) apply a similar method to calculate portfolio returns, where the calculation is based on the weighted average of fund returns.

Mutual fund family's categorization, High Emitters, Medium Emitters, and Low Emitters, enabled the analysis of financial performance in relation to environmental impact, with a focus on determining whether families with lower emissions achieved better financial returns. The analysis involved calculating the weighted average annual returns for each category of emitters, with returns weighted by the market value of the funds to ensure fair comparison among families of varying sizes.

We proceed to evaluate the financial performance of mutual fund families categorized by their greenhouse gas (GHG) emission intensities, aiming to understand how these families respond to traditional financial risk factors such as market risk, size, value, momentum, profitability, and investment. This analysis seeks to uncover the financial and environmental dynamics that drive the performance of mutual fund families. The analysis involves several key steps: calculating value-weighted returns for each mutual fund family, determining excess returns, and applying a series of multifactor models to assess the influence of various financial factors on these returns.

To accurately assess the performance of mutual fund families, we begin by calculating the value-weighted returns for each family. For each portfolio within a family, the monthly return is weighted by the portfolio's market value, ensuring that larger portfolios have a proportionate impact on the family's overall return. The value-weighted return for the entire mutual fund family on a given date is then computed by aggregating these weighted returns across all portfolios within the family. Once the value-weighted returns are calculated, the next step involves computing the excess return for each mutual fund family. Excess return is defined as the difference between the value-weighted return of the mutual fund family and the risk-free rate.

Next, we apply three well-established multifactor models: the Fama-French 3-factor model, the Carhart 4-factor model, and the Fama-French 5-factor model. These models are employed to explain the variations in excess returns and to identify the impact of different financial risk factors.

1) **Fama-French 3-Factor Model:** The Fama-French 3-factor model is an extension of the Capital Asset Pricing Model (CAPM), which originally accounted only for the market risk premium. The 3-factor model adds two additional factors: size and value. The regression equation for this model is:

$$r_i - r_f = \alpha + \beta_i(r_M - r_f) + \beta_{SMB}SMB + \beta_{HML}HML + \varepsilon_i$$

Where:

- r_i is the return of the mutual fund family i,
- r_f is the risk-free rate,
- r_M is the return on the market,
- α represents the intercept (alpha), capturing the return unexplained by the factors,
- β_i is the sensitivity of the mutual fund family's return to the market risk premium,
- SMB (Small Minus Big) represents the size factor,
- HML (High Minus Low) represents the value factor,
- ϵ_i is the error term, representing the residuals of the regression.

2) **Carhart 4-Factor Model:** The Carhart 4-factor model builds on the Fama-French 3-factor model by adding a momentum factor, which accounts for the tendency of stocks that have performed well in the past to continue performing well in the future. The regression equation is:

$$r_i - r_f = \alpha + \beta_i(r_M - r_f) + \beta_{SMB}SMB + \beta_{HML}HML + \beta_{MOM}MOM + \varepsilon_i$$

Where:

- MOM (Momentum) represents the momentum factor, capturing the tendency of stocks with higher past returns to maintain that performance in the short term.

3) **Fama-French 5-Factor Model:** The Fama-French 5-factor model further extends the 3-factor model by incorporating two additional factors: profitability and investment. These factors help explain the performance of stocks based on their operating profitability and investment strategies. The regression equation is:

$$r_i - r_f = \alpha + \beta_i(r_M - r_f) + \beta_{SMB}SMB + \beta_{HML}HML + \beta_{RMW}RMW + \beta_{CMA}CMA + \varepsilon_i$$

Where:

- RMW (Robust Minus Weak) represents the profitability factor, measuring the difference in returns between firms with robust profitability and those with weak profitability,
- CMA (Conservative Minus Aggressive) represents the investment factor, capturing the difference in returns between firms that invest conservatively and those that invest aggressively.

To apply these models, time-series regressions are conducted for each mutual fund family category—High Emitters, Medium Emitters, and Low Emitters. The regressions use the excess return as the dependent variable and the factors from the respective models as independent variables. This analysis allows us to assess how sensitive the returns of mutual fund families are to various financial risk factors, including market conditions, size, value, momentum, profitability, and investment strategies. The financial factor data required for the multifactor models, including the market risk premium (mktrf), size (SMB), value (HML), momentum (MOM), profitability (RMW), and investment (CMA), is sourced from Kenneth R. French's data library[2]. The regression models are estimated using the Ordinary Least Squares (OLS) method through the Python statsmodels library. The statistical significance of the estimated coefficients is tested against the null hypothesis that alpha equals zero, with p-values compared to significance levels of 1%, 5%, and 10%.

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

Chapter 2:
Results and Analysis

2.1 Overview of Dataset

The dataset includes actively-managed U.S. domestic equity mutual funds from the CRSP Mutual Fund Database and their corresponding holdings, and GHG emissions data from Trucost. Given the process for identifying and selecting qualified portfolios and families based on defined criteria, the final dataset covers the period from 2016 to 2022 and includes 1,671 unique portfolios and 47 unique families.

Table 4: Overview of families' holdings

This table provides a summary of the total market value and number of portfolios for each parent company from 2016 to 2022. The parent companies are listed in descending order based on their percentage of total market value. The last row of the table presents the overall totals for all parent companies, indicating that the combined total market value amount to approximately 215.07 trillion, with 1,671 portfolios, accounting for 100% of the total market value.

	Family	No_Portfolio	market_val (in millions)	market_val %
1	Fidelity	148	57,429,630	26.77
2	Vanguard	33	14,885,570	6.94
3	JPMorgan	31	12,323,570	5.75
4	Invesco	56	11,746,310	5.48
5	MFS	33	11,596,400	5.41
6	T. Rowe Price	31	10,834,030	5.05
7	Columbia Threadneedle	64	9,944,323	4.64
8	Franklin Templeton	60	8,264,200	3.85
9	Manulife	53	6,040,088	2.82
10	The Hartford	26	5,903,821	2.75
11	Prudential	48	4,914,309	2.29
12	Equitable	56	4,896,145	2.28
13	Principal	32	4,845,381	2.26
14	Morgan Stanley	40	3,817,926	1.78
15	Wells Fargo	34	3,124,741	1.46
16	Macquarie	35	2,991,716	1.39
17	BlackRock	35	2,517,842	1.17

	Family	No_Portfolio	market_val (in millions)	market_val %
18	SEI Investments	43	2,462,617	1.15
19	Janus Capital	25	2,421,825	1.13
20	American Century	37	2,306,939	1.08
21	New York Life	19	2,083,348	0.97
22	Victory Capital	38	2,019,602	0.94
23	BNY Mellon	36	1,719,708	0.80
24	AIG	38	1,644,037	0.77
25	Alger	23	1,640,349	0.76
26	Voya	31	1,511,667	0.70
27	Putnam	33	1,444,191	0.67
28	Neuberger Berman	24	1,368,793	0.64
29	Jackson National	31	1,301,058	0.61
30	Brighthouse Financial	23	1,287,520	0.60
31	Aegon	37	1,281,779	0.60
32	Paper Excellence	19	1,278,474	0.60
33	Lord Abbett	24	1,276,100	0.59
34	Thrivent	28	1,252,646	0.58
35	Aristotle	42	1,130,327	0.53
36	MassMutual	34	1,127,235	0.53
37	Nationwide	36	1,124,133	0.52
38	Goldman Sachs	32	968,991	0.45
39	Deutsche Bank AG	18	915,985	0.43
40	Virtus	22	899,943	0.42
41	Nuveen	28	873,520	0.41
42	Federated Hermes	17	867,658	0.40
43	AMG	36	819,701	0.38
44	Lincoln National	21	503,285	0.23
45	Western & Southern	21	484,427	0.23
46	Royce	18	314,598	0.15
47	Allianz	22	95,851	0.04
	Total	**1,671**	**214,502,309**	**100**

Table 4 displays the distribution of market value among selected mutual fund families, revealing that Fidelity leads with a significant market value, representing 26.70% of the total market value, managed through 148 portfolios. Vanguard follows with a 6.92% across 34 portfolios. JPMorgan, Invesco, MFS, and T. Rowe Price also hold substantial market values, each managing over 30 portfolios, making up 5-6% of the total market value each. Overall, the total market value managed by all 48 families is approximately 215.07 trillion dollars. This data underscores the concentration of market value among a few large families, indicating their significant influence on market practices and trends, while providing insights into the scale and scope of investments across different families.

2.2 GHG Emission Analysis

In the pursuit of sustainable investment strategies, understanding the carbon footprint of mutual fund families is crucial. The Weighted Average Carbon Intensity metric serves as a key indicator of a portfolio's exposure to carbon-intensive companies, thereby highlighting potential risks associated with climate change. This analysis evaluates the trends in greenhouse gas (GHG) emissions intensities of families from 2016 to 2022, providing insights into how investment strategies are evolving in response to environmental challenges and regulatory pressures. By analyzing the GHG emission intensities of portfolios, investors can assess the extent to which mutual fund families are aligning their investment strategies with sustainability goals. This analysis distinguishes between Scope 1 and 2 emissions, which cover direct and energy-related impacts, and Scope 1, 2, and 3 emissions, which encompass the full value chain impact. Understanding these differences is critical for investors aiming to make informed decisions based on a comprehensive assessment of environmental impact.

Figure 5: Trends in weighted average GHG emission intensities

The line plot shows the trends in average GHG emission intensities, distinguishing between Scope 1 and 2 emission intensity (blue line) and Scope 1, 2, and 3(Upstream) emission intensity (red line) from 2016 to 2022.

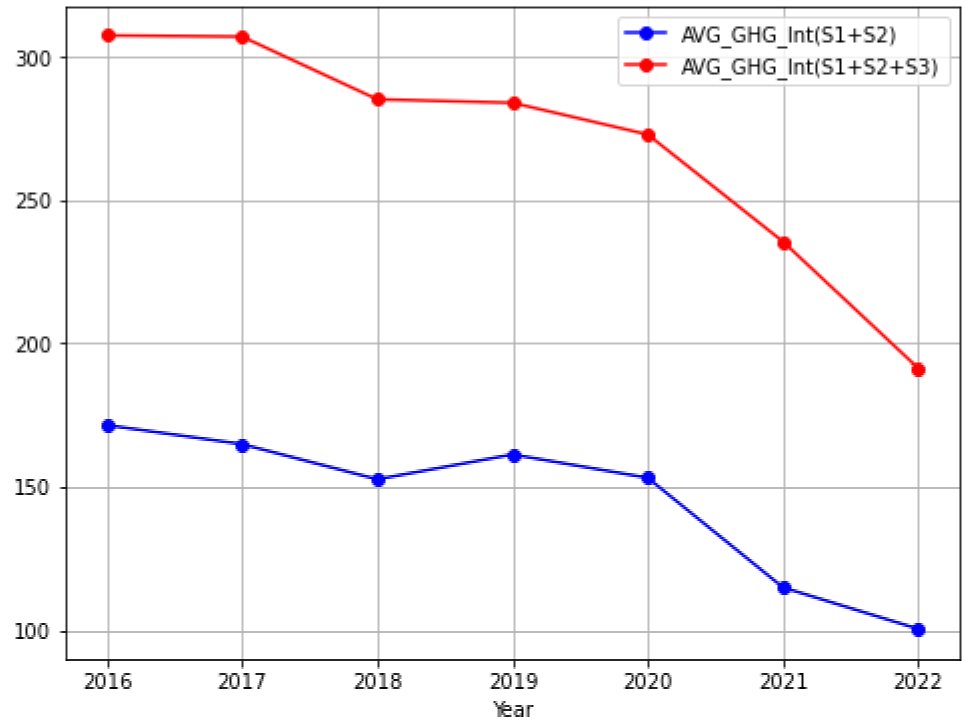


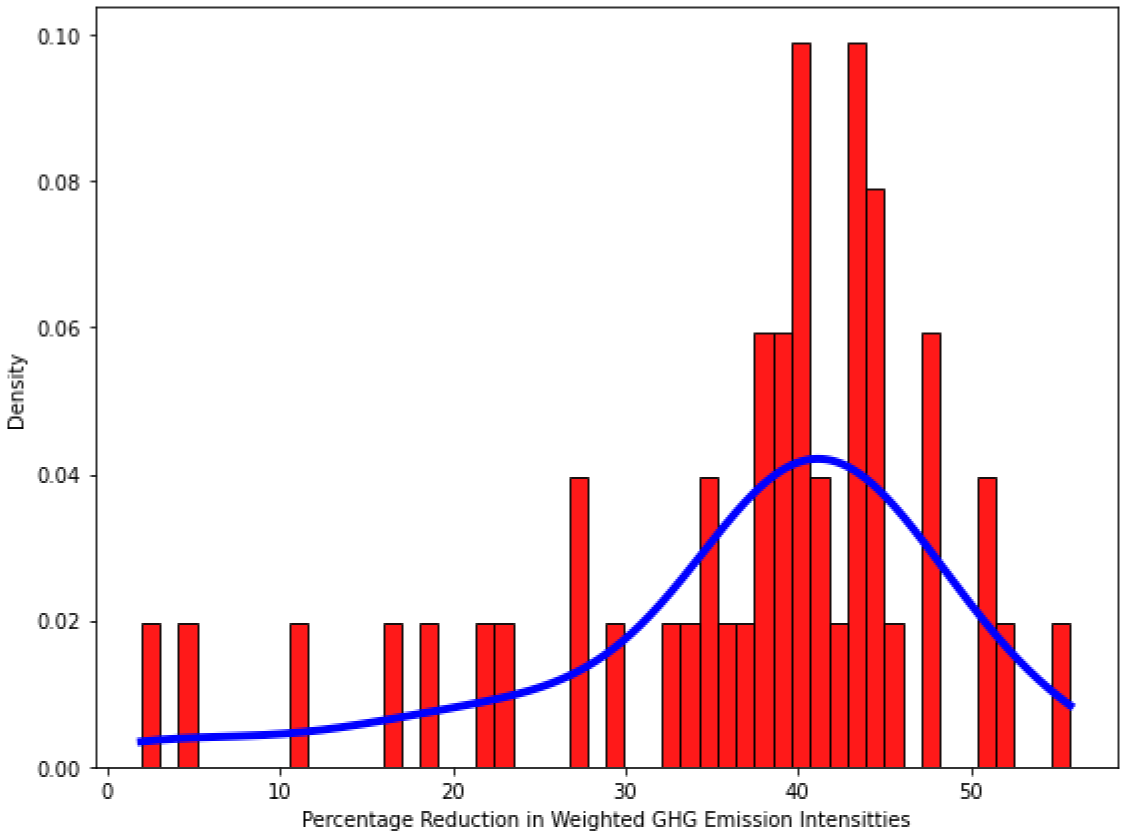
Figure 5 illustrates the trends in weighted average GHG emission intensities, distinguishing between Scope 1+2 and Scope 1+2+3 emissions. Both metrics (Scope 1+2 and Scope 1+2+3) exhibit a downward trend over the years. This indicates a general reduction in GHG emissions among the companies in the sample. The average GHG emissions for Scope 1+2 decreased from 171.52 in 2016 to 100.41 in 2022. The average GHG emissions for Scope 1+2+3 decreased more sharply from 307.32 in 2016 to 191.16 in 2022. The sharper decline in Scope 1, 2, and 3 emissions suggests that companies are making more significant efforts to reduce not only their direct emissions (Scope 1 and 2) but also their indirect emissions (Scope 3). The observed downward trends in GHG emissions suggest that mutual fund families are increasingly aligning their investments with sustainable practices.

