Lara Spaans

Kriekenpitplein 20-21

3584EC Utrecht, Netherlands

(+31) 644214268

l.j.spaans@uu.nl

Subject: Application for NBER Climate Finance Workshop PhD Workshop

Dear Professors Caroline Flammer and Stefano Giglio,

With great excitement, I am applying to the Climate Finance Graduate Student Workshop organized by the National Bureau of Economic Research (NBER) and supported by Norges Bank Investment Management. As an ambitious young scholar at the start of her academic career in sustainable finance, I believe that this workshop is an ideal platform for me to gain valuable feedback from renowned scholars in the field. Additionally, I am convinced the workshop will inspire young graduate scholars to develop new (collaborative) projects that tackle essential and unanswered research questions of the financial market's consideration of climate change risks.

I recently entered the final writing stages of my Ph.D. in Economics at Utrecht University with a focus on sustainable investments. My supervisors are Professors Kees Koedijk and Jeroen Derwall. I expect to complete my thesis in the winter of 2025. My working paper "Informative Discretionary ESG Trading" discusses how a global sample of equity mutual funds incorporates both backward and forward-looking sustainability information into their portfolio allocation. We argue that although some ESG-mandated funds are effective at identifying stocks with lower future environmental and social risks, ESG funds, on average, cater to an investor base with revealed preferences for stocks that have historically received leading ESG scores. I believe the paper makes an important contribution to existing climate finance literature (e.g., Flammer, 2023; Bolton et al., 2024) by i) quantifying mutual funds' use of both backward- and forward-looking sustainability information in their discretionary trading decisions, ii) identifying the extent of ESG stock-picking skill of institutional investors, and iii) detailing funds' tradeoff between skillfully identifying ESG stocks versus catering to flows through top-ESG-rated stocks. However, I wish to strengthen the paper's discussion of its refuting results of the analyses on stock-level and fund-level 'ESG-skill'. It would be interesting to discuss my paper in light of Professor Giglio's 2025 paper on investor beliefs and ESG portfolios.

As I will continue my academic career as a postdoctoral researcher on topics on Impact Investing at the University of Amsterdam with professors Paul Smeets and Aleksandar Andonov, I am eager to expand and deepen my academic network to researchers that enthusiastically work on climate finance topics such as climate considerations in the decisions of open-end mutual funds, cross-trading of climate risks by fixed-income fund families, and biodiversity risks for local economies. For my project on biodiversity losses in Brazil, I would consider the implications of climate risk in the global South, a region often neglected in academic research.

During my Ph.D. I have been in a research collaboration with Robeco Asset Management. Having been granted access to an international asset manager and first-hand seeing the complexities and limitations that come with financial market participants' role in catering to the investment preferences of their clients, while abiding by their responsibilities to integrate climate risk. Recent months have shown that these responsibilities are subject to changing political climates. While my PhD focused on public investing, my interest in the complexities of quantifying ESG risks for investors has evolved. I am

especially intrigued by the opportunities that the hands-on investment strategies of private investing can create for impactful investing. One of my greater academic goals is to research private investment portfolios and outline the trade-offs between their financial costs and opportunities for mitigating climate transition risk.

Attending the NBER Climate Finance workshop would provide me with a great opportunity to learn from inspiring researchers who are at the forefront of crucial climate finance research. Moreover, the intimate setting of the workshop is ideal for allowing for interesting and in-depth discussions with other young scholars.

Thank you for considering my application. I look forward to meeting you in person.

Yours sincerely,



Lara Spaans

LARA J. SPAANS

Utrecht School of Economics
Utrecht University
Kriekenpitplein 20-21
3584 EC, Utrecht, Netherlands

Email: l.j.spaans@uu.nl
Phone: +31 (0) 6 44214268

RESEARCH INTERESTS

Institutional portfolio allocation, Biodiversity, Mutual Fund Families, Shareholder engagement

REFERENCES

Prof. Dr. K. Koedijk
Department of Economics
Utrecht University
c.g.koedijk@uu.nl

Prof. Dr. J.P.J. de Jong
Department of Economics
Utrecht University
j.p.j.dejong@uu.nl

Dr. J.M.M. Derwall
Department of Finance
Maastricht University &
Utrecht University
j.derwall@maastrichtuniversity.nl

Dr. J.J. Huij
Department of Finance
Erasmus University Rotterdam &
Robeco Asset Management
jhuij@rsm.nl

EDUCATION

Utrecht University, Utrecht *09/2021 - (exp.) 12/2025*
PhD in Sustainable Financial Investments
Advisors: Prof. dr. Kees Koedijk & Dr. Jeroen Derwall
Collaboration: Robeco Asset Management with Dr. Joop Huij

- MPhil courses: Economics Research Master Utrecht University & Tinbergen Institute
- Exams in e.g., Asset Pricing, Microeconomics, Mathematics, Econometrics, Behavioral Economics, Development Economics, & Climate Finance

Erasmus University, Rotterdam *2019 - 2020*
MSc Financial Economics,

- Honours course Private Equity with Prof. dr. Han Smit and Hal Investments Rotterdam

Utrecht University, Utrecht *2015 – 2018*
BSc Economics & Business Economics, *cum laude*

- Honours curriculum
- Minor in Economic Geography
- Exchange Wirtschaftsuniversität Wien (WU), Vienna, Austria

ACADEMIC WORK EXPERIENCE

University of Amsterdam, Postdoctoral Researcher (full-time, 0.8fte) *09/2025 - (exp.) 2027*
Part of the Research Centre for Sustainable Investments and Insurance.
With Prof. dr. Paul Smeets and Prof. dr. Aleksandar Andonov.

Maastricht University, Postdoctoral Researcher (part-time, 0.2fte) *10/2025 - (exp.) 2026*
With Dr. Jeroen Derwall.

Utrecht University, Junior Researcher (full-time) *09/2020 – 08/2021*
Assembled and analyzed qualitative data at the Erasmus Medical Center for Prof. dr. Jeroen de Jong.
Researched Employee Ownership within the Netherlands for Prof. dr. Erik Stam and Techleap NL.

Erasmus University, Research Assistant *02/2020 – 08/2020*
Assisted with research and help renewing education for Prof. dr. Han Smit.

Erasmus Medical Center/ Utrecht University, Intern/ Student Assistant *02/2020 – 08/2020*
Collected data on health care innovations.
Conducted interviews with health care specialists.

Utrecht University, Student Assistant *04/2019 – 07/2019*
Co-organized the Open and User Innovation (OUI) Conference with Prof. dr. Jeroen de Jong.

VISITS

Maastricht University *05/2024 - 07/2024*
Visiting PhD Student, Finance Department

AWARDS

2023 USE Research Talent Prize (€1,000), Utrecht University School of Economics

PUBLICATIONS

1. de Jong, J. P., Rigtering, C., & **Spaans, L**. (2023). Heroes of diffusion: Making user innovations widely available. Research Policy, 52(8), 104840. doi.org/10.1016/j.respol.2023.104840

- *USE Research Talent Prize 2023.*

2. Stam, E., Kleverlaan, R., & **Spaans, L**. (2021). Making employee ownership work in startups and SMEs. European Centre for Alternative Finance.