Analysis of GHG Emission Reductions in Mutual Fund Families

The purpose of this analysis is to assess the effectiveness of mutual fund families in reducing their GHG emission intensities between 2016 and 2022. By examining the percentage reductions in weighted GHG emission intensities, which include Scope 1, Scope 2, and Scope 3 (upstream) emission intensities, we aim to identify the fund families that have made notable progress in lowering their GHG emission. Additionally, this analysis seeks to understand the broader distribution of these reductions across the industry, providing insights into the varying levels of reduction among different families in their sustainability efforts.

To calculate these reductions, we calculated the weighted GHG emission intensity for each fund by dividing the total GHG emission intensities (Scope 1 + Scope 2 + Scope 3_Upstream) by the market value of the fund's holdings, ensuring that larger funds had a proportional impact on the overall emissions of the family. The percentage reduction in GHG emissions for each family was determined by comparing the weighted GHG emission intensities between the earliest and latest years of data. This percentage reduction was then used to rank the families, highlighting those that have made the most notable progress in reducing their emissions. By analyzing these results, we can better understand the effectiveness of GHG reduction approaches across the mutual fund industry and identify best practices that other families can follow.

Figure 6: Distribution of weighted GHG emission % reduction for families (2016-2022). This figure illustrates the distribution of percentage reductions in weighted GHG emission intensities among mutual fund families from 2016 to 2022. These reductions are calculated based on the percentage change between the earliest and latest weighted averages of Scope 1, Scope 2, and Scope 3 (upstream) emissions over the period. The red histogram represents the density of reductions, with the height of each bar indicating the relative frequency of families achieving specific levels of reduction. The histogram is normalized to display probability density rather than absolute counts, allowing for a clearer comparison of reduction levels across different families. The blue Kernel Density Estimate (KDE) curve provides a smoothed visualization of the data distribution, highlighting the overall trend and concentration of reduction levels among the mutual fund families.



From the Figure 6, it is evident that most families achieved reductions clustered around the central range, with fewer families reaching the extreme high or low ends of the spectrum. The distribution is skewed, with a peak around moderate reductions, indicating that most mutual fund families have achieved moderate GHG reductions. However, the right skew suggests that some families have achieved higher reductions.

Table 7: Families with the highest reductions in GHG emission intensities over 2016-2022. This table identifies mutual fund families in the 75th percentile for GHG emission intensity reductions. The families listed achieved the most significant reductions in GHG emission intensities from 2016 to 2022. The ranking is based on the percentage reduction in their weighted average GHG emission intensities, which aggregate Scope 1, Scope 2, and Scope 3 (upstream) emissions across their portfolios. The "GHG % Reduction" column reflects the percentage decrease in GHG emission intensities over this period. The "No_Portfolio" column indicates the number of portfolios within each family over this period.

	Family	No_Portfolio	GHG %_Reduction
1	BlackRock	35	55.77
2	Lord Abbett	24	52.46
3	Macquarie	35	50.89
4	Federated Hermes	17	50.59
5	Equitable	56	47.86
6	American Century	37	47.73
7	Principal	32	47.38
8	SEI Investments	43	45.73
9	Janus Capital	25	44.69
10	Deutsche Bank AG	18	44.26
11	Alger	23	44.24
12	T. Rowe Price	31	44.22

Table 7 lists families such as BlackRock, Lord Abbett, Macquarie, and Federated Hermes, which have achieved reductions of more than 50% in GHG emission intensities from 2016 to 2022. These reductions are calculated based on the percentage change between the earliest and latest weighted averages of Scope 1, Scope 2, and Scope 3 (upstream) emissions over the period. These families stand out for their strong commitment to reducing GHG emission intensities, serving as exemplary models for other fund families to follow. In contrast, as Figure 6 reveals, some of their peers, such as Allianz and Western & Southern, have shown lower percentage reductions over the same period.

Evaluating GHG Emission Intensities Reduction Among Mutual Fund Families

To evaluate the GHG emission reduction within mutual fund families, we first compared their annual weighted average GHG emission intensities (Scope 1 + Scope 2 + Scope 3_Upstream) to assess the overall reduction over time. This process involved calculating the weighted average

GHG emission intensities for each fund and then for each mutual fund family by dividing the total weighted GHG emission intensities by the total market value of the family. This normalization ensured that emission intensities were adjusted for the size of the investment, allowing for fair comparisons between families of different sizes.

Families were categorized into high, medium, and low emitters based on the 25th and 75th percentiles of their initial, 2016, weighted average GHG emission intensities. Families with emissions at or below the 25th percentile were classified as low emitters, while those at or above the 75th percentile were classified as high emitters. Those in between were categorized as medium emitters. By analyzing trends in weighted average GHG emission intensity reductions from 2016 to 2022 across these categories, we aimed to determine which groups demonstrated greater reductions. Additionally, the analysis sought to identify specific mutual fund families within each category that achieved higher reductions in GHG weighted average emission intensities.

Table 5: Categorized families based on the GHG emission reduction from 2016 to 2022.
This table categorizes mutual fund families into "High," "Medium," and "Low" emitters based on their weighted average GHG emission intensities in 2016, which include the aggregate Scope 1, Scope 2, and Scope 3 (upstream) emission intensities. The "Reduc %" column indicates the percentage reduction in these weighted average GHG emission intensities from 2016 to 2022. The table also tracks the trends of these GHG emission intensities across the years for each fund family. Fund families are sorted first by their 2016 emission category and then by the magnitude of their reduction, with higher reductions listed first.

	Family	2016	2017	2018	2019	2020	2021	2022	Reduc %
Medium	BlackRock	323.12	302.14	277.60	243.23	209.21	173.96	142.91	55.77
	Macquarie	328.24	320.61	295.22	264.49	260.18	203.01	161.19	50.89
	Equitable	320.92	294.97	285.50	269.82	250.43	214.64	167.33	47.86
	Principal	331.76	329.96	289.54	271.16	264.04	220.51	174.57	47.38
	T. Rowe Price	331.19	312.23	277.32	288.45	277.11	238.79	184.75	44.22
	AIG	298.04	294.77	263.47	255.91	241.34	207.32	168.38	43.50
	Prudential	308.49	287.59	265.37	265.54	267.70	228.84	174.54	43.42
	Invesco	324.91	367.56	339.61	330.67	337.56	271.18	184.41	43.24
	The Hartford	311.47	310.96	275.92	268.53	254.44	218.66	180.33	42.10
	Jackson National	317.40	290.09	280.35	283.48	286.50	267.28	186.74	41.17
	Vanguard	307.86	303.88	290.50	294.06	285.45	239.93	181.90	40.91
	Putnam	333.00	306.46	314.43	310.10	296.05	249.00	200.48	39.80

	Family	2016	2017	2018	2019	2020	2021	2022	Reduc %
	Nationwide	331.39	327.09	288.23	294.32	287.99	253.55	199.63	39.76
	Aegon	324.76	321.12	316.61	270.35	234.34	208.02	197.08	39.32
	Brighthouse Financial	314.71	288.04	262.98	271.08	273.68	242.63	191.69	39.09
	Voya	322.74	293.98	272.90	310.15	296.30	282.63	198.38	38.53
	BNY Mellon	312.90	310.17	282.21	298.99	308.81	246.47	197.16	36.99
	Lincoln National	310.44	314.35	296.98	295.45	285.12	249.80	201.86	34.98
	Aristotle	308.76	321.27	291.74	286.88	290.72	244.90	202.38	34.45
	Columbia Threadneedle	313.68	318.49	310.91	310.15	304.91	268.21	227.20	27.57
	MFS	295.71	276.57	274.85	281.72	292.53	262.99	216.29	26.86
	Nuveen	326.90	345.02	302.20	340.15	340.15	337.07	265.87	18.67
	Allianz	307.65	321.35	320.51	402.32	391.08	423.19	301.63	1.96
	Janus Capital	280.05	261.04	252.38	295.72	247.94	216.58	154.89	44.69
	Deutsche Bank AG	290.11	301.71	286.57	250.08	260.17	190.07	161.71	44.26
	Alger	202.29	203.71	188.01	154.39	139.97	133.88	112.81	44.23
	MassMutual	284.50	277.79	261.01	269.84	248.72	212.94	170.19	40.18
	Morgan Stanley	243.14	237.45	219.40	239.86	224.79	187.97	146.37	39.80
Low	Fidelity	269.38	269.46	248.54	233.82	215.29	198.76	173.83	35.47
	Royce	284.14	311.04	299.24	274.13	283.02	250.54	186.93	34.21
	AMG	282.29	259.74	248.67	237.63	241.77	237.11	217.92	22.80
	New York Life	215.13	224.88	262.28	248.90	228.62	187.76	168.32	21.76
	Wells Fargo	259.67	326.28	309.72	329.75	307.40	254.37	217.61	16.20
	Thrivent	256.26	276.92	255.59	279.55	297.48	262.34	227.31	11.30
	Western & Southern	180.99	222.61	198.97	214.00	229.07	201.65	173.36	4.22
	Lord Abbett	404.69	395.67	358.73	324.85	306.71	231.29	192.38	52.46
	Federated Hermes	583.25	630.03	538.65	465.24	407.54	327.66	288.16	50.59
	American Century	346.94	304.79	285.63	246.67	240.42	228.96	181.34	47.73
	SEI Investments	334.41	334.99	275.98	287.51	268.13	233.24	181.48	45.73
	Virtus	367.72	365.65	423.30	349.54	285.10	241.51	206.62	43.81
High	Manulife	343.14	334.43	284.90	297.11	295.63	267.22	194.38	43.35
	Goldman Sachs	364.38	344.15	297.16	331.07	321.61	262.08	218.80	39.95
	Paper Excellence	411.23	370.89	343.28	368.55	363.96	313.81	252.16	38.68
	JPMorgan	346.18	341.60	322.04	338.85	327.11	272.19	214.74	37.97
	Neuberger Berman	354.37	336.47	331.29	330.21	302.33	257.10	221.35	37.54
	Franklin Templeton	429.85	436.44	387.74	393.21	396.24	365.96	291.45	32.20

	Family	2016	2017	2018	2019	2020	2021	2022	Reduc %
	Victory Capital	380.29	405.47	362.45	344.98	347.88	333.49	268.73	29.34

The data indicates that most mutual fund families have made substantial efforts to reduce their GHG emission intensities over the period from 2016 to 2022. High emitters generally show more significant reductions, likely due to the higher initial levels of emissions and more aggressive reduction strategies. Medium and Low emitters also demonstrate commendable reductions, with some families achieving nearly 50% reduction, reflecting their commitment to sustainability and emissions management.

Figure 7: Yearly distribution of weighted average GHG emission intensities by category. This figure presents box plots of weighted average GHG emission intensities, aggregated from Scope 1, Scope 2, and Scope 3 (upstream) emission intensities, for mutual fund families across the years 2016 to 2022. The mutual fund families are categorized into "High," "Medium," and "Low" emission groups based on their 2016 emission intensities. The box plots display the range, interquartile range (25th to 75th percentile), median, with the median indicated by a horizontal line inside the box, and outliers for the emission intensities in each year. The red, grey, and green boxes correspond to the "High," "Medium," and "Low" emission categories, respectively.

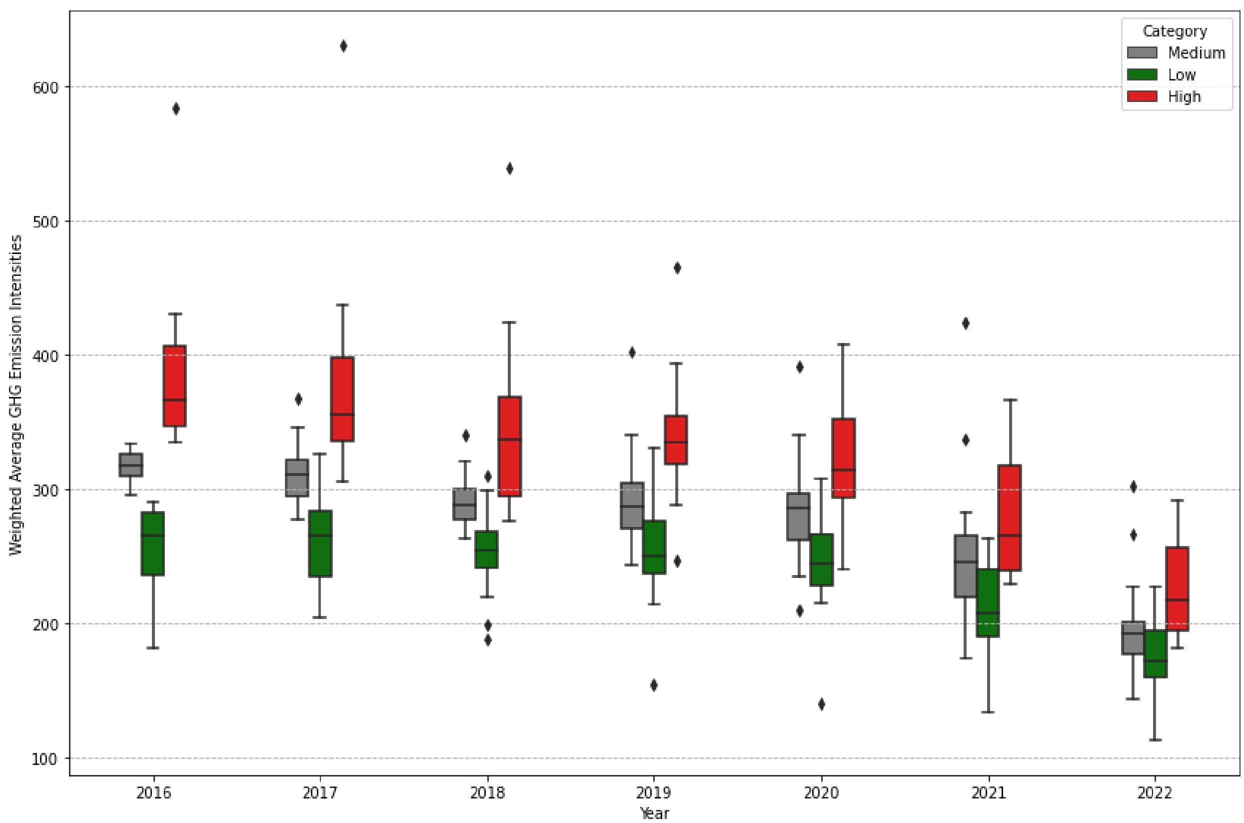


Figure 7 visualizes the distribution of weighted average GHG emission intensities for mutual fund families categorized as High, Medium, and Low emitters from 2016 to 2022. It provides insights into the average differences in medians across these three categories. There is noticeable variability in GHG emissions within the High category, as evidenced by a wide interquartile range (IQR) in some years and the presence of multiple outliers. In contrast, the IQR for Medium emitters tends to be narrower, suggesting less variability within this category. High emitters exhibit the most significant reductions in GHG emission intensities, with an average reduction of 41.61%. Medium emitters follow with an average reduction of 38.19%. Low emitters show relatively stable emissions, with less pronounced reductions, averaging 29.93%.

Systematic and Variable Approaches to GHG Emission Intensity Reductions Among Mutual Fund Families

We have observed that many mutual fund families successfully reduced their GHG emissions from 2016 to 2022. The next step is to evaluate whether these families employed systematic approaches to reducing greenhouse gas (GHG) emissions over time. By distinguishing between families with consistent reductions and those with variable outcomes, we aim to shed light on the effectiveness and consistency of GHG reduction approaches within these fund families.

To achieve this, we first calculate the weighted average GHG emission intensities for each fund and determine the overall percentage change in GHG emissions over the specified period. We then assess the dispersion of these reductions by calculating the standard deviation of the overall percentage change in GHG emissions for each family. This standard deviation serves as a measure of variability, indicating how consistent the GHG reductions have been across the funds within each family. Finally, we categorize the families based on this variability by establishing thresholds at the 25th and 75th percentiles of the standard deviation values, allowing us to identify families with systematic versus more variable approaches to GHG emission reduction.

Table 8: Families with the highest dispersion GHG emission intensity reductions. This table lists the mutual fund families with the highest dispersion in their GHG emission intensity reductions, as measured by the standard deviation of the percentage change in GHG emission intensities across their portfolios. The percentage change is calculated between the earliest and latest years of GHG emission intensities (aggregating Scope 1, Scope 2, and Scope 3 upstream emission intensities) for each portfolio within the fund families. The table includes key statistics, such as the number of portfolios within each family, the standard deviation (std_dev) of the reduction percentages, and the range of reductions (maximum and minimum values). Additionally, the 25th percentile, median, and 75th percentile values are provided to illustrate the distribution of emission reductions within each family.

	Family	No_Portfolio	std_dev	max	min	25th	Median	75th
1	Victory Capital	38	41.63	165.85	-55.74	-41.92	-32.12	-9.99
2	AMG	36	40.46	91.38	-62.85	-26.64	-12.82	24.62
3	Jackson National	31	33.45	78.43	-57.54	-40.46	-24.97	0.00
4	Federated Hermes	17	32.94	86.15	-56.76	-46.50	-34.19	-21.52
5	New York Life	19	29.79	50.30	-56.65	-50.20	-41.73	-14.15
6	BNY Mellon	36	29.75	48.88	-53.74	-38.65	-31.64	-9.27
7	Columbia Threadneedle	64	26.77	96.01	-63.07	-43.62	-32.74	-10.84
8	Deutsche Bank AG	18	26.40	28.37	-74.58	-50.95	-23.96	-10.72
9	Wells Fargo	34	26.19	60.59	-71.84	-40.82	-29.30	-0.10
10	Janus Capital	25	25.67	53.63	-58.36	-50.34	-26.75	-18.82
11	Lincoln National	21	25.65	49.76	-64.26	-47.43	-40.66	-28.84
12	Royce	18	25.16	46.50	-50.65	-37.70	-27.79	-2.91

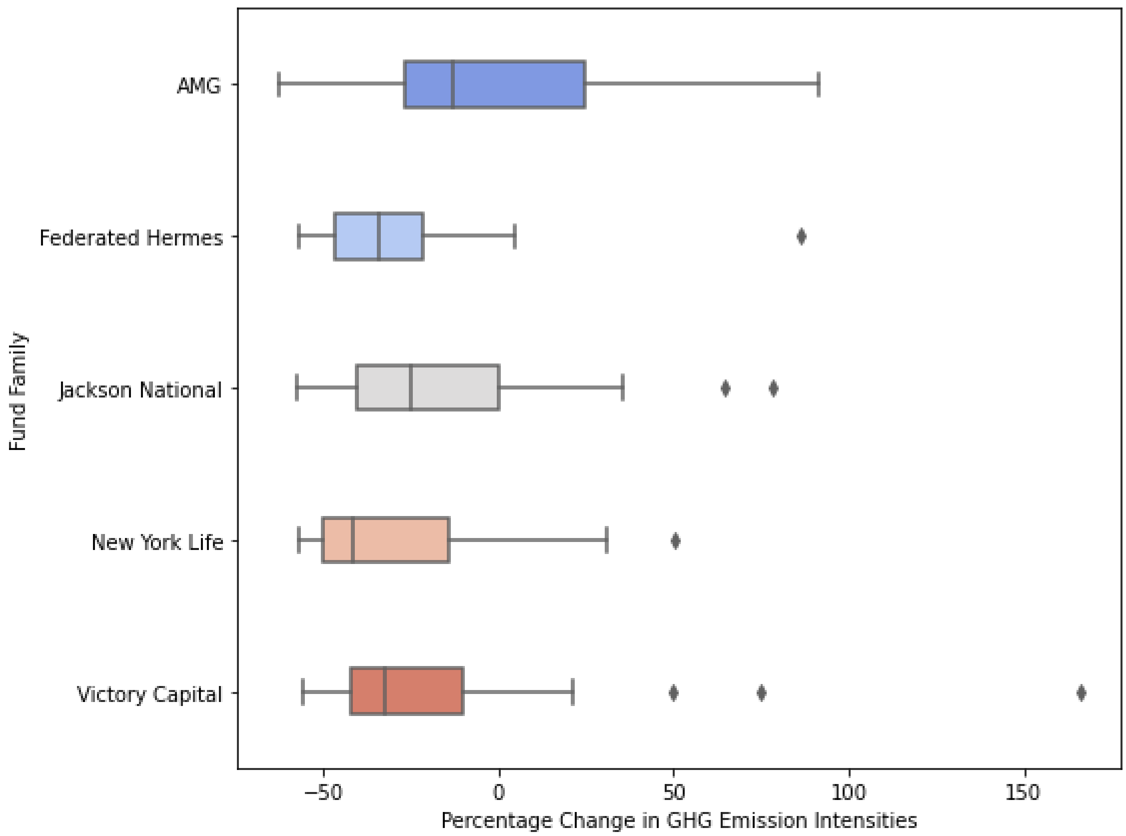
Table 9: Families with the lowest dispersion in GHG emission intensity reductions. This table lists the mutual fund families with the lowest dispersion in their GHG emission intensity reductions, as measured by the standard deviation of the percentage change in GHG emission intensities across their portfolios. The percentage change is calculated between the earliest and latest years of weighted average GHG emission intensities (aggregating Scope 1, Scope 2, and Scope 3 upstream emissions) for each portfolio. The table includes key statistics such as the number of portfolios within each family, the standard deviation (std_dev) of the reduction percentages, and the range of reductions (maximum and minimum values). Additionally, the 25th percentile, median, and 75th percentile values are provided to illustrate the distribution of emission reductions within each family.

	Family	No_Portfolio	std_dev	max	min	25th	Median	75th
1	Equitable	56	17.77	10.45	-61.27	-43.43	-32.23	-15.10
2	MFS	33	17.24	4.51	-59.50	-49.08	-42.70	-36.93
3	Principal	32	16.96	13.39	-61.67	-42.46	-34.33	-22.14

	Family	No_Portfolio	std_dev	max	min	25th	Median	75th
4	The Hartford	26	16.77	14.78	-63.74	-50.46	-43.63	-30.58
5	SEI Investments	43	16.64	21.12	-52.36	-39.95	-32.32	-19.92
6	Brighthouse Financial	23	16.54	4.69	-66.19	-42.51	-33.25	-19.00
7	Fidelity	148	16.54	29.75	-65.56	-34.88	-27.72	-11.70
8	Vanguard	33	16.31	9.60	-58.77	-43.48	-36.79	-22.37
9	Goldman Sachs	32	15.83	8.64	-58.77	-41.20	-32.46	-23.52
10	Aristotle	42	15.60	7.60	-55.71	-31.21	-20.73	-10.71
11	Alger	23	13.16	-13.60	-55.55	-50.22	-44.46	-34.61
12	T. Rowe Price	31	11.23	-12.81	-50.44	-44.36	-39.09	-34.30

Tables 8 and 9 provide insights into the variability of GHG emission intensity reductions among mutual fund families, highlighting the range of approaches and outcomes within these families. Table 8 lists the families with the highest dispersion in their GHG emission intensity reductions. These families exhibit high variability in how their portfolios have managed GHG emissions over 2016 to 2022. For instance, Victory Capital exhibits the highest standard deviation of 41.63, suggesting substantial inconsistency in reducing emissions across its 38 portfolios, with changes ranging from a maximum of 165.85% to a minimum of -55.74%. Similarly, AMG shows high variability, pointing to differing approaches and effectiveness in managing emissions reduction. In contrast, Table 9 presents the families with the lowest dispersion in their GHG emission intensity reductions. These families demonstrate more consistent performance across their portfolios, as indicated by the narrower range of reductions and lower standard deviation. The relatively uniform reductions suggest that these families may have implemented a more coordinated or uniform approach to managing GHG emissions across their portfolios. Notably, families with a large number of portfolios, such as Fidelity and Vanguard, display a relatively low standard deviation, underscoring their systematic efforts to reduce emissions consistently across their entire portfolio lineup.

Figure 8: Top 5 Families with the highest dispersion in GHG emission intensities reduction. This plot illustrates the top 5 mutual fund families with the highest dispersion in their GHG emission intensity reductions, as measured by the standard deviation of the percentage change in GHG emission intensities across their portfolios. The percentage change is calculated between the earliest and latest years of weighted average GHG emission intensities, which aggregate Scope 1, Scope 2, and Scope 3 upstream emissions for each portfolio. The box plot provides a visual summary of the variability in GHG emission intensity reductions within each family. Each box represents the interquartile range (IQR), capturing the middle 50% of the data, with the median marked inside the box. The whiskers extend to the minimum and maximum values, excluding outliers, which are shown as individual points.



Victory Capital, positioned at the top of the plot, displays several outliers, indicating significant deviations in emission reduction performance among its portfolios relative to the median. AMG, with its wide interquartile range (IQR) and long whiskers, shows high dispersion among the listed families. This suggests that while some portfolios within AMG are achieving notable emission reductions, others are not keeping pace. In contrast, Federated Hermes, Jackson National, and New York Life exhibit progressively narrower IQRs and fewer outliers compared to AMG and Victory Capital, indicating less variability in their GHG emission intensity reductions compared to them.

2.3 Sector Analysis

Sectors were categorized into Brown (high climate impact) and Green (low climate impact) to determine investment trends over time. The analysis relied on the detailed sector classification provided by S&P Global Trucost. The detailed sectors provided in the Appendix A and B.

Figure 9: Evolution of market value composition by sector for families (2016-2022). This stacked bar plot illustrates the annual distribution of market value across three key sector classifications—Brown, Green, and Other—within the selected US actively managed domestic equity funds from 2016 to 2022. The analysis is based on portfolios that meet a coverage threshold. Specifically, each portfolio included in the analysis achieved, on average, 75% coverage of Total Net Assets (TNA) matched with Trucost data, with a minimum threshold of 70% for any given year. The "Brown" sector represents industries with high environmental impact, particularly those contributing to greater greenhouse gas emissions, such as fossil fuels and heavy manufacturing. The "Green" sector includes industries that are environmentally sustainable, focusing on lower emissions and cleaner technologies. The "Other" category encompasses sectors that do not strictly fall into either the Brown or Green classifications. The detailed sectors provided in the Appendix A and B.