WORKING PAPERS

1. **Sustainable Finance Disclosure Regulation: voluntary signaling or mandatory disclosure?**
with Dr. Jeroen Derwall, Prof. dr. Kees Koedijk, & Dr. Joop Huij. CEPR Discussion Paper DP18881.

Expected Thesis Chapters and Other Papers

2. **Informed Discretionary ESG Trading**
with Dr. Jeroen Derwall and Dr. Joop Huij.
3. **ESG cross-trading within (fixed income) mutual fund families.**
with Laura Wollny.
4. **Employee Ownership: A Systematic Literature Review**
with Prof. dr. Erik Stam, Anne-Sophie Halbertsma, & Ronald Kleverlaan

CONFERENCES/ SEMINARS/ WORKSHOPS

2024
Robeco Asset Management, Indices (*Seminar Presentation*), 9th Annual GRASFI Conference (*Presentation*), UU LEG Faculty Dean's Dinner 2023-2024 (*Poster Presentation*), 6th JRC Summer School on Sustainable Finance (*Presentation*), European Sustainable Finance PhD Workshop 2024 (*Presentation & Discussion*), FECS Dutch Sustainable Finance Workshop (*Presentation*), Maastricht University (*Seminar Finance Department*), Utrecht University (*Seminar Finance Section*).

2023
European Sustainable Finance PhD Workshop 2023 (*Discussion*).

2022
Robeco Asset Management, Indices (*Client Presentation*), European Sustainable Finance PhD Workshop 2022 (*Presentation & Discussion*), Utrecht University (*Seminar Finance Section*).

2021
Open & User Innovation Society 2021 (*Presentation & Discussion*), 5th European Alternative Finance Research Conference (*Presentation & Discussion*), Utrecht University (*Seminar Entrepreneurship Section*).

TEACHING AND SUPERVISION

Lecturer/ TA MSc Sustainable Finance and Investments, Utrecht University
Impact Investing, 2023/2024, 2024/2025
Teaching Assistant MSc Banking and Finance, Utrecht University
Risk Management, 2021/2022, 2022/2023
First supervisor Master Theses, 2021-2025, 12 students, Utrecht University
Guest lecturer MSc Sustainable Finance and Investments, Utrecht University
Finance Research Project, 2023/2024
Teaching Assistant, 200 MSc students, Utrecht University
Professional Skills, 2020/2021

PROFESSIONAL ACTIVITIES

Refereeing
Journal of Environmental Economics and Management.

Representation
PhD Network Utrecht (PROUT) member, Utrecht University 2023 - 2025
PhD council member, UU Faculty Law, Economics, and Governance 2022 - 2024

Organization of Conferences/ Workshops
"European Sustainable Finance PhD Workshop 2022", Utrecht University
"Open and User Innovation Conference 2019", Utrecht University
"Economic Conference 2019", Utrecht University

OTHER PROFESSIONAL EXPERIENCE

Erasmus University, Rotterdam 2020
Member of the Erasmus School of Economics 'benoemingsadviescommissie'.

Joust B.V., Utrecht 2019 - 2020
Young Professionals Recruiter.

Utrecht University 2018 - 2019
Full-time student representative of Utrecht University School of Economics.
Student member undergraduate & graduate education boards.

SKILLS

Programming Languages and Software
LaTeX, Python, STATA, R, ArcMap, MS Office

Languages
Dutch (native), English (C2), German (B2)

Nationality
Dutch

Informed Discretionary ESG Trading

Lara Spaans*, Jeroen Derwall†, Joop Huij‡, Kees Koedijk§

August 2025

Abstract

We study the extent to which funds' portfolio trades are informative about the future development in the ESG performance of their portfolio firms. Using data on institutional portfolio trades, we analyze mutual funds' discretionary trades, which we measure for individual stocks by the shares that funds trade beyond what can be expected if new capital flows were invested proportionally. We demonstrate that some ESG-mandated funds are effective at identifying stocks with fewer future environmental and social incidents. We find that mutual funds significantly make use of both backward- and forward-looking sustainability information in their discretionary trading decisions of stocks. Strikingly, unlike for ESG-identifying skill, ESG funds are rewarded with significant positive quarterly flows for being more reliant on ESG scores in their portfolio trading. This suggests that ESG funds primarily cater to an investor base with revealed preferences for stocks that have historically received leading ESG scores.

*__Corresponding author__. Utrecht University School of Economics, Kriekenpitplein 21-22, 3584 EC Utrecht; l.j.spaans@uu.nl

†Maastricht University, European Center for Sustainable Finance (ECCE), and Utrecht University, Tongersestraat 53, 6211 LM Maastricht; j.derwall@maastrichtuniversity.nl; phone: 0031433882222

‡Rotterdam School of Management and Robeco Institutional Asset Management; Burgemeester Oudlaan 50, 3062 PA Rotterdam; jhuij@rsm.nl; phone: 0031104082295

§Utrecht University School of Economics, and Centre for Economic Policy Research (CEPR) London, Kriekenpitplein 21-22, 3584 EC Utrecht; c.g.koedijk@uu.nl; phone: 0031302539800

1 Introduction

Institutional investors are incorporating information on sustainability (environmental and social) issues in their investment decisions. The Global Sustainable Investment Alliance (GSIA) in 2022 estimates that USD 30.1 trillion is invested in sustainable assets worldwide. This number is predicted to grow due to regulatory programs such as the European Sustainable Finance Disclosure Regulation (SFDR)[1]. Additionally, A survey conducted by Morgan Stanley in October 2023 found that 84 percent of US individual investors are interested in sustainable investing Morgan Stanley Institute for Sustainable Investing (2024)[2]. Hence, the literature has begun to study institutional investors' processing of sustainability information for portfolio allocation decisions more extensively (e.g., Bolton et al., 2024; Berg et al., 2024; Gantchev et al., 2023; Chen et al., 2024; Azarmsa and Shapiro, 2023; Cremers et al., 2024). Less researched is the extent to which institutional investors add value for clients who have non-pecuniary preferences.

Institutional investors, such as mutual funds, have in the past demonstrated superior future returns resulting from successful stock-picking abilities (Kacperczyk et al., 2014; Zambrana and Zapatero, 2021). Institutional investors typically have greater resources to analyze financial information and leverage market frictions, such as information asymmetries, to their advantage. This enables them to select stocks that outperform within their category (i.e, US equity, value, growth, etc)[3]. With a growing base of investors demanding sustainable assets, the financial market is seeing an increasing need to fulfill the non-pecuniary utility needs of this investor base (Riedl and Smeets, 2017; Goldstein et al., 2022). This trend adds a new dimension to the stock picking debate that has received little attention so far: do ESG funds make informed trades concerning firms' future social and environmental performance?