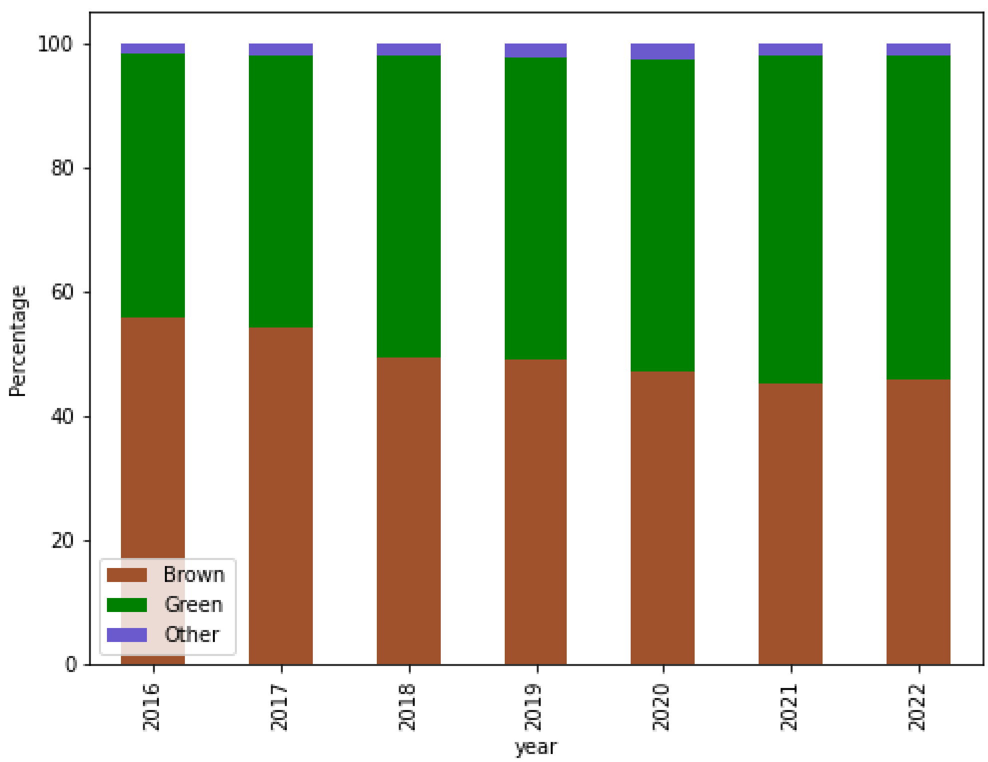
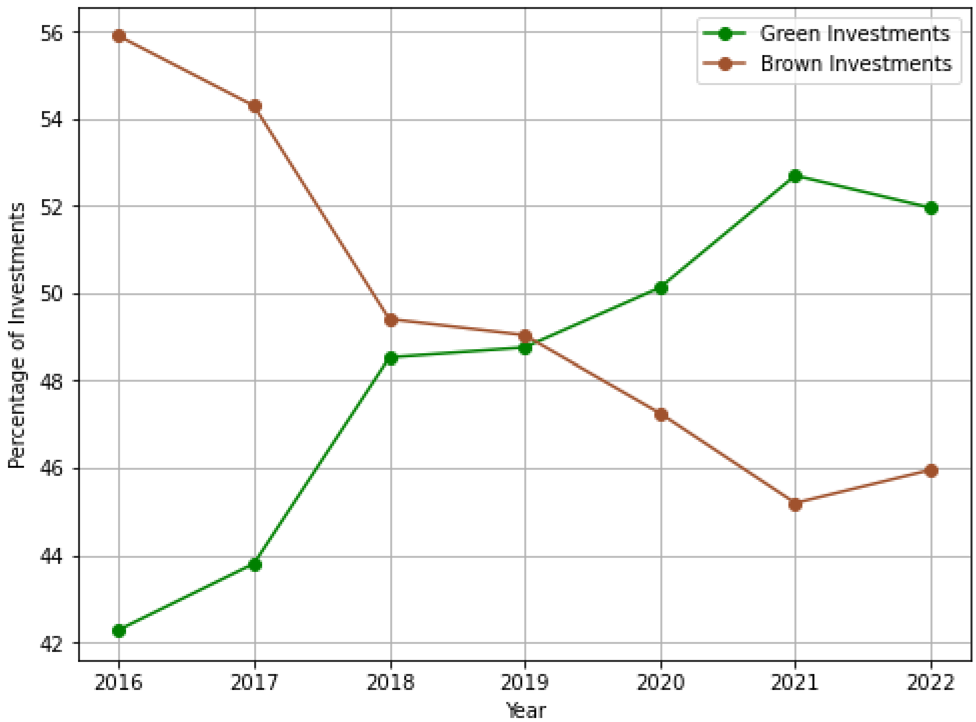


Figure 9 represents these shifts, with green investments growing larger and brown investments shrinking as a proportion of the total over the years. This trend is further corroborated by Figure 10, which clearly depicts an upward trajectory for green investments and a corresponding downward trajectory for brown investments. The crossing point around 2019-2020 indicates a pivotal moment when green investments began to surpass brown investments in terms of their proportion within the portfolios.

Figure 10: Trends of Green and Brown investments.

This line plot tracks the shifting percentages of Green and Brown investments within the selected mutual fund families from 2016 to 2022. We begin with the portfolios of US actively managed domestic equity funds from 2016 to 2022. These portfolios meet a coverage threshold, ensuring, on average, 75% of Total Net Assets (TNA) are matched with Trucost data, with a minimum threshold of 70% for any given year. From this set, portfolios belonging to major families (90th percentile) holding the majority of market value were selected, resulting in 47 families and 1671 portfolios over this period. The "Brown" sector represents industries with high environmental impact, particularly those contributing to greater greenhouse gas emissions, such as fossil fuels and heavy manufacturing. In contrast, the "Green" sector encompasses industries that are environmentally sustainable, focusing on reducing emissions and advancing cleaner technologies.



Figures 9 and 10 illustrate the shifting investment trends from 2016 to 2022, highlighting the transition from brown investments to green investments within the analyzed portfolios. Furthermore, these visualizations collectively suggest a high reallocation of assets towards greener investments, reflecting a broader industry trend towards sustainability.

Variability in Brown Holdings Among Mutual Fund Families

This section analyzes the variability in brown holdings—holdings of companies with high environmental impact—among selected mutual fund families from 2016 to 2022. The primary objective of this analysis is to understand how different mutual fund families manage these brown holdings and identify which families exhibit high or low variability in their investment. To analyze the variability in Brown holdings among mutual fund families, we calculated key dispersion metrics for each family's portfolios from 2016 to 2022. We began by determining the percentage of each portfolio's market value invested in Brown sectors, defined as high-impact, environmentally detrimental industries. We then calculated the standard deviation, range, and percentiles of these Brown holdings across all portfolios within each family. These metrics provided insights into how consistently or variably each family allocated funds to Brown sectors, with a high standard deviation indicating significant variability and a low standard deviation suggesting uniformity.

To identify families with notably high or low variability, we classified them based on their standard deviation of Brown holdings. High dispersion families, with standard deviations above the 75th percentile, showed considerable variation in their Brown investments. In contrast, low dispersion families, with standard deviations below the 25th percentile, displayed more consistent Brown holdings across their portfolios. This analysis highlights the diversity of approaches among mutual fund families in managing exposure to high-impact sectors.

Table 6: High dispersion fund families in Brown holdings

This table presents the dispersion metrics for the selected mutual fund families with the highest variability in Brown stock investments from 2016 to 2022. The analysis was conducted on a sample of US actively managed domestic equity funds that met a stringent coverage threshold: on average, 75% TNA were matched with Trucost data, with a minimum threshold of 70% for any given year. From this sample, portfolios of major families (90th percentile) holding the majority of market value were selected, resulting in a final dataset of 47 families and 1671 portfolios. To calculate the dispersion metrics, we first determined the percentage of each portfolio's market value invested in Brown sectors, which are defined as high-impact, environmentally detrimental industries. We then computed the standard deviation, range, and percentiles (25th, median, 75th) of these Brown holdings across all portfolios within each family. The standard deviation measures the variability in Brown investments within each family's portfolios, while the range shows the difference between the maximum and minimum Brown holdings. The percentiles provide additional insight into the distribution of Brown investments within each family.

	Family	std_dev	range	25th	Median	75th
1	Fidelity	21.15	100.00	40.74	49.34	55.52
2	Western & Southern	14.98	86.31	40.92	51.46	62.20
3	Virtus	14.87	100.00	43.14	51.97	58.40
4	Deutsche Bank AG	13.28	69.18	43.42	52.22	60.77
5	Putnam	13.19	82.58	47.96	53.87	59.85
6	Vanguard	12.75	73.96	49.84	56.15	65.60
7	T. Rowe Price	11.95	68.23	45.89	53.17	57.33
8	Invesco	11.88	80.83	47.70	52.55	57.49
9	Morgan Stanley	11.81	66.26	43.66	50.22	56.52
10	Wells Fargo	11.73	66.30	46.97	52.04	57.21
11	BlackRock	11.63	65.43	42.88	48.76	53.57
12	Manulife	11.21	69.57	45.01	50.90	56.31

The high dispersion families are characterized by significant variability in their brown stock investments. For instance, Fidelity, with the highest standard deviation of 21.15, exhibits considerable inconsistency in managing brown stocks, suggesting a flexible investment strategy that adjusts to market conditions or strategic shifts. Similarly, Western & Southern and Virtus shows high variability with a standard deviation of 14.98 and 14.87. Manulife, BlackRock, and Wells Fargo show lower variability within the high dispersion group, indicating a more stable approach to brown stock investments. These results highlight diverse investment strategies within these fund families, pointing to decentralized decision-making or varying fund objectives.

Table 7: Low dispersion fund families in Brown holdings

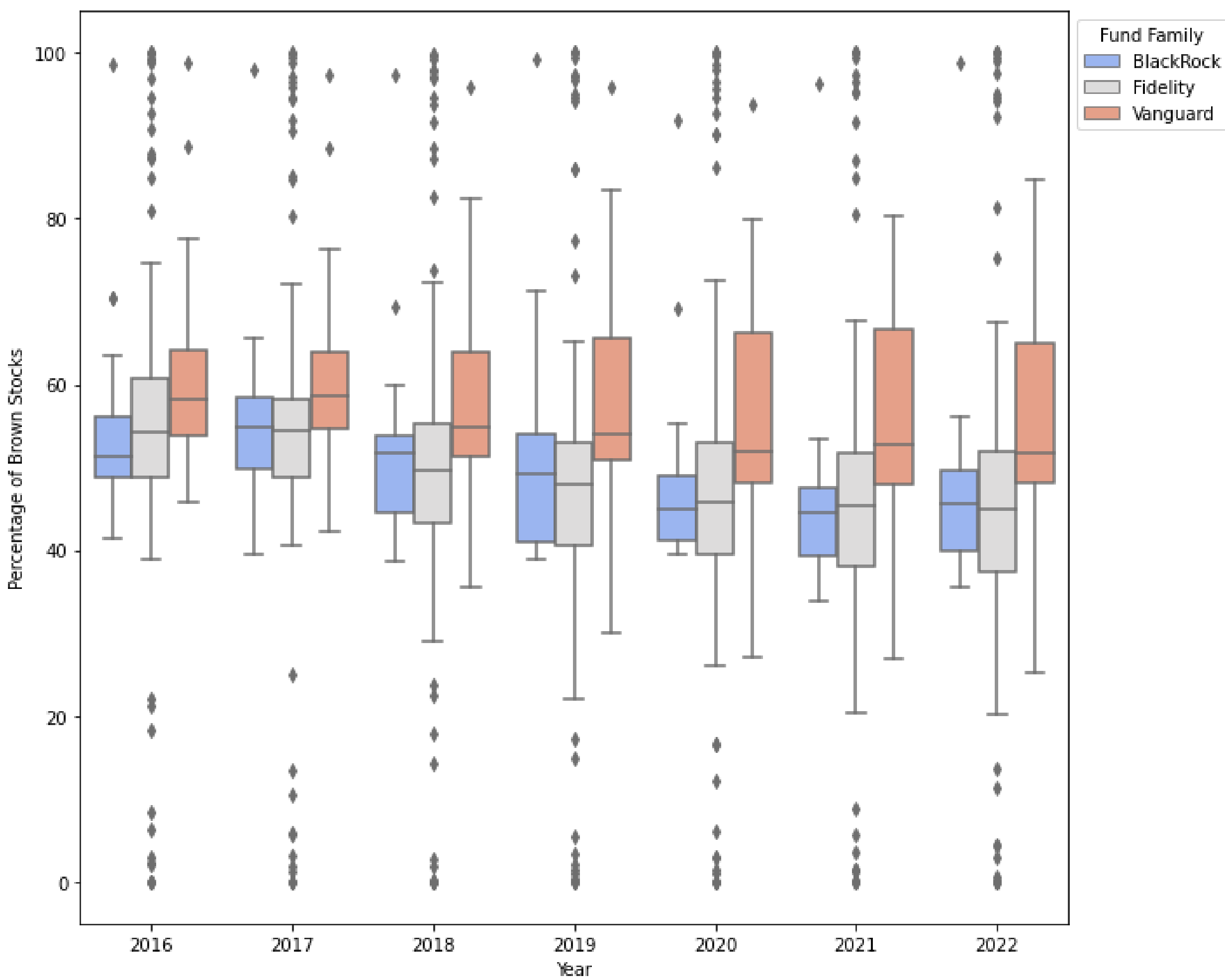
This table presents the dispersion metrics for the selected mutual fund families with the lowest variability in Brown stock investments from 2016 to 2022. The analysis was conducted on a sample of US actively managed domestic equity funds that met a stringent coverage threshold: on average, 75% TNA were matched with Trucost data, with a minimum threshold of 70% for any given year. From this sample, portfolios of major families (90th percentile) holding the majority of market value were selected, resulting in a final dataset of 47 families and 1671 portfolios. To calculate the dispersion metrics, we first determined the percentage of each portfolio's market value invested in Brown sectors, which are defined as high-impact, environmentally detrimental industries. We then computed the standard deviation, range, and percentiles (25th, median, 75th) of these Brown holdings across all portfolios within each family. The standard deviation measures the variability in Brown investments within each family's portfolios, while the range shows the difference between the maximum and minimum Brown holdings. The percentiles provide additional insight into the distribution of Brown investments within each family.

	Family	std_dev	range	25th	Median	75th
1	JPMorgan	5.66	28.69	48.06	52.42	56.86
2	The Hartford	6.66	32.91	47.06	51.81	56.11
3	MFS	6.81	36.48	47.35	51.62	56.08
4	Allianz	7.04	35.77	46.24	51.44	55.46
5	BNY Mellon	7.14	33.05	46.06	51.38	56.62
6	Nationwide	7.16	40.65	46.95	51.11	55.08
7	Thrivent	7.36	36.28	45.46	50.74	54.20
8	SEI Investments	7.37	53.66	48.90	53.08	56.82
9	Equitable	7.50	45.21	45.60	50.29	55.35
10	Columbia Threadneedle	7.52	40.11	46.37	51.73	57.34
11	Prudential	7.73	47.50	45.77	50.60	54.83
12	MassMutual	7.92	42.55	48.34	52.56	57.20

In contrast, low dispersion families demonstrate a consistent approach to managing brown stock investments. JPMorgan exhibits the lowest standard deviations, followed by The Hartford and MFS indicating a stable investment strategy regarding brown stocks. This analysis highlights the diversity in investment strategies among mutual fund families regarding brown holdings. By understanding these variations, investors can make more informed decisions aligned with their sustainability goals and risk tolerance. The findings underscore the importance of examining fund-level data to discern the underlying investment philosophies and how they align with broader environmental and financial objectives. High dispersion families exhibit significant variability in their investment strategies, with some funds heavily investing in brown stocks and others not. This inconsistency may stem from decentralized decision-making or diverse fund objectives. Conversely, low dispersion families maintain a consistent approach to brown stock investments, suggesting centralized policies or strict guidelines followed by all funds within the family.

To analyze this dispersion further, we compare the variability in brown stock holdings among three prominent mutual fund families—Fidelity, Vanguard, and BlackRock—over the period from 2016 to 2022. By examining the distribution of brown stock percentages each year, we aim to understand how consistently these families manage their investments in high GHG-emitting companies.

Figure 11: Fidelity, Vanguard, and BlackRock % brown stocks distribution.
This box plot illustrates the distribution of the percentage of Brown stocks for Fidelity, Vanguard, and BlackRock from 2016 to 2022, highlighting the annual variability in Brown stock holdings within each fund family.



Fidelity, with 148 funds, displays the highest variability in Brown stock holdings. Across most years, the interquartile range (IQR) for Fidelity is comparable to that of Vanguard, with both families exhibiting a wide spread in their Brown stock percentages. However, in some years, Fidelity's IQR is slightly narrower than Vanguard's, indicating somewhat less variability during those periods. Despite this, Fidelity stands out due to its numerous outliers, suggesting that while the central range of holdings is relatively stable, many of its funds diverge highly from the median. The standard deviation in Fidelity's Brown holdings can vary by up to 21%, reflecting this high level of dispersion. Vanguard, which manages 33 funds, shows a similar pattern of variability as Fidelity, but with a wider IQR in some years. This suggests that Vanguard’s funds can exhibit greater variability in Brown holdings during those periods. However, Vanguard has fewer outliers compared to Fidelity, indicating that while its funds also vary, they tend to remain within a more consistent range overall. BlackRock, with 35 funds, generally exhibits the most consistency in its Brown stock holdings. BlackRock's IQR is typically 20-30% narrower than both Fidelity's and Vanguard's across most years, indicating a tighter range of Brown stock percentages. Although there are years where BlackRock's IQR expands, showing some variability, it generally maintains a more uniform distribution of Brown holdings with fewer outliers compared to the other two families.

Systematic Divestment Analysis of Mutual Fund Families

The primary objective of this analysis is to examine whether mutual fund families are systematically divesting from brown holdings—investments in companies with high environmental impact—over the period from 2016 to 2022. By determining the average annual change in brown holdings for each fund family, we aim to highlight trends in the management of carbon-intensive assets and provide insights into the consistency of sustainability strategies within fund families. The analysis calculates the average annual change in brown holdings for each mutual fund family by averaging the year-over-year percentage changes in brown stock investments across the entire period from 2016 to 2022. This metric provides a quantitative measure of how fund families adjust their portfolios in response to environmental concerns and sustainability trends. The focus is on identifying fund families with high reductions in brown stock investments, which may indicate an approach to divesting from carbon-intensive assets.

Figure 12: Average annual change in % brown stocks among fund families (2016-2022)

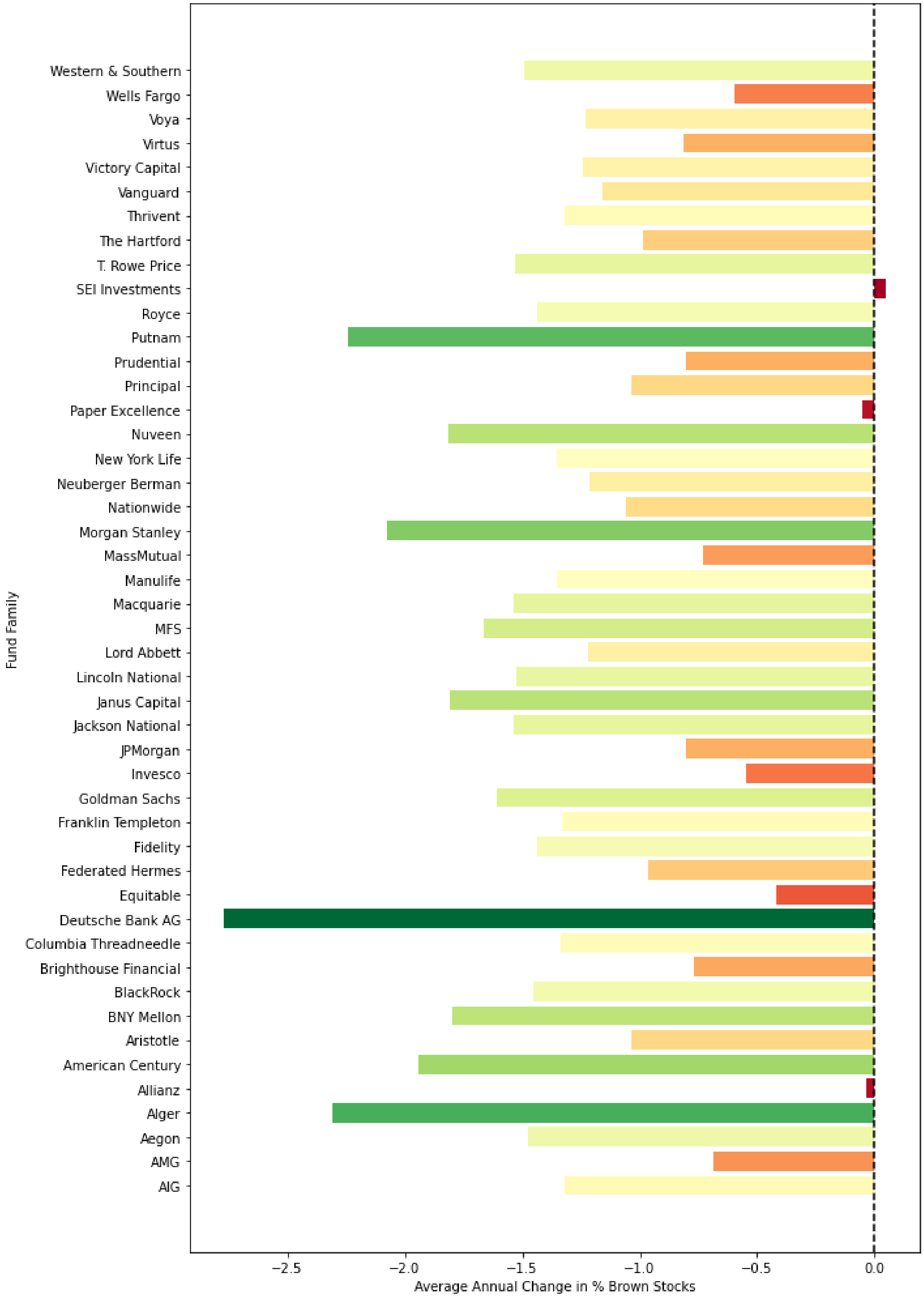


Figure 12 illustrates the average annual change in Brown stock holdings for various mutual fund families from 2016 to 2022, assessing whether these families are divesting from or increasing their investments in high-impact, carbon-intensive industries. The analysis focused on US actively managed domestic equity funds that met a stringent coverage threshold: on average, 75% of Total Net Assets (TNA) were matched with Trucost data, with a minimum threshold of 70% for any given year. From this dataset, portfolios of major families (90th percentile) holding the majority of market value were selected, resulting in 47 families and 1671 portfolios. To calculate the average annual change, we first determined the year-over-year percentage change in Brown stock holdings for each fund. These changes were then averaged across all years to produce a single metric for each fund family. The plot uses a color gradient, with shades ranging from dark green, representing significant reductions in brown holdings, to red, indicating increases or minimal reductions. The vertical black dashed line at 0% change distinguishes families that are reducing their Brown holdings from those that are increasing them. This visualization highlights the varying approaches among mutual fund families in managing their environmental impact, with some actively divesting from Brown stocks and others increasing their exposure.

The analysis reveals that several mutual fund families have actively reduced their brown holdings over the study period. For instance, families such as Deutsche Bank AG, Alger, and Putnam exhibit notable declines in their average annual brown stock percentages, suggesting a concerted effort to align their investment with sustainability objectives. These reductions are visualized by longer green bars, highlighting their substantial divestment activities. Conversely, some families, such as SEI Investments, Allianz, and Paper Excellence, show minimal reductions or even increases in brown holdings, indicated by yellow and red bars.

Then, we analyzed trends in divestment strategies across different mutual fund families, categorized by their initial levels of brown holdings. The goal is to determine which families demonstrate greater efforts to reduce their environmental impact through divestment. To categorize the mutual fund families, we used the 25th and 75th percentiles of the 2016 weighted average brown holdings percentages. Families with percentages at or below the 25th percentile were classified as Low Brown, those at or above the 75th percentile as High Brown, and those in between as Moderate Brown. We then analyzed the trends in brown holdings for each category over the period from 2016 to 2022, focusing on identifying which families exhibited significant and consistent reductions.

Table 8: Annual brown holdings % and divestment trends among families (2016-2022). This table provides a detailed view of the annual percentages of Brown holdings—investments in companies with high environmental impact—and the average annual percentage change in these holdings for the selected mutual fund families over the period from 2016 to 2022. The analysis is based on a sample of US actively managed domestic equity funds that met a stringent coverage threshold: on average, 75% of Total Net Assets (TNA) were matched with Trucost data, with a minimum threshold of 70% for any given year. From this dataset, portfolios of major families (90th percentile) holding the majority of market value were selected, resulting in a final dataset of 47 families and 1671 portfolios. he mutual fund families are categorized into three groups based on their initial Brown holdings in 2016: Moderate Brown, Low Brown, and High Brown. These categories are determined by the 25th and 75th percentiles of their 2016 weighted average Brown holdings percentages. The columns show the percentage of Brown holdings each year, allowing for a year-by-year comparison of how each family managed its exposure to carbon-intensive sectors. The Avg.Ann% column represents the average annual change in Brown holdings over the period, indicating the general trend of each family—whether they have been divesting from Brown stocks or maintaining/increasing their holdings. A negative value in this column signifies a reduction in Brown holdings, suggesting that the family is moving towards less carbon-intensive investments, while a positive value indicates an increase in Brown holdings.