We measure for each firm-fund pair the quarterly discretionary trades, defined as the active changes in stock positions, net of changes that can be expected to occur when a fund trades purely due to fund flows. Discretionary trades reflect trades made upon the arrival of new information. If ESG mutual funds indeed make ESG-informed investment decisions, we would expect that their discretionary trades convey more information about firms' future ESG performance compared to those of conventional funds. Specifically, after aggregating trades of ESG funds and conventional

[1] As of 2021, the SFDR requires asset managers to report information about the sustainability risks and objectives of their funds (and their holdings) sold in the EU

[2] Despite the ESG backlash in the US, in October 2023 Chuka Umunna, JPMorgan's global head of sustainable solutions, reports "If you peel away all the noise and look at what investors are doing, it isn't so different, albeit they may not be using the labels quite in the way that we do in Europe"

[3] Another form of stock picking ability is denoted as market timing, where fund managers can forecast certain market trends and hence seek firms that correlate with the systematic risk exposure (Kacperczyk et al., 2014; Zambrana and Zapatero, 2021).

funds to firm level, we test whether changes in aggregate discretionary ownership by ESG funds relate (i) more positively to changes in a firm's MSCI ESG score, (ii) more negatively to changes in future carbon intensity, and (iii) more negatively to the number of environmental and social incidents.

We provide partial evidence that ESG funds' discretionary trades are informative about firms' future ESG performance. Specifically, firms with increased discretionary ownership by ESG mutual funds in a given quarter do not experience a significant change in the unweighted MSCI ESG scores and carbon intensity in the next quarter. However, they exhibit an increased change in unweighted MSCI ESG score after four quarters. Similarly, firms with more discretionary ownership by conventional funds do not change significantly their ESG performance in the short term, but do exhibit a decreased industry-adjusted MSCI ESG score.

However, as pointed out by the literature, ESG scores are prone to measurement and accuracy errors and may change due to factors other than the actual underlying ESG behavior of the firms[4]. Hence, we turn to RepRisk incidents to test the extent to which institutional investors are informed of the environmental and social (ES) risks of firms. We find evidence more consistent with a stock picking hypothesis: more discretionary ownership by ESG mutual funds is associated with fewer ES incidents in the next two to four quarters, whereas conventional funds' discretionary trades are unrelated to future incidents.

Next, we ask if discretionary trades of more concentrated funds are more informative about firms' future ESG performance. Literature documents that specialized funds and funds with less-diversified portfolios show more skill in terms of financial returns (e.g., Kacperczyk et al., 2005). Stock picking based on ES risks requires detailed micro-level information about stocks. In addition to financial statements and earnings forecasts, in terms of ES risks, this could entail firm-level disclosures, firm implementations of shareholder proposals, or other private information (He et al., 2023). Interestingly, we find no evidence that more concentrated (ESG) mutual funds better pick stocks that will improve ESG performance going forward. In fact, in our sample, the less concentrated ESG funds make trades that better anticipate which firms experience fewer ES incidents over the next four quarters.

Nevertheless, we also find that discretionary trades by ESG funds are most informative for stocks with relatively greater volatility in ESG score and ES incidents. This suggests that ESG stock picking may pay off more in certain concentrated portfolios that are exposed to additional

[4]Examples of this literature are Berg et al. (2024); Azarmsa and Shapiro (2023); Starks (2023)

idiosyncratic risk.

While our main analysis uses Morningstar's sustainable fund classifications to distinguish ESG funds from conventional funds, we consider alternative approaches to identify mutual funds that are more likely to assess and integrate firms' ES risks. First, studies suggest that finance professionals in Europe have a stronger ESG orientation compared to U.S. investors Gibson Brandon et al. (2022), and exhibit possibly greater ESG skill Ceccarelli et al. (2023). We group discretionary trades of European mutual funds and compare these with those of U.S. funds, but find no evidence that European funds make ESG-motivated trades that are more informed.

Second, we consider EU-regulated funds' SFDR classification[5]. Under the SFDR—which was introduced in 2019 and implemented in 2021—funds are required to disclose the extent to which ESG issues are considered, which effectively leads funds to adopt one of three SFDR labels Spaans et al. (2024). Broadly, Article-9 funds claim to have sustainable investments as an objective, and must report on how they aim to achieve it, whereas Article-8 funds state they "promote social or environmental characteristics". The SFDR is informative regarding funds' incorporation of ES risks: Article 8 and Article 9 funds face more stringent disclosure requirements at both the fund and portfolio holding levels. Similar to our main results on ESG-labeled funds, we find that greater discretionary ownership by Article 8/9 funds is associated with fewer ESG incidents measured over the next two to four quarters. In contrast, discretionary trades of Article-6 funds, which do not explicitly consider environmental and social criteria, are unrelated to firms' future ESG performance. These results further support an ESG-skill hypothesis.

Having focused on whether discretionary trades predict firm-level ESG performance, we subsequently ask if these trades predict future stock returns. Ex ante, it is not clear that future returns increase or decrease with discretionary ESG ownership, if at all. Literature to date is divided on whether firms increase or decrease profits and shareholder returns by managing ESG objectives[6]. Moreover, even if fund managers actively trade on ESG information that is financially material, this information may be instantaneously impounded in stock prices[7]. Interestingly, our results indicate

[5]SFDR refers to the Sustainable Finance Disclosure Regulation. REGULATION (EU) 2019/2088: `https://eur-lex.europa.eu/eli/reg/2019/2088/oj/eng`

[6]For recent mixed evidence on the relation between ESG-related factors and stock returns or profitability, see e.g. Eccles et al. (2014); Khan et al. (2016); Bolton and Kacperczyk (2021); Pedersen et al. (2021); Pástor et al. (2022); Ardia et al. (2023); Bolton and Kacperczyk (2023); Karolyi et al. (2023); Sautner et al. (2023); Berg et al. (2024); Edmans et al. (2024); Alves et al. (2022); Galema and Gerritsen (2025); Zhang (2025); Lin et al. (2025).

[7]For example, several studies conclude that after a firm experiences negative ESG news, its stock price decreases (Krüger, 2015) and analysts quickly lower their expectations of the firm's future cash flows (Derrien et al., 2022) However, an alternative body of work suggest that analysts and investors may not respond instantly to publicly available ESG-and climate-related information that affects firms or industries, which could imply that stock prices may—at least in the short run—not immediately reflect all value-relevant ESG information; see, e.g., Edmans (2011); Borgers et al. (2013); Addoum et al. (2023); Pankratz et al. (2023); Hong et al. (2019).

that discretionary ownership by ESG funds, and by European Article 8/9 funds, positively relates to stock return in the next quarter, whereas more discretionary ownership by conventional funds, but not Article 6 funds, is associated with lower future returns. Discretionary ownership by ESG funds especially relates to next quarter's stock returns for stocks that are relatively more volatile in ES incidents. Although these results are initially surprising, considering that conventional funds are expected to make financially informed trades, we note that discretionary ownership exhibits a relation to future returns that appears to be economically small and short-term. Specifically, we find that these return effects are temporary and may even somewhat revert for Article 8/9 funds.

On average, ESG Funds do not seem to trade economically significantly on new information that matters for understanding a firm's future ESG performance; i.e., an ESG skill hypothesis. We use the holding data of our sample of mutual funds to identify *individual funds* that have a higher propensity to increase their discretionary ownership in firms that have fewer ES incidents in the future. While we indeed find significant differences in the cross-section of funds' propensity to invest with future ES risks in mind, we find no differences in excess or abnormal returns between funds that have a high versus low propensity to increase their discretionary ownership in firms that in the future see fewer ES incidents.