	Family	#Port.	2016	2017	2018	2019	2020	2021	2022	Avg.Ann%
Moderate Brown	Alger	23	55.20	52.77	46.27	47.22	41.80	37.72	39.19	-2.31
	Morgan Stanley	40	54.90	56.83	49.57	49.32	47.28	44.22	42.75	-2.08
	Nuveen	28	57.68	55.44	51.23	51.68	48.34	49.31	49.36	-1.82
	MFS	33	56.19	53.27	49.32	48.79	46.81	45.02	47.14	-1.66
	Jackson National	31	56.47	54.00	50.45	49.51	48.30	44.69	46.03	-1.54
	T. Rowe Price	31	56.58	54.33	48.86	48.59	46.52	40.93	41.58	-1.53
	Lincoln National	21	56.58	55.18	52.24	51.07	48.27	45.28	45.79	-1.53
	Aegon	37	54.96	54.97	48.96	46.96	45.56	42.11	41.96	-1.48
	Columbia Threadneedle	64	56.54	55.44	53.41	53.26	49.51	48.30	50.12	-1.33
	AIG	38	54.99	54.36	49.57	49.45	48.37	46.45	46.83	-1.32
	Voya	31	57.37	56.41	52.74	51.00	50.19	43.47	45.37	-1.23
	Lord Abbett	24	57.20	59.78	59.58	55.69	50.27	47.45	47.12	-1.22
	Neuberger Berman	24	57.44	57.56	56.27	55.51	52.77	50.21	52.24	-1.21
	Nationwide	36	57.03	56.53	52.27	50.68	48.19	46.83	47.92	-1.06
	Aristotle	42	54.49	53.68	49.69	50.05	49.32	47.63	48.70	-1.03
	Principal	32	54.36	53.24	49.23	48.33	45.68	42.91	44.17	-1.03
	The Hartford	26	55.69	52.80	48.59	50.52	49.71	49.79	48.92	-0.98

	Federated Hermes	17	56.99	57.07	58.49	50.52	46.84	43.93	46.42	-0.96
	JPMorgan	31	56.29	54.56	50.46	52.43	50.92	50.42	52.19	-0.80
	Brighthouse Financial	23	54.97	55.00	51.82	51.75	50.43	48.56	48.89	-0.77
	AMG	36	54.33	53.60	49.54	47.65	46.78	44.90	48.98	-0.69
	Invesco	56	53.92	54.10	51.22	51.13	51.23	50.03	48.11	-0.55
	Paper Excellence	19	55.47	56.48	55.16	54.59	53.84	52.17	53.69	-0.05
Low Brwon	Western & Southern	21	43.91	50.83	45.04	47.49	47.04	48.13	48.87	-1.49
	BlackRock	35	53.43	52.19	48.12	45.49	43.56	39.72	40.38	-1.45
	Fidelity	148	53.65	50.86	42.90	42.02	41.07	40.12	40.27	-1.43
	Manulife	53	52.72	52.76	47.09	48.60	47.26	48.71	50.01	-1.36
	New York Life	19	53.63	52.28	46.77	44.69	40.26	34.90	40.91	-1.35
	Thrivent	28	52.98	52.56	44.83	46.66	48.49	46.75	48.33	-1.32
	Prudential	48	53.33	52.79	49.63	49.16	46.49	43.83	45.17	-0.80
	MassMutual	34	53.80	53.87	52.33	53.97	51.17	47.89	48.21	-0.73
	Wells Fargo	34	53.74	54.69	52.08	53.54	50.30	47.45	48.46	-0.60
	Equitable	56	53.16	52.21	51.48	50.30	48.98	48.58	49.57	-0.42
	Allianz	22	52.00	54.07	48.85	49.77	50.79	49.24	56.26	-0.04
	SEI Investments	43	53.25	52.96	48.32	51.99	49.14	46.71	47.47	0.05
High Brown	Deutsche Bank AG	18	62.35	62.17	53.18	48.72	45.06	42.73	41.19	-2.77
	Putnam	33	61.96	59.98	55.73	52.54	48.90	47.00	49.99	-2.24
	American Century	37	61.72	61.62	56.45	54.09	48.34	45.66	46.96	-1.94
	Janus Capital	25	59.10	54.28	50.61	48.63	46.18	44.41	46.46	-1.81
	BNY Mellon	36	58.39	56.71	50.31	49.66	48.98	45.68	47.78	-1.80
	Goldman Sachs	32	59.82	58.97	55.11	51.46	49.90	48.82	49.50	-1.61
	Macquarie	35	62.77	61.53	59.05	56.22	53.74	49.54	47.89	-1.54
	Royce	18	71.49	71.57	71.07	67.85	66.03	64.62	64.99	-1.44
	Franklin Templeton	60	58.73	58.43	54.97	51.66	50.06	46.27	47.35	-1.33
	Victory Capital	38	59.93	59.38	54.70	53.67	52.09	52.74	55.97	-1.24
	Vanguard	33	64.27	62.94	59.65	59.89	57.20	54.94	54.83	-1.16
	Virtus	22	59.41	61.11	60.40	53.61	52.77	52.51	52.74	-0.81

Table 8 highlights the varying degrees of effort made by different mutual fund families in reducing their Brown holdings. For instance, in the Moderate Brown category, families such as Alger and

Morgan Stanley show noticeable reductions in their Brown holdings. Similarly, in the Low Brown category, families like Western & Southern and BlackRock also demonstrate a great deal of reductions, but from a lower starting point. The High Brown category features families such as Deutsche Bank AG and Putnam, which are making significant efforts to reduce their Brown holdings, starting from a higher baseline.

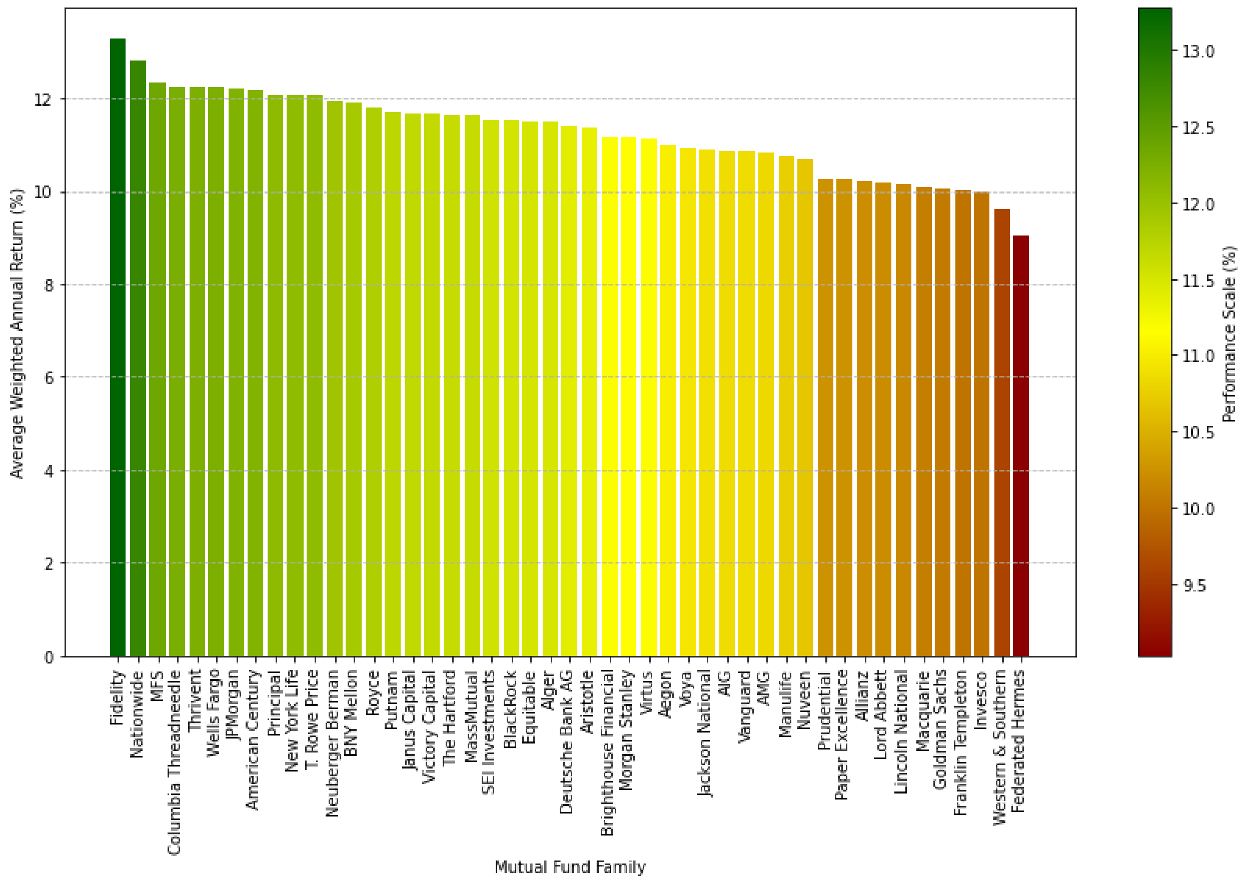
2.4 Return Analysis

The financial performance of mutual fund families from 2016 to 2022 was compared by calculating their weighted average annual returns. Our analysis included 47 mutual fund families and their corresponding 1,671 portfolios, all of which met the coverage threshold and other criteria outlined in the Mutual Fund Family Selection section. The study begins by calculating annual returns for each mutual fund by aggregating monthly returns over each fiscal year. The expense ratio was added back to these annual returns to provide insights into the gross performance before fees. These returns were then integrated with portfolio holdings data, linking each fund's financial performance to its parent fund family and their corresponding holdings through unique identifiers. Specifically, for each portfolio within a fund family, the annual return was calculated and then weighted by the portfolio's market value. This approach ensures that larger portfolios, which have a greater financial impact, appropriately influence the overall return for the family. The resulting weighted returns were then averaged across the years to provide a comprehensive measure of each family's financial performance over the analysis period.

Figure 13 presents these average weighted annual return percentages for the mutual fund families for the period 2016 to 2022, using a color gradient that shifts from dark green to dark red, comparing the performance of each family relative to others, with dark green indicating the highest performers and dark red indicating the lowest.

Figure 13: Average weighted annual return (%) by mutual fund family.

This figure shows the average weighted annual return percentage by mutual fund family for the period of 2016 to 2022. The analysis began by using the fund return table, which contains monthly returns. These monthly returns were aggregated to calculate the annual returns for each fund. Next, the expense ratios were added back to these annual returns to reflect the gross performance before fees. Using the portfolio map table, each fund's returns were linked to their corresponding portfolios. The weighted average annual return for each family was then calculated by weighting the annual returns of each portfolio within the family by its market value. This method ensures that larger portfolios have a proportional impact on the overall return of the family. Each bar in the figure represents a mutual fund family, with colors ranging from green (indicating higher returns) to red (indicating lower returns), providing a visual comparison of financial performance across different mutual fund families.



Then, we explore the intersection between environmental sustainability and financial performance in the mutual fund industry by analyzing the average weighted annual returns of mutual fund families categorized based on their GHG emission intensities. The mutual fund families were categorized according to their GHG emission intensity levels in 2016, which were calculated by taking the sum of Scope 1, Scope 2, and Scope 3 (upstream) emission intensities for each portfolio and weighting them by their market values. Based on these weighted averages, families were divided into three distinct groups: High Emitters (above the 75th percentile), Medium Emitters (between the 25th and 75th percentiles), and Low Emitters (below the 25th percentile). The analysis involves calculating the weighted average annual return for each group of emitters across multiple years. The returns are weighted by the market value of the funds to ensure that larger funds with significant capital have an appropriate influence on the results. This weighted approach provides a fair comparison of returns, considering the size of the investments within each category.

Figure 14: Weighted average annual return by emission category and year.

This figure displays the weighted average annual return for mutual fund families categorized by their GHG emission intensity levels (High Emitters, Medium Emitters, and Low Emitters) across the years 2016 to 2022. The categorization of mutual fund families into High, Medium, and Low Emitters was based on their GHG emission intensities in 2016. Specifically, families were grouped into these categories according to the 25th and 75th percentiles of their 2016 GHG emission intensities. High Emitters are those above the 75th percentile, Low Emitters are those below the 25th percentile, and Medium Emitters fall between these two thresholds. The full list of families with their corresponding category can be found in Table 5. The returns were calculated by aggregating each fund's monthly returns for each year and then adjusting them by adding back the expense ratios to reflect gross performance. These returns were then linked to their corresponding portfolios, and the weighted average annual return for each family was calculated by weighting the annual returns of each portfolio within the family by its market value. Each line in the figure represents one of the three emission categories: High Emitters (red), Medium Emitters (blue), and Low Emitters (green).

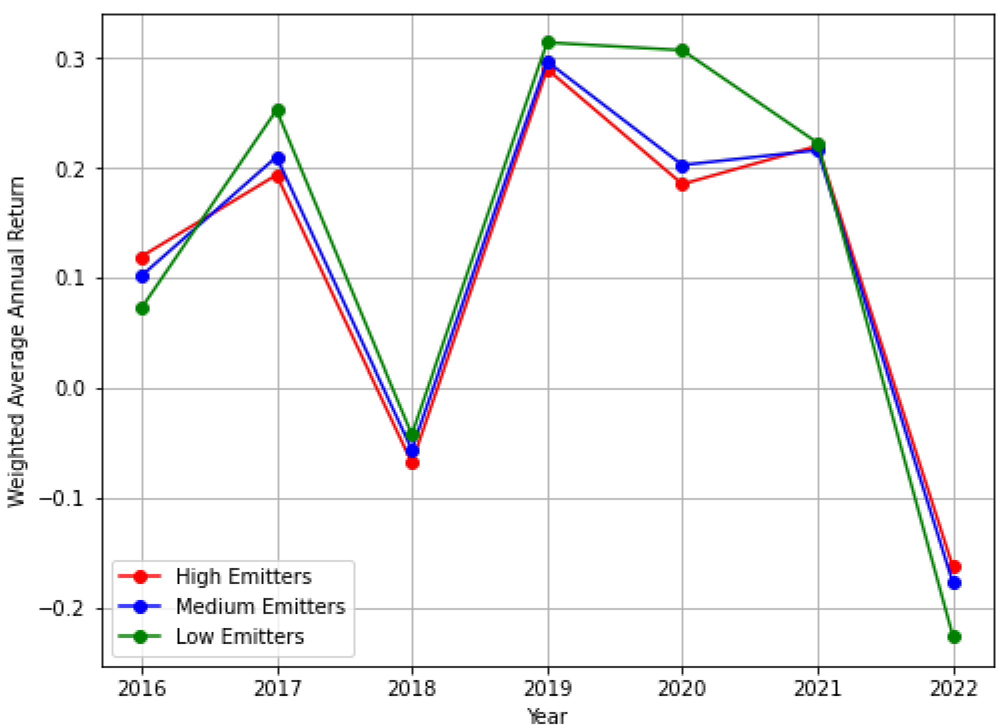


Figure 14 is used to visualize the performance trends of the High, Medium, and Low Emitters over the analyzed period. The graph reveals that all three categories exhibit fluctuations in their returns, highlighting the inherent volatility in mutual fund performance. Notably, Low Emitters occasionally outperform their counterparts, suggesting that sustainable investments can yield competitive financial returns. Medium Emitters generally follow market trends, while High Emitters demonstrate competitive performance in certain years, possibly reflecting favorable conditions for high-carbon sectors. This suggests that sustainable investment strategies can coexist with competitive financial returns, highlighting the potential for environmentally responsible investment practices to achieve both sustainability and profitability.

We further continue this analysis to explore how the financial performance of mutual fund families correlates with their GHG emission intensities over the period from 2016 to 2022. By categorizing mutual fund families into High Emitters, Medium Emitters, and Low Emitters based on their initial weighted average GHG emission intensities—calculated from the sum of Scope 1, Scope 2, and Scope 3 (upstream) emission intensities in 2016, weighted by market values—this study aims to compare the financial dynamics that drive the performance of mutual fund families in each category. To perform this analysis, the study employs three well-established multifactor models: the Fama-French 3-Factor Model, the Carhart 4-Factor Model, and the Fama-French 5-Factor Model. These models allow for a comprehensive evaluation of the impact of various financial risk factors—such as market risk, size, value, momentum, profitability, and investment—on the excess returns of mutual fund families. By conducting time-series regressions on excess returns (defined as the difference between the value-weighted return and the risk-free rate), this analysis seeks to uncover the financial dynamics that drive the performance of mutual fund families.

Table 9: Regression results of families' returns using multifactor models.

These tables present the results of time-series regressions using the Fama-French 3-Factor, Carhart 4-Factor, and Fama-French 5-Factor models to assess the financial performance of mutual fund families categorized by their greenhouse gas (GHG) emission intensities from 2016 to 2022. The families were categorized into High Emitters, Medium Emitters, and Low Emitters based on their weighted average GHG emission intensities, calculated from the sum of Scope 1, Scope 2, and Scope 3 (upstream) emissions for each portfolio within the family. Specifically, families were grouped into these categories according to the 25th and 75th percentiles of their GHG emission intensities in 2016, with the full list of categorized families provided in Table 5. The value-weighted return for each mutual fund family was calculated by first determining the monthly return for each portfolio and then weighting these returns by the portfolio's market value. The aggregated weighted returns across all portfolios within a family provided the overall value-weighted return for the family on each date. Excess returns, defined as the difference between the value-weighted return and the risk-free rate, were then regressed against key financial risk factors: market risk premium (RM-Rf), size (SMB), value (HML), momentum (MOM), profitability (RMW), and investment (CMA). The R-squared values indicate the proportion of variance in returns explained by the models, while t-statistics (in parentheses) assess the significance of each factor. Significance levels are calculated for 1%, 5%, and 10%, respectively.

Regression results for High emitters families

	Fama-French 3-Factor	**Carhart 4-Factor**	**Fama-French 5-Factor**
Constant	0.0003	0.0003	0.0003
	(0.0006)	(0.0006)	(0.0006)
R_M-R_f	0.9538***	0.9489***	0.9475***
	(0.0130)	(0.0141)	(0.0144)
SMB	0.0980***	0.0923***	0.1038***
	(0.0236)	(0.0245)	(0.0274)
HML	0.0684***	0.0637***	0.0771***
	(0.0155)	(0.0163)	(0.0216)
MOM		-0.0177	
		(0.0197)	
CMA			-0.0290
			(0.0333)
RMW			0.0207
			(0.0318)
R-Squared	0.9878	0.9879	0.9880
No. Obs.	84	84	84
No. Family	12	12	12
No. Portfolio	392	392	392

***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Regression results for Medium emitters families

	Fama-French 3-Factor	Carhart 4-Factor	Fama-French 5-Factor
Constant	0.0000	0.0001	0.0001
	(0.0006)	(0.0006)	(0.0006)
R_M-R_f	0.9438***	0.9387***	0.9362***
	(0.0130)	(0.0140)	(0.0143)
SMB	0.0408*	0.0349	0.0456*
	(0.0236)	(0.0244)	(0.0272)
HML	0.0126	0.0076	0.0262
	(0.0154)	(0.0163)	(0.0215)
MOM		-0.0188	
		(0.0197)	
CMA			-0.0405
			(0.0331)
RMW			0.0207
			(0.0316)
R-Squared	0.9872	0.9873	0.9875
No. Obs.	84	84	84
No. Family	23	23	23
No. Portfolio	816	816	816

***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Regression results for Low emitters families

	Fama-French 3-Factor	Carhart 4-Factor	Fama-French 5-Factor
Constant	0.0004	0.0003	0.0008
	(0.0007)	(0.0007)	(0.0007)
R_M-R_f	0.9881***	0.9960***	0.9819***
	(0.0143)	(0.0154)	(0.0155)
SMB	0.0184	0.0276	0.0029
	(0.0261)	(0.0268)	(0.0295)
HML	-0.1084***	-0.1007***	-0.0722***
	(0.0171)	(0.0179)	(0.0233)
MOM		0.0289	
		(0.0216)	

CMA			-0.0773**
			(0.0359)
RMW			-0.0189
			(0.0343)
R-Squared	0.9855	0.9859	0.9864
No. Obs.	84	84	84
No. Family	12	12	12
No. Portfolio	429	429	429

***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

The regression analysis reveals distinct patterns in how mutual fund families, categorized by their GHG emission intensities, respond to traditional financial risk factors. Across all categories—High, Medium, and Low Emitters—the market risk factor (RM-Rf) consistently shows a strong and significant correlation with returns, indicating that the financial performance of these families is closely tied to overall market movements.

For high emitters, the analysis highlights significant positive sensitivity to both size (SMB) and value (HML) factors, suggesting that smaller, value-oriented portfolios within these families tend to perform better. This positive loading on the HML factor indicates that high-emitting mutual fund families are more inclined to follow value strategies, investing in undervalued stocks that typically offer higher returns relative to their growth counterparts. In contrast, other factors such as momentum (MOM), profitability (RMW), and investment (CMA) do not significantly influence the returns of high-emission families, indicating that these additional factors have less relevance in this group.

For medium emitters, while the market risk factor remains a key driver of returns, the influence of the size factor (SMB) is weaker, and the value factor (HML) generally does not significantly impact returns. This suggests that traditional size and value characteristics are less influential for medium-emitting families. The lack of significance for momentum, profitability, and investment factors further supports the idea that these financial risk factors play a limited role in the returns of medium-emitting fund families.

Low emitters, however, exhibit a different profile. The value factor (HML) is significantly negative across the models, indicating a preference for growth stocks over value stocks within low-emitting families. This negative loading suggests that low-emitting mutual fund families are more aligned with growth strategies, favoring stocks with higher potential for future earnings rather than undervalued ones. Additionally, the investment factor (CMA) is significant and negative in the 5-factor model, suggesting that portfolios with conservative investment strategies may underperform in this category. The size factor (SMB) does not have a significant impact on the returns of low emitters.

Overall, the analysis suggests that while market risk is a dominant factor influencing returns across all mutual fund families, the impact of other financial factors such as size, value, momentum, profitability, and investment varies depending on the level of GHG emission intensities. High emitters tend to favor value-oriented strategies, whereas low emitters are more growth-oriented, reflecting distinct approaches to investment based on their environmental profiles.

Conclusion

The purpose of this study was to analyze the environmental impact of mutual fund families' investment strategies by examining the greenhouse gas (GHG) emissions in their holdings, sectoral compositions, and financial performance. Utilizing a comprehensive dataset from the CRSP Mutual Fund Database and Trucost's environmental data, the analysis covered actively managed U.S. domestic equity mutual funds over the period from 2016 to 2022. By analyzing greenhouse gas emission intensities, sectoral allocations, and financial returns, the research sheds light on how mutual fund families are integrating sustainability into their investment decisions.

The study reveals a significant reduction in GHG emissions across mutual fund portfolios, underscoring a broader commitment to sustainability. The Weighted Average Carbon Intensity metric shows substantial declines, with average Scope 1+2 emissions dropping from 171.52 in 2016 to 100.41 in 2022, and Scope 1+2+3 emissions falling from 307.32 to 191.16 over the same period. This trend highlights the proactive efforts of mutual fund families to mitigate climate-related risks and align their investment strategies with environmental objectives. These findings are consistent with the observations by Li et al. (2023), who reported that non-ESG funds are increasingly incorporating high-ESG stocks, indicating a shift towards sustainability across the financial sector. The sectoral analysis further illustrates the transition from brown (high climate impact) to green (low climate impact) investments, with green investments surpassing brown investments around 2019-2020. This shift aligns with global initiatives such as the Paris Agreement and underscores the financial sector's role in supporting sustainable development. Mutual fund managers are increasingly prioritizing companies with lower carbon footprints, resulting in a significant reallocation of assets towards green sectors. This strategic pivot not only aligns with environmental goals but also positions mutual fund families to capitalize on emerging opportunities in sustainable industries. These trends align with the findings of Baily and Gnabo (2022), who noted a convergence of investment strategies towards sustainability.

The return analysis reveals that sustainable investment strategies can align with favorable financial outcomes. The study categorized mutual fund families into High, Medium, and Low Emitters based on their GHG emission intensities and analyzed their weighted average annual returns. The results show that Low Emitters occasionally outperformed their counterparts, indicating that investments aligned with sustainability goals can be financially beneficial. Medium Emitters generally followed broader market trends, while High Emitters exhibited strong performance in certain years, particularly when market conditions favored high-carbon sectors. The analysis also highlighted distinct factor loadings across these categories. Across all groups, the market risk factor (RM-Rf) consistently showed a strong and significant correlation with returns, indicating that the financial performance of these mutual fund families is closely tied to overall market movements. High Emitters demonstrated significant positive sensitivity to the value factor (HML), suggesting a preference for value-oriented investments, while Low Emitters had a negative loading on the HML factor, indicating a tilt towards growth stocks. These findings suggest that High Emitters are more aligned with value investing, whereas Low Emitters favor growth-oriented strategies. These results suggest that environmentally responsible investment practices do not necessarily compromise financial performance and can coexist with traditional financial objectives. This aligns with the conclusions of Avramov et al. (2022), who noted the potential for sustainable investing to contribute to both fund diversity and financial success.

The variability analysis of brown holdings among mutual fund families reveals diverse investment strategies. High dispersion families, such as Fidelity and Western & Southern, exhibit significant variability in managing brown stocks, indicating flexible approaches that respond to market conditions. In contrast, low dispersion families, like JPMorgan and MFS, demonstrate more consistent strategies, reflecting centralized policies or strict guidelines. This analysis underscores the importance of understanding fund-level data to discern the underlying investment philosophies and how they align with broader environmental and financial objectives. These findings align with Peng et al. (2023), who found that SRI mutual funds prioritize companies with superior ESG performance and demonstrate diverse investment strategies.

This study has several limitations. It focused primarily on the investment strategies of management companies, leaving out the potential influence of fund advisor companies. Future research could expand this analysis to include fund advisors, evaluating their impact on investment decisions and determining whether these decisions are more influenced by management companies or advisors. Additionally, the study relied on available GHG emissions data, which may not fully capture all aspects of environmental impact. Future studies could incorporate additional sustainability metrics to provide a more comprehensive view of ESG performance.

In conclusion, this study highlights the increasing alignment of mutual fund families with sustainable investment practices. By reducing GHG emissions, shifting towards green sectors, and maintaining competitive financial returns, mutual fund families are positioning themselves as pivotal players in the transition to a low-carbon economy. The integration of ESG criteria into investment decision-making processes reflects a broader industry trend towards environmental responsibility. These findings suggest that sustainable investment strategies not only drive positive environmental change but also enhance financial performance, reinforcing the importance of sustainability in the investment landscape. As the market continues to evolve, the alignment of financial performance with sustainability goals is expected to become more pronounced, underscoring the critical role of sustainable investing in shaping the future of the financial sector. This conclusion is further supported by Nitsche and Schroder (2015), who highlighted the alignment of investment strategies with ESG objectives in SRI funds, confirming that mutual fund families are genuinely integrating sustainability into their core strategies.

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Appendix A

High Climate Impact Sectors (labeled as Brown); Source: S&P Global Trucost

High Climate Impact Sectors	
Abrasive product manufacturing	Biomass Power Generation
Adhesive manufacturing	Bituminous Coal and Lignite Surface Mining
Air and gas compressor manufacturing	Bituminous Coal and Lignite Surface Mining - Thermal Coal
Air conditioning, refrigeration, and warm air heating equipment manufacturing	Bituminous Coal and Lignite Surface Mining - Metallurgical Coal
Air purification and ventilation equipment manufacturing	Bituminous Coal and Lignite Surface Mining - Other Coal
Air transportation	Bituminous Coal Underground Mining
Aircraft engine and engine parts manufacturing	Bituminous Coal Underground Mining - Thermal Coal
Aircraft manufacturing	Bituminous Coal Underground Mining - Metallurgical Coal
Alkalis and chlorine manufacturing	Bituminous Coal Underground Mining - Other Coal
All other basic inorganic chemical manufacturing	Blind and shade manufacturing
All other chemical product and preparation manufacturing	Boat building
All other converted paper product manufacturing	Bread and bakery product manufacturing
All other crop farming	Breakfast cereal manufacturing
All other food manufacturing	Breweries
All other forging, stamping, and sintering	Brick, tile, and other structural clay product manufacturing
All other miscellaneous electrical equipment and component manufacturing	Biomass Power Generation
All other miscellaneous manufacturing	Broadcast and wireless communications equipment
All other miscellaneous wood product manufacturing	Broad woven fabric mills
All other paper bag and coated and treated paper manufacturing	Broom, brush, and mop manufacturing
All other petroleum and coal products manufacturing	Building Material and Garden Equipment and Supplies Dealers
All other textile product mills	Car washes
All other transportation equipment manufacturing	Carbon and graphite product manufacturing
Alumina refining and primary aluminum production	Carbon black manufacturing
Aluminum product manufacturing from purchased aluminum	Carpet and rug mills
Ammunition manufacturing	Cattle ranching and farming
Analytical laboratory instrument manufacturing	Cement manufacturing
Animal (except poultry) slaughtering, rendering, and processing	Cheese manufacturing