We argue that ESG-skilled mutual funds may rely differently on historic ESG data to make decisions affecting their funds' portfolio allocation. On the one hand, it is conceivable that ESG-driven trades partly follow standard ESG metrics that are relatively easy to obtain. Earlier evidence suggests that mutual funds, especially those that are ESG-oriented, significantly trade on historic firm-level ESG data (e.g., Gibson Brandon et al., 2022; Berg et al., 2024). On the other hand, we expect that ESG-skilled discretionary trades arise from proprietary ESG analysis made by funds, which is, however, difficult to observe. Hence, we shift our perspective from ESG skill—consisting of incorporating forward-looking ES risks—to mutual funds' usage of ESG information. We undertake three analyses to shed more light on ESG and conventional funds' use of ESG data in trading.

First, we study how mutual funds trade after stocks' inclusion in the MSCI All Companies World Index (ACWI) and its ESG-screened twin, the ACWI ESG Leaders Index. We explore the staggered difference-in-difference setting of firms entering only the MSCI ACWI and firms entering both the MSCI ACWI and ESG Leaders indices. Following De Chaisemartin and d'Haultfoeuille (2024), we estimate the treatment effects of the firms that enter the MSCI indices over time. Interestingly, we find limited evidence that discretionary trading by ESG funds goes towards firms that enter the ACWI or ESG Leaders index. Instead, conventional funds respond to firms entering the MSCI

ACWI index, leading to increased net buys towards those firms in the first treatment quarter. Firms that additionally enter the MSCI ACWI ESG Leaders sub-index experience increased net sales by conventional funds. While we find evidence that ownership increases in firms that enter world indices (see e.g., Kacperczyk et al., 2021), we also note that this is not the sole driver of changes in funds' portfolio composition. Specifically, discretionary trades by ESG funds are unaffected by changes in the MSCI ACWI ESG Leader sub-index, suggesting that ESG funds make trading decisions based on other sources of information, potentially of a predictive nature for environmental and social risks.

Second, previous work suggests that ESG-focused institutional investors substantially rely on ESG scores from MSCI ESG Research (e.g., Gibson Brandon et al., 2022; Berg et al., 2024). To shed light on the importance of past ESG data in trading, we extend our focus on mutual funds' discretionary trades to their total quarterly position changes in response to firm-level ESG scores and incidents from the previous quarter. Results indicate that conventional mutual funds tend to decrease their positions in stocks with higher ESG ratings, whereas ESG funds increase their positions. Conventional funds increase their positions after an ESG-rating increase (decrease), but less so than ESG funds.

Next to focusing on funds' consideration of stock ESG information (in terms of ESG scores and an ESG benchmark), we analyse how fund managers ruminate on negative ES incidents of their holdings. ESG Funds lower their positions in stocks that experienced a (severe) ES incident, but increase their position in stocks with the highest ESG scores even if they experience a negative ES incident. We do not note this for conventional funds; instead, this subset of funds trades away from stocks that have higher ESG ratings and a higher number of ES incidents. To filter out funds' expected trades from funds' total trades, we also replace position changes for fund discretionary trades (Coval and Moskowitz, 1999; Huang et al., 2023; Van der Beck, 2021; Heath et al., 2023). Contrasting the results from total fund trades, ESG funds lower their discretionary ownership in stocks that are affected by ES incidents in previous quarters, regardless of whether the stock has a high or low ESG score. This discrepancy in trading behavior of ESG funds may indicate that ESG Funds follow firm ESG scores closely for their expected trading, but to some extent move away from these stocks following ES incidents. These results corroborate that mutual funds, in particular ESG funds, do significantly trade on historical firm-level ESG data.

Third, we measure the fund managers' reliance on firm-level ESG information. Following the methodological framework of Kacperczyk and Seru (2007) and Fang et al. (2014), we estimate a

proxy of funds' reliance on public ESG information (i.e., ESG scores or knowledge of ES incidents). We find that ESG funds are rewarded in terms of additional investor flows if they have historically used MSCI ESG scores for their portfolio trading decisions. On the other hand, we see that ESG funds see a slight outflow following a stronger reliance on ES incidents.

Our paper complements the wide literature that examines the non-pecuniary preferences within the financial market (Riedl and Smeets, 2017; Hartzmark and Sussman, 2019; Barber et al., 2021; Geczy et al., 2021; Pástor et al., 2021; Pedersen et al., 2021; Kim and Yoon, 2023; Derwall et al., 2011; Starks, 2023). A large number of funds market the integration of environmental, social, and/or governance (ESG) issues in investment decisions, either for the benefit of financial return and/ or for the pursuit of certain social and environmental objectives. Our study shows that ESG-oriented fund managers have an incentive to trade on information that is relevant for predicting future changes in firms' ES risks. On a firm level, we find that ESG (or similar ESG-focused) mutual funds' discretionary trades are to a degree informative about changes in firms' future environmental and social performance, compared to discretionary trades by conventional, financially focused mutual funds.

It follows that our results contribute to a few related papers that study the use of ESG information in active investment management. Cremers et al. (2024) measure for each U.S. mutual fund an ESG ratings distribution at the portfolio level, based on different third-party ESG ratings of underlying holdings, relative to the ESG distribution of an associated benchmark. They argue that the difference in ESG rating distribution between the fund and the benchmark ('Active ESG Share') captures the use of discretionary ESG information, which could predict fund returns if this information is financially material. They document that Active ESG Share positively predicts returns of ESG funds, but not returns of conventional funds in the U.S.. The former is especially when ESG funds hold stocks with greater ESG ratings divergence. They further document that ESG funds with a higher Active ESG share profit from future return increases from stocks that see future ESG rating upgrades. This hence suggests a ratings anticipation channel. In a related study, Chen et al. (2024) conclude that U.S. mutual funds trade on financially material ESG information by linking fund holdings to ESG TruValueLabs' "pulse scores" that specifically focus on industry-specific financially material issues identified by the Sustainability Accounting Standards Board (SASB). They also document that funds with a greater propensity to weigh pulse scores in investments have higher returns. However, these studies do not directly test whether active ESG funds anticipate future ESG performance changes to start with.

Furthermore, Ceccarelli et al. (2023) measure fund-level 'ESG skill' in a given period by how many 'proactive' trades were previously made in stocks that exhibited subsequent improvements in ESG scores. If a fund manager possesses ESG skills, they expect that these proactive trades will continue to be forward-looking in the subsequent period. Consistent with such persistence, they find that U.S. funds with more proactive ESG trades exhibit greater future improvement in ESG scores, but they do not exhibit better 'alpha'. However, counting the number of trades in stocks that experience improvements in ESG scores may not necessarily measure proactive trading on ESG informativeness, but instead capture expected trades that funds are expected to make because of induced fund flows (in accordance with the mechanism outlined by Van der Beck, 2021; Wardlaw, 2020). In our paper, we distinguish flow-driven expected trades from discretionary trades, and we document that ESG funds' discretionary mutual fund trades relate to both future changes in firms' ESG performance and future stock returns in the short term.