High Climate Impact Sectors	
Animal production, except cattle and poultry and eggs	Chocolate and confectionery manufacturing from cacao beans
Anthracite mining	Clay and nonclay refractory manufacturing
Apparel accessories and other apparel manufacturing	Clothing and clothing accessories stores
Apparel knitting mills	Coal power generation
Apparel, piece goods, and notions wholesalers	Coated and laminated paper, packaging paper and plastics film manufacturing
Arms, ordnance, and accessories manufacturing	Coating, engraving, heat treating and allied activities
Artificial and synthetic fibers and filaments manufacturing	Coffee and tea manufacturing
Asphalt paving mixture and block manufacturing	Commercial and industrial machinery and equipment repair and maintenance
Asphalt shingle and coating materials manufacturing	Clay and nonclay refractory manufacturing
Audio and video equipment manufacturing	Clothing and clothing accessories stores
Automatic environmental control manufacturing	Coal power generation
Automobile manufacturing	Communication and energy wire and cable manufacturing
Automotive repair and maintenance, except car washes	Computer storage device manufacturing
Ball and roller bearing manufacturing	Computer terminals and other computer peripheral equipment manufacturing
Bare printed circuit board manufacturing	Concrete pipe, brick, and block manufacturing
Bauxite mining	Confectionery manufacturing from purchased chocolate
Beet sugar manufacturing	Construction machinery manufacturing
Biological product (except diagnostic) manufacturing	Cookie, cracker, and pasta manufacturing
Copper mining	Dental laboratories
Copper rolling, drawing, extruding and alloying	Distilleries
Cotton farming	Dog and cat food manufacturing
Couriers and messengers	Doll, toy, and game manufacturing
Crown and closure manufacturing and metal stamping	Drilling oil and gas wells
Crude petroleum and natural gas extraction	Dry, condensed, and evaporated dairy product manufacturing
Curtain and linen mills	Electric bulk power transmission and control
Custom architectural woodwork and millwork manufacturing	Electric lamp bulb and part manufacturing
Custom roll forming	Electric power distribution
Cut and sew apparel contractors	Electrical and electronic goods wholesalers
Cut stone and stone product manufacturing	Electricity and signal testing instruments manufacturing
Cutlery, utensil, pot, and pan manufacturing	Electromedical and electrotherapeutic apparatus manufacturing
Cutting tool and machine tool accessory manufacturing	Electron tube manufacturing

High Climate Impact Sectors	
Dairy cattle and milk production	Electronic and precision equipment repair and maintenance
Dental equipment and supplies manufacturing	Electronic capacitor, resistor, coil, transformer, and other inductor manufacturing
Furniture and home furnishings stores	Electronic computer manufacturing
Gasket, packing, and sealing device manufacturing	Electronic connector manufacturing
Gasoline stations	Electronics and appliance stores
General merchandise stores	Engineered wood member and truss manufacturing
Geothermal power generation	Fabric coating mills
Glass container manufacturing	Fabricated pipe and pipe fitting manufacturing
Glass product manufacturing made of purchased glass	Farm machinery and equipment manufacturing
Gold ore mining	Fats and oils refining and blending
Grain farming	Federal electric utilities
Greenhouse, nursery, and floriculture production	Ferrous metal foundries
Grocery and related product wholesalers	Fertilizer manufacturing
Ground or treated mineral and earth manufacturing	Fiber, yarn, and thread mills
Guided missile and space vehicle manufacturing	Fishing
Handtool manufacturing	Flat glass manufacturing
Hardware manufacturing	Flavoring syrup and concentrate manufacturing
Heating equipment (except warm air furnaces) manufacturing	Flour milling and malt manufacturing
Heavy duty truck manufacturing	Fluid milk and butter manufacturing
Household cooking appliance manufacturing	Fluid power process machinery
Household laundry equipment manufacturing	Food, beverage, health, and personal care stores
Household refrigerator and home freezer manufacturing	Footwear manufacturing
Hunting and trapping	Forest nurseries, forest products, and timber tracts
Hydroelectric power generation	Frozen food manufacturing
Ice cream and frozen dessert manufacturing	Fruit and vegetable canning, pickling, and drying
Industrial gas manufacturing	Fruit farming
Industrial mold manufacturing	Knit fabric mills
Industrial process furnace and oven manufacturing	Laboratory apparatus and furniture manufacturing
Industrial process variable instruments manufacturing	Laminated plastics plate, sheet (except packaging), and shape manufacturing
Institutional furniture manufacturing	Landfill gas power generation
In-vitro diagnostic substance manufacturing	Lawn and garden equipment manufacturing
Iron and steel mills and ferroalloy manufacturing	Lead ore and zinc ore mining
Iron ore mining	Leather and hide tanning and finishing
Irradiation apparatus manufacturing	Light truck and utility vehicle manufacturing
Jewelry and silverware manufacturing	Lighting fixture manufacturing
Nickel mining	Lime and gypsum product manufacturing
Nonchocolate confectionery manufacturing	Logging
Nonferrous metal (except copper and aluminum) rolling, drawing, extruding and alloying	Lumber and other construction materials wholesalers
Nonferrous metal foundries	Machine shops

High Climate Impact Sectors	
Nonresidential commercial and health care structures	Magnetic and optical recording media manufacturing
Nonresidential maintenance and repair	Manufactured home (mobile home) manufacturing
Nonresidential manufacturing structures	Material handling equipment manufacturing
Non-store retailers	Mattress manufacturing
Non-upholstered wood household furniture manufacturing	Mechanical power transmission equipment manufacturing
Nonwoven fabric mills	Medicinal and botanical manufacturing
Nuclear electric power generation	Men's and boys' cut and sew apparel manufacturing
Office furniture manufacturing	Metal and other household furniture manufacturing
Office supplies (except paper) manufacturing	Metal can, box, and other metal container (light gauge) manufacturing
Oilseed farming	Metal cutting and forming machine tool manufacturing
Ophthalmic goods manufacturing	Metal tank (heavy gauge) manufacturing
Optical instrument and lens manufacturing	Military armored vehicle, tank, and tank component manufacturing
Ornamental and architectural metal products manufacturing	Mineral wool manufacturing
Other aircraft parts and auxiliary equipment manufacturing	Mining and oil and gas field machinery manufacturing
Other animal food manufacturing	Miscellaneous durable goods wholesalers
Other basic organic chemical manufacturing	Miscellaneous nondurable goods wholesalers
Other commercial and service industry machinery manufacturing	Miscellaneous nonmetallic mineral products
Other communications equipment manufacturing	Miscellaneous store retailers
Other concrete product manufacturing	Motor and generator manufacturing
Other cut and sew apparel manufacturing	Motor home manufacturing
Other electric power generation	Motor vehicle and machinery, equipment, and supplies wholesalers
Other electronic component manufacturing	Motor vehicle and parts dealers
Other engine equipment manufacturing	Motor vehicle body manufacturing
Other fabricated metal manufacturing	Motor vehicle parts manufacturing
Other general purpose machinery manufacturing	Motorcycle, bicycle, and parts manufacturing
Other industrial machinery manufacturing	Musical instrument manufacturing
Other leather and allied product manufacturing	Narrow fabric mills and schiffli machine embroidery
Other major household appliance manufacturing	Natural gas distribution
Other metal ore mining	Natural gas liquid extraction
Other nonmetallic mineral mining and quarrying	Natural gas power generation
Other nonresidential structures	Other residential structures
Other plastics product manufacturing	Other rubber product manufacturing
Other pressed and blown glass and glassware manufacturing	Owner-occupied dwellings
Printing	Packaging machinery manufacturing
Printing ink manufacturing	Paint and coating manufacturing
Propulsion units and parts for space vehicles and guided missiles	Paper mills
Pulp mills	Paperboard container manufacturing
Pump and pumping equipment manufacturing	Paperboard mills

High Climate Impact Sectors	
Rail transportation (diesel)	Pesticide and other agricultural chemical manufacturing
Rail transportation (electric)	Petrochemical manufacturing
Railroad rolling stock manufacturing	Petroleum lubricating oil and grease manufacturing
Ready-mix concrete manufacturing	Petroleum power generation
Real estate	Petroleum refineries
Reconstituted wood product manufacturing	Petroleum, chemical, and allied products wholesalers
Relay and industrial control manufacturing	Pharmaceutical preparation manufacturing
Residential maintenance and repair	Photographic and photocopying equipment manufacturing
Residential permanent site single- and multi-family structures	Pipeline transportation
Rolling mill and other metalworking machinery manufacturing	Plastics and rubber industry machinery manufacturing
Rubber and plastics hoses and belting manufacturing	Plastics bottle manufacturing
Sand, gravel, clay, and ceramic and refractory minerals mining and quarrying	Plastics material and resin manufacturing
Sanitary paper product manufacturing	Plastics packaging materials and unlaminated film and sheet manufacturing
Sawmills and wood preservation	Plastics pipe and pipe fitting manufacturing
Seafood product preparation and packaging	Plate work and fabricated structural product manufacturing
Search, detection, and navigation instruments manufacturing	Plumbing fixture fitting and trim manufacturing
Seasoning and dressing manufacturing	Polystyrene foam product manufacturing
Secondary smelting and alloying of aluminum	Postal service
Semiconductor and related device manufacturing	Pottery, ceramics, and plumbing fixture manufacturing
Semiconductor machinery manufacturing	Poultry and egg production
Ship building and repairing	Poultry processing
Showcase, partition, shelving, and locker manufacturing	Power boiler and heat exchanger manufacturing
Sign manufacturing	Power, distribution, and specialty transformer manufacturing
Small electrical appliance manufacturing	Power-driven hand tool manufacturing
Snack food manufacturing	Prefabricated wood building manufacturing
Soap and cleaning compound manufacturing	Primary battery manufacturing
Soft drink and ice manufacturing	Primary smelting and refining of copper
Solar power generation	Primary smelting and refining of nonferrous metal (except copper and aluminum)
Soybean and other oilseed processing	Printed circuit assembly (electronic assembly) manufacturing
Special tool, die, jig, and fixture manufacturing	Stationery product manufacturing
Speed changer, industrial high-speed drive, and gear manufacturing	Steel product manufacturing from purchased steel
Sporting and athletic goods manufacturing	Stone mining and quarrying
Spring and wire product manufacturing	Storage battery manufacturing
Vegetable and melon farming	Sugar cane mills and refining

High Climate Impact Sectors	
Vending, commercial, industrial, and office machinery manufacturing	Sugarcane and sugar beet farming
Veneer and plywood manufacturing	Support activities for agriculture and forestry
Warehousing and storage	Support activities for oil and gas operations
Waste management and remediation services	Support activities for other mining
Watch, clock, and other measuring and controlling device manufacturing	Support activities for printing
Water transportation	Support activities for transportation
Water, sewage and other systems	Surgical and medical instrument manufacturing
Wave & tidal power generation	Surgical appliance and supplies manufacturing
Wet corn milling	Switchgear and switchboard apparatus manufacturing
Wind power generation	Synthetic dye and pigment manufacturing
Wineries	Synthetic rubber manufacturing
Wiring device manufacturing	Tar sands extraction
Women's and girls' cut and sew apparel manufacturing	Telephone apparatus manufacturing
Wood container and pallet manufacturing	Textile and fabric finishing mills
Wood kitchen cabinet and countertop manufacturing	Textile bag and canvas mills
Wood windows and doors and millwork	Tire manufacturing
Turbine and turbine generator set units manufacturing	Tobacco farming
Turned product and screw, nut, and bolt manufacturing	Tobacco product manufacturing
Unlaminated plastics profile shape manufacturing	Toilet preparation manufacturing
Upholstered household furniture manufacturing	Tortilla manufacturing
Uranium-radium-vanadium ore mining	Totalizing fluid meters and counting devices manufacturing
Urethane and other foam product (except polystyrene) manufacturing	Transit and ground passenger transportation
Valve and fittings other than plumbing	Travel trailer and camper manufacturing
Truck trailer manufacturing	Tree nut farming
Truck transportation	

Appendix B

Low Climate Impact Sectors (labeled as Green); Source: S&P Global Trucost

Low Climate Impact Sectors	
Accounting, tax preparation, bookkeeping, and payroll services	Insurance agencies, brokerages, and related activities
Advertising and related services	Insurance carriers
All other miscellaneous professional, scientific, and technical services	Internet publishing and broadcasting
Amusement parks, arcades, and gambling industries	Internet service providers and web search portals
Architectural, engineering, and related services	Investigation and security services
Automotive equipment rental and leasing	Junior colleges, colleges, universities, and professional schools
Book publishers	Legal services
Bowling centers	Lessors of nonfinancial intangible assets
Business support services	Management of companies and enterprises
Cable and other subscription programming	Management, scientific, and technical consulting services
Child day care services	Medical and diagnostic labs and outpatient and other ambulatory care services
Civic, social, professional, and similar organizations	Monetary authorities and depository credit intermediation
Commercial and industrial machinery and equipment rental and leasing	Motion picture and video industries
Community food, housing, and other relief services, including rehabilitation services	Museums, historical sites, zoos, and parks
Computer systems design services	Newspaper publishers
Custom computer programming services	Non-depository credit intermediation and related activities
Data processing, hosting, and related services	Nursing and residential care facilities
Death care services	Office administrative services
Directory, mailing list, and other publishers	Offices of physicians, dentists, and other health practitioners
Dry-cleaning and laundry services	Other accommodations
Elementary and secondary schools	Other amusement and recreation industries
Employment services	Other computer related services, including facilities management
Environmental and other technical consulting services	Other educational services
Facilities support services	Other federal government enterprises

Low Climate Impact Sectors	
Fitness and recreational sports centers	Other information services
Food services and drinking places	Other personal services
Funds, trusts, and other financial vehicles	Other state and local government enterprises
General and consumer goods rental except video tapes and discs	Other support services
General federal defense government services	Performing arts companies
General federal nondefense government services	Periodical publishers
General state and local government services	Personal and household goods repair and maintenance
Grantmaking, giving, and social advocacy organizations	Personal care services
Home health care services	Photographic services
Hospitals	Private households
Hotels and motels, including casino hotels	Promoters of performing arts and sports and agents for public figures
Independent artists, writers, and performers	Radio and television broadcasting
Individual and family services	Religious organizations
Scientific research and development services	Spectator sports
Securities, commodity contracts, investments, and related activities	State and local government electric utilities
Services to buildings and dwellings	State and local government passenger transit
Software publishers	Telecommunications
Software, audio, and video media reproducing	Travel arrangement and reservation services
Sound recording industries	Veterinary services
Specialized design services	Video tape and disc rental