We contribute to the literature on specialization by institutional investors. Cremers et al. (2024) measures proprietary ESG information by considering the differences in aggregated portfolio and benchmark weights at the MSCI ESG rating level. Our study sheds additional light on what this proprietary ESG information consists of—complementary to He et al. (2023), we find evidence that ESG funds in their trading decisions show some forward-looking perspective on negative ES incidents. However, we also note that funds that are more 'skilled' with regard to future firm ES risks are not rewarded for this in terms of alpha or relative fund flows. We build upon the recent work of Azarmsa and Shapiro (2023), which describes how ESG preferences of investors are catered to with 'generalized' ESG ratings. They theoretically predict that when investors value the asset's performance of more than one specific ESG component, ESG raters will split their efforts over the different ESG rating categories. In our paper, we find evidence that ESG Funds, in the same manner, 'generalize' their ESG portfolio decisions. For ESG Funds that have used changes in MSCI ESG scores up to four lagged quarters in their portfolio trading decisions more extensively, we find higher relative fund flows. The opposite is true for ESG funds that have used information on their holdings' negative ES incidents: they experience some outflows. Literature indeed has shown evidence that funds with higher ESG scores or sustainability indicators are rewarded with additional investors flows (even if temporarily) (Hartzmark and Sussman, 2019; Gantchev et al., 2023; Ceccarelli et al., 2024; Spaans et al., 2024)[8]. However, while Berg et al. (2024) indicates that ESG funds merely change their ownership of stocks in line with their ESG ratings to abide by

[8]Even on the stock level there has been evidence that investors can respond strongly to changes in ESG scores (see e.g., Rzeźnik et al., 2022)

their ESG mandate, in our paper, we find evidence that, additionally, ESG investors through their flows respond to ESG funds' stock selection based on changes in stock ESG scores. Similar to the reasoning provided by Solomon et al. (2014), we find that ESG investors are aware of the extent to which ESG Funds invest in the top 'greenest' stocks[9].

2 Data

2.1 Fund level data

From Morningstar Direct, we retrieved monthly data (in USD) on a sample of European and US open-end equity mutual funds between December 2014 and December 2022. We filter our sample of mutual funds for those that are domiciled in Europe[10], or the United States, and following Ceccarelli et al. (2024), we remove regional and sector-specific equity funds[11]. We drop funds that we cannot match to the FactSet Ownership data. While Morningstar provides data on the share class level, we utilize the FundId identifier to aggregate returns and assets under management (AUM). To aggregate the share class returns to the fund level, we value-weight the returns using the share classes' lagged total net assets. We calculate the age of the fund by using the inception date of the oldest share class.

Table 1 reports the descriptions of various quarterly fund-level variables such as assets under management (TNA), fund flows, returns, portfolio turnover, age, percentage of portfolio that is cash, and sustainability classifications. Following Ceccarelli et al. (2024), we limit our sample to fund periods in which mutual funds are at least 1 year old. Additionally, we require them to have assets under management of at least 1 million USD in our sample. In addition, consistent with the price pressure literature, we remove funds that experienced extreme changes in TNA (Coval and Stafford, 2007; Falato et al., 2021). We require funds to see TNA changes within the bounds of -0.5 to 2:

$$-0.5 < \Delta TNA_{i,t}/TNA_{i,t-1} < 2.0$$

[9]Solomon et al. (2014) show that winner stocks in funds' portfolios attract investor flows if they had been featured in the media. Through, for example, the funds' display of their top 10 holdings on trading platforms, (retail) investors have easy access to the ESG scores of individual stocks (Rzeźnik et al., 2022; Hartzmark and Shue, 2023).

[10]This includes all countries part of the EEA as well as the United Kingdom, Norway, Switzerland, and Liechtenstein.

[11]We include funds with the following Morningstar Categories: 'Europe Equity Mid/Small Cap', 'Global Equity Large Cap', 'Europe Equity Large Cap', 'US Equity Small Cap', 'Equity Miscellaneous','US Equity Mid Cap', 'US Equity Large Cap Blend', 'Global Equity Mid/Small Cap', 'US Equity Large Cap Growth', 'US Equity Large Cap Value', 'UK Equity Large Cap', 'UK Equity Mid/Small Cap'

The median quarterly fund flows is -0.92% and in line with the literature that investigates fund flows of equity funds (Gantchev et al., 2023; Wang, 2024), but the values on the 1st and 99th percentiles show extensive variation in fund in- and outflows over time.

We reduce the fund-quarter observations for which cash as a percentage of assets under management exceeds the 0.5 and 99.5 percentiles[12].

Funds, on average, hold 178 to 179 holdings. Although we condition the age of the fund to be at least one year since the inception of the oldest share class, the median number of holdings is 64 holdings, which is consistent with the literature on portfolio concentration of actively managed funds (Kacperczyk et al., 2005).

To identify the funds that are classified as 'ESG' funds, we make use of the Morningstar Sustainable Attributes framework that identifies funds that are considered a 'General ESG Investment'. Morningstar in 2022 describes that "General ESG Investments endeavor to promote sustainability and minimize negative impact, without focusing on a specific theme or area of action". Morningstar determines whether mutual funds are an ESG Investment "after a review of the prospectus or offering documents most relevant in the investment products country of registration. We consider a mutual fund to be an 'ESG' fund if, during the majority of our time series, the respective fund is classified as such by Morningstar. Of our sample of fund quarters, 28% are from ESG Funds. We consider the other 72% to come from conventional funds.

We additionally consider potential differences in ESG considerations between European and US-domiciled funds (Gibson Brandon et al., 2022; Dyck et al., 2019; Gibbon et al., 2023). Of our sample, 68% of the fund-quarters come from funds domiciled in countries that are part of the European Union, including Norway, Liechtenstein, Switzerland, and the United Kingdom. 32% of the fund quarters come from funds that are domiciled in the US.

Lastly, we are interested in funds that are bound to consider sustainability risks and adverse impacts with more care in the composition of their portfolios. The European Sustainable Finance Disclosure Regulation (SFDR) was established in 2021 to overcome information asymmetries between investors, regulators, and financial market participants regarding the integration of sustainability risks, consideration of adverse sustainability impacts, and promotion of environmental and social

[12]We control for sudden abnormalities in the FactSet ownership data. For example, for fund Sparinvest SICAV - European Value with ISIN code LU1616402803, FactSet Ownership for $<$ Q1 2017 shows an average percentage of cash and or short-term positions of about 2.5%. In Q1 2017 and Q2 2017, the weights of the stock holdings are inflated to make up a total stock portfolio of 2,181.69% and 2,286.69%, respectively. Hence, FactSet Ownership sets the total weights of the cash and short-term positions equal to a respective -2,080.69% and -2,186.69% to ensure that the final equity portfolio adds up to 100.0%. From Q3 2017 onward, the fund's percentage of cash within the portfolio falls to 1.64-2.10%. A search in the official Sparinvest semiannual report for Q2 2017 showed that cash as a percentage of net assets in reality was 3.44%.

characteristics of funds and their underlying portfolios (Spaans et al., 2024; Busch, 2023). The regulation requires European mutual funds to provide this non-financial information on their website, in (semi)annual reporting, marketing, and pre-contractual documentation. A key component of the SFDR is the labeling component that dictates the degree to which funds *promote* sustainable investment (referred to as Article 8 products) or additionally see it as their *objective* (referred to as Article 9 products). Article 6 funds do not promote sustainable investing but are nevertheless required to report on their sustainability risks. For European funds, Morningstar retrieves from the fund's prospectus which SFDR Article the fund aligns with. Table 1 shows that of our sample of European funds, 59.6% say they take on an Article 8 or 9 label. The other 40.4% of fund quarters are from our sample of Article 6 funds.

2.2 Holdings panel

We are able to match our Morningstar fund database to mutual fund holding information provided by the FactSet ownership module (see also the work by Ferreira and Matos, 2008; Ceccarelli et al., 2023). Using the ISINs of the share classes as reported by Morningstar, we gathered information from FactSet (formerly Lionshares) on the quarterly equity holdings of our equity mutual fund sample from December 2014 to December 2022.

Per quarter (our sample consists of 33 calendar quarters starting on 2014-12 and ending at 2022-12), we retrieved for our sample of funds the local FactSet identifier[13], the position, and the weight in the fund's portfolio. Although funds are often made up of multiple share classes, they are matched to one single portfolio of holdings. Therefore, for every fund, in every quarter, we identify the first share class for which FactSet reports its holdings. As a result, our share class level holding data is mapped to the fund level. In total, our sample of funds contains 53,603 unique FactSet holding identifiers.

To identify and link the holdings with company-level data, we match the holding identifiers to FactSet's permanent security identifier "*FSYM_SECURITY_ID*"[14]. From FactSet Prices and FactSet Reference Data, we additionally retrieve information on the exact security type of the

[13]In FactSet's ownership module, we use the function "*OS_TOP_HLDG_LOCID*" to gather the identifier for the holdings. FactSet uses the historical ticker, the header ticker, the Sedol, or cusip to identify the individual holdings.

[14]In cases FactSet did not provide a link between holding identifier, *OS_TOP_HLDG_LOCID*, and the permanent security identifier, "FSYM_SECURITY_ID", we would (1) identify the specific funds and quarters in which that holding was present, and (2) we would manually download the specific funds' holdings again using an alternative identifier from the FactSet ownership module, using OS_TOP_HLDG_SEDOL or OS_TOP_HLDG_CUSIP and OS_TOP_HLDG_NAME to assign a different identifier as well as the correct holding name to the local holding identifier *OS_TOP_HLDG_LOCID*. Lastly, (3) we would use the manually gathered identifier to make a correct match to FactSet's permanent security identifier.

holdings. In our fund holdings panel, we only keep the holdings that are categorized as shares. Lastly, from FactSet Fundamentals, we retrieve information on whether the stock in our holdings database is the primary security of the respective company[15]. Hence, our final sample contains 31,824 unique global *FSYM_SECURITY_IDs*.

To assemble our fund holdings panel, we transpose the holding information into a long-form fund-holding panel for every quarter. To identify unique fund-holding combinations, in every quarter we combine the Morningstar *FundId* with the FactSet Permanent Security Identifier, *FSYM_SECURITY_ID*. We make sure that the fund-holding-quarter panel is balanced by creating an empty dataframe ranging from Q4 2014 to Q4 2022 for all unique *FundId -FSYM_SECURITY_ID* combinations. To this balanced panel, we merge the fund-holding-quarter level data, such as the holding positions and weights of the respective funds. As we are interested in measuring trades of funds based on the current and last quarter's reporting date, we drop funds for which we find that FactSet has gaps concerning the funds' holding information. We find that 361 Morningstar *FundId*s have gaps in their holdings data as gathered through FactSet Ownership. Additionally, we follow the literature and impose that the funds in our sample should have at least 10 individual holdings in their portfolio at one moment[16].

2.2.1 Stock level characteristics

To our global sample of 31,824 primary stocks, we match quarterly Compustat (and CRSP) accounting- and market-based data following Jensen et al. (2022). To see whether mutual funds are able to select stocks that in the future will see improvements in their sustainability behavior, we consider various metrics that we match to our fund-holding-quarter panel: 1) Revenue-weighted Scope 1 and 2 carbon emissions from Refinitiv, 2) MSCI ESG scores (industry-weighted and equal-weighted), and 3) RepRisk incidents.

Refinitiv (LSEG) estimates firm-level carbon intensity using data from publicly disclosed documents by the firm, such as annual reports, sustainability reports, or company websites and or filings. The CPD data are used for data from 2015 onward. Quarterly level carbon intensity is measured in tonnes of Scope 1 and Scope 2 CO2 emissions per million USD of firm revenue. Refinitiv winsorizes

[15] As multiple local FactSet identifiers can be matched to a single FactSet permanent security identifier, we gather this data for both identifiers. First, we filter out the FactSet permanent identifiers that are not the primary security. We then additionally filter out the remaining FactSet local identifiers that are not deemed a primary security.

[16] Here, we follow Huang et al. (2023) as we are interested in the variation in changes in the portfolio allocations of funds. Work on pressure trading and position changes by Coval and Stafford (2007) and Gantchev et al. (2023) impose a restriction of at least 20 holdings per fund in their sample period.

outliers in the reported data, and extrapolates reported years to non-reported years[17]. To measure future improvements in firm CO2 emissions, we calculate the percentage change between a firm's current carbon intensity in quarter t and future carbon intensity in quarter $t+s$ in which s denotes the number of lead quarters. We winsorize $\Delta CarbonIntensity_{j,t+s}$ at the 1st and 99th percentiles. Table 2 shows that for our sample of issuers, the median change in carbon intensity between the current quarter and the quarter in a year is 0.57%[18].

Recent literature emphasizes the role that firm ESG ratings play in influencing the trading decisions of mutual funds (Gantchev et al., 2023; Berg et al., 2024; Ceccarelli et al., 2023; Chen et al., 2024). MSCI in particular seems to be one of the most influential (Berg et al., 2024; Serafeim and Yoon, 2023): of the largest 100 ESG funds globally, 17% of these used MSCI for benchmarks and ESG data in 2022[19]. ESG scores issued by MSCI assess the extent to which firms are exposed to financially material Environmental, Social, and Governance risks. Moreover, MSCI assesses how the firm manages these risks. MSCI calculates two ESG scores, a raw "Weighted Average Key Issue Score" that weights all ESG issue based on financial materiality, and an "Industry-Adjusted Score" that benchmarks raw key issue scores to industry peers. Both scores range from 0 to 10, where a score of 0 indicates the worst management of ESG risks. Industry-Adjusted Company scores are finally mapped to MSCI's letter ratings, aiding investors in distinguishing the leaders, laggards, and average ESG-performing firms. We calculate the absolute future change in quarterly raw or industry-weighted MSCI ESG scores between the current quarter t and quarter $t+s$ in which s denotes the number of lead quarters: $\Delta MSCI_{j,t+s} = MSCI_{j,t+s} - MSCI_{j,t}$. We use both the raw and the industry-weighted ESG score, as the firm's former score is not affected by the behavior of its peers. Hence, we want to see whether funds are able to predict the ESG risk management of a firm or whether they are able to predict changes in a firm's ESG score with respect to their peers. The average change in the raw MSCI ESG scores between t and $t+1$ is 0.02 points and 0.09 points between t and $t+4$. The standard deviation is higher for future changes in industry-weighted MSCI scores, suggesting that the behavior of industry peers creates additional variation in firm ESG scores.

We complement these two metrics with data from RepRisk. RepRisk screens, on a daily basis, large sets of documents and media (e.g., print media, government bodies, social media, and newsletters), in which it monitors material ESG risks of companies in 23 different languages. They pur-

[17] https://www.lseg.com/content/dam/data-analytics/en_us/documents/methodology/lseg-climate-data-package-ghg-emissions-methodology-process.pdf

[18] The median change in carbon intensity between the current quarter and the next is 0.00%, suggesting that reductions in carbon intensity happen on a longer term. The mean, on the other hand, is -0.052%.

[19] https://www.opimas.com/research/874/detail/

posely omit information coming from company-disclosed information. From 2007 onward, RepRisk has recorded company-level risk incidents, classifying them according to 28 mutually exclusive ESG issues[20]. Environmental issues include, for example, climate change, pollution, and waste. Social issues include child labor, human rights abuses, and discrimination.

In this paper, we collect the number of incidents labeled by RepRisk as negative environmental or social issues for each firm-quarter. RepRisk's coverage increases over time both in terms of reported incidences as well as unique firms (He et al., 2023; Derrien et al., 2022). RepRisk, additionally, ranks the reported incidents on 'severity' based on the incident's consequences regarding ESG issues. Severity is measured on a scale from one to three, where two and three represent 'Severe' and 'Very severe', respectively. # environmental and social incidents$_{t+s}$ denotes the number of all RepRisk incidents of firm j that are characterized as an environmental or social issue in quarter(s) $t+s$ with $s \in \{1, 2, 3, 4\}$. In $t+4$, we cumulatively count all E and S incidents that happen in quarters $t+1$ to $t+4$. # severe environmental and social incidents$_{t+s}$ denotes the number of all RepRisk incidents of firm j that are characterized as an environmental or social issue with severity rank two or three in quarter(s) $t+s$ with $s \in \{1, 2, 3, 4\}$. Table 2 shows that the median number of environmental and social incidents per firm per quarter is 0. The mean (0.28 vs. 0.09) and 99th percentile (5 vs. 2 incidents) show that the majority of RepRisk's environmental and social incidents are not severe[21]. As RepRisk is news-based instead of being based on company disclosures, it may better reflect the company's outcomes of management of ESG risks than ESG scores. Investors may use forward-looking information to stock pick holdings that see fewer environmental and social incidents in the future.

All non-USD market information is converted to USD using the foreign-USD exchange rates from Compustat. Following Jensen et al. (2022), all accounting data assumes a four-month lag between the end of the firm's fiscal period and the public availability of the data. Values in local, non-US currencies are again converted using the last available foreign exchange rate of Compustat. We follow Bolton et al. (2024): 1) We calculate the natural logarithm of the company's market capitalization, *Log Market Cap.*; 2) we gather data on the firm's number of shares in the previous quarter in millions of shares, *# Shares*; 3) the quarterly stock return *Quarterly stock returns*; 4) the firm's book value over the most recent market capitalization, *Book/ Market*; 5) stock momentum which is the most recent 12 month stock return, omitting month $t-1$, *Momentum*; 6) capital

[20]The Issues were defined per key international standards set by, for example, the World Bank, OECD, and United Nations. `https://www.reprisk.com/content/static/reprisk-esg-issues-definitions.pdf`

[21]An example of a non-severe (ranked one on RepRisk's severity scale) is Dunkin' Donuts sourcing palm oil from suppliers that contribute to the destruction of rainforests.

expenditure over the book value of a firm's assets, *CAPEX/ Assets*; 7) the market beta of the firm's primary stock calculated over the daily returns of the last 12 months, *Beta*; 8) the annualized standard deviation of daily returns over the previous 12 months, *Return volatility*; 9) the firm's quarterly income scale by the book value of equity, *ROE*; 10) the ratio of gross debt to book value of assets, *Leverage*. We report the descriptives in Table 2

From FactSet's MSCI module, we retrieve the data on the index inclusion of the firm in MSCI's All Country World Index and MSCI's All Country World ESG Leaders Index. We winsorize the continuous control variables on the 1st and 99th percentiles.

2.3 Measuring trades by mutual funds

For our sample of European and US mutual funds, we investigate their trading behavior in terms of backward and forward-looking sustainability information. Specifically, our analysis focuses on stock selection behavior on the future sustainability behavior of portfolio firms. Skilled investors form portfolios that consider forward-looking ESG information. Stock picking means (net) buying—more than expected—stocks that will see improvements in terms of fewer RepRisk incidents, improvements in MSCI ESG scores, or reductions in carbon intensity.

To determine the trading behavior, we first determine the quarterly flows of fund i between quarters $t-1$ and t following Sirri and Tufano (1998):

$$flow_{i,t} = \frac{[TNA_{i,t} - TNA_{i,t-1} * (1 + R_{i,t})]}{TNA_{i,t-1}} \tag{1}$$

where $TNA_{i,t}$ is the total net assets for fund i at the end of the quarter t, and $R_{i,t}$ is the quarterly return for fund i in quarter t. As our fund data from Morningstar is on a monthly basis, we compound our monthly fund returns into quarterly fund returns.

The literature on mutual fund flow-induced trading (Coval and Stafford, 2007; Van der Beck, 2021; Wardlaw, 2020; Huang et al., 2023; Heath et al., 2023) describes two sources of trading. The first is trading that is 'expected' assuming that mutual funds maintain their percentage of holdings of stock j at the beginning of the quarter, $w_{i,j,t-1}$, and reinvest incoming dollar flows proportionally. Coval and Stafford (2007) finds that between 1980 and 2004, funds maintain 27 to 45 percent of their positions following different degrees of inflows and outflows. For our baseline, we define expected trades of stock j for every quarter t as the buys of shares (sales) resulting from a prorated dollar flow coming in (out of) the fund:

$$ExpectedTrading_{j,t} = \frac{\sum_i (Position_{i,j,t-1} \times flow_{i,t} | flow_{i,t} > 0)}{ShareOutstanding_{j,t-1}} + \frac{\sum_i (Position_{i,j,t-1} \times flow_{i,t} | flow_{i,t} < 0)}{ShareOutstanding_{j,t-1}} \quad (2)$$

where $Position_{i,j,t-1}$ is the number of shares held of stock j by fund i in quarter $t-1$ and $flow_{i,t}$ is defined as in equation (1). $ExpectedTrading_{j,t}$ denotes the net expected buys of stock j. Stocks that in quarter $t-1$ were not being held by the fund (i.e., $Position_{i,j,t-1} = 0$) would see an expected trade of 0. We normalize expected trades by the shares outstanding of firm j to prevent creating a mechanical correlation with returns (Wardlaw, 2020). We can split expected trading into expected buys and expected sales:

$$ExpectedBuy_{j,t} = \frac{\sum_i (Position_{i,j,t-1} \times flow_{i,t} | flow_{i,t} > 0)}{ShareOutstanding_{i,t-1}}$$

and

$$ExpectedSell_{j,t} = \frac{\sum_i (Position_{i,j,t-1} \times flow_{i,t} | flow_{i,t} < 0)}{ShareOutstanding_{i,t-1}}$$

Different from measuring flow-induced price pressure (Van der Beck, 2021) or determining future trades from past ESG trades (Ceccarelli et al., 2023; Heath et al., 2023), we are particularly interested in measuring deviations of the expected trading behavior of funds.

Literature on price pressure and fire sales has made use of the definition of Coval and Stafford (2007) to determine the actual trades of stock holding i induced by large in and outflows:

$$PressureTrading_{i,t} = \frac{\sum_i (max(0, \Delta Holdings_{i,j,t}) | flow_{i,t} > 90\%ile)}{ShareOutstanding_{j,t-1}} - \frac{\sum_i (max(0, -\Delta Holdings_{i,j,t}) | flow_{i,t} < 10\%ile)}{ShareOutstanding_{j,t-1}} \quad (3)$$

where $PressureTrading_{i,t}$ describes the number of shares j bought by fund i as a result of in and outflows beyond the 90th and 10th percentiles (i.e., 'extreme flows'), respectively[22]. In our baseline analysis, we are interested in stock-picking behavior as a consequence of all degrees of fund flows. Hence, we extend the measure to

$$ActualTrading_{i,t} = \frac{\sum_i (max(0, \Delta Position_{i,j,t} | flow_{i,t} > 0)}{ShareOutstanding_{j,t-1}} - \frac{\sum_i (max(0, -\Delta Position_{i,j,t} | flow_{i,t} < 0)}{ShareOutstanding_{j,t-1}} \quad (4)$$

[22]During extreme flows the measure of expected trades as defined in equation (2) can simply be adjusted to $ExpectedTrading_{j,t} = \frac{\sum_i (Position_{i,j,t-1} \times flow_{i,t} | flow_{i,t} > 90\%tile) + \sum_i (Position_{i,j,t-1} \times flow_{i,t} | flow_{i,t} < 10\%tile)}{ShareOutstanding_{j,t-1}}$

where similarly to Coval and Stafford (2007) and Huang et al. (2023) we consider the net buys in the shares of stock j held by fund i between quarter $t-1$ and quarter t. $flows_{i,t}$ are percentage flows as defined in equation (1). Additionally, in this specific measure, we merely focus on buys during inflows and sales during outflows. However, even in this concentrated setting, funds are still *choosing* which stocks to purchase or sell. To measure the deviations in expected trading, resulting in changes to the portfolio composition, we follow Huang et al. (2023) so that we define discretionary trading of stock j as

$$DiscretionaryTrading_{j,t} = ActualTrading_{j,t} - ExpectedTrading_{j,t} \tag{5}$$

where we can split discretionary trading into discretionary trades during inflows and discretionary trades during outflows:

$$DiscretionaryBuy_{j,t} = \frac{\sum_i (max(0, \Delta Position_{i,j,t} | flow_{i,t} > 0)}{ShareOutstanding_{j,t-1}} - \frac{\sum_i (Position_{i,j,t-1} \times flow_{i,t} | flow_{i,t} > 0)}{ShareOutstanding_{i,t-1}}$$

and

$$DiscretionarySell_{j,t} = -\frac{\sum_i (max(0, -\Delta Position_{i,j,t} | flow_{i,t} < 0)}{ShareOutstanding_{j,t-1}} - \frac{\sum_i (Position_{i,j,t-1} \times flow_{i,t} | flow_{i,t} < 0)}{ShareOutstanding_{i,t-1}}$$

In our balanced fund-holding-quarter panel, we fill in a 0 for the quarter the fund does not hold a specific holding. Thus, we include discretionary trades made by funds to holdings they, in the previous quarter $t-1$, did not yet hold. Similarly, we include holdings that are completely sold off between quarter $t-1$ and t. We reason that, also on the extensive margin, funds make informed decisions about which holdings to include and which to divest fully.

To distinguish whether ESG funds are better in stock picking based on forward-looking ESG information, we calculate $DiscretionaryTrading_{j,t}$ for various subsets of our sample of funds (see section 2.1): 1) funds that are assigned as an ESG fund or conventional fund following the Morningstar Sustainable Attributes framework; 2) funds that are domiciled in Europe or the United States; 3) funds that fall under the European Sustainable Finance Disclosure Regulation (SFDR) and either take on an Article 8 or 9 and Article 6 label. We report the calculated discretionary and expected trades for different subsections in panel A of Table 3. To limit the influence of outliers, we winsorize all discretionary and expected trades on the 0.5 and 99.5 percentiles[23].

Panel A of Table 3 shows summary statistics on the firm-level measures of discretionary trading for ESG funds and non-ESG (conventional) funds, and for funds grouped by SFDR article, by region (Europe or US), and by portfolio concentration. Panel B shows summary statistics for funds

[23] In Table 33 we report the results of Table 6 on different winsorizing and trimming options.

experiencing extreme flows in a specific quarter. One insight from Table 3 is that discretionary trades exhibit greater volatility. Part of this discretionary trade variation arises whenever a fund includes (drops), in a given quarter, a company that was not held (dropped) in the previous quarter. To better understand how discretionary ownership relates to a firm's future ESG performance, we report standardized coefficients across all regressions that are central to this paper. Furthermore, as expected, the correlation matrix shown in Table 4 indicates that discretionary and expected trades are only weakly correlated.

3 Empirical results

3.1 Do ESG funds' net discretionary buys anticipate changes in a firm's future ESG performance?

Table 5 reports on the relation between firm-level changes in discretionary shareholdings by ESG mutual funds and next-quarter changes in firm-level sustainability outcomes:

$$\begin{aligned}\Delta Sustainability_{j,t+1} = \beta_0 + \beta_1 DiscretTrades_{j,t} + \beta_2 ExpectedTrades_{j,t} \\ + \gamma^{'} \mathbf{X}_{j,t} + \theta_j + \theta_t + \varepsilon_{j,t+1}\end{aligned} \tag{6}$$

where $\Delta Sustainability_{j,t+1}$ denotes the change in carbon intensity (column 1), MSCI key issue ESG score (column 2), and MSCI industry-weighted ESG score (column 3), respectively. We control for the unrelated component of $DiscretTrades_{j,t}$, $ExpectedTrades_{j,t}$. We further control for time-varying firm and stock-level characteristics such as described in Section 2.2.1, and control for firm and year-quarter fixed effects. Since for each firm the discretionary trades are summed across all funds and then divided by the firm's shares outstanding, the standardized coefficients estimate how a standard-deviation change in firm-level discretionary ownership relates to future changes in firm-level carbon intensity and MSCI ESG score. We differentiate between the MSCI key issue ESG score and industry-weighted ESG score, as the former does not consider the ESG performance of the firm with respect to its respective industry peers. We argue that the MSCI key issue score approximates to a closer degree the *absolute* ESG behavior of the firm.

The 'ESG-skill hypothesis' predicts that the discretionary change in ownership by ESG mutual funds carries a negative sign in models of carbon intensity and positive sign in models of MSCI's ESG scores. Inconsistent with this hypothesis, we find that the change in net discretionary buys by

ESG funds relates neither significantly to future changes in carbon intensity nor to changes in the MSCI ESG score. As for the discretionary trades of conventional funds, they exhibit no significant coefficient in Table 4. In contrast, the change in ESG funds' expected ownership negatively relates to the change in MSCI ESG score in the next quarter, whereas expected changes in conventional ownership positively relate to the change in future carbon intensity. That expected ownership changes may relate to firms' future ESG performance underscores the importance of distinguishing flow-induced trades from trades that likely reflect fund managers' use of new ESG information.

Since Berg et al. (2024) describe that a change in ownership may be slow in response to new information, we elongate the lead between the current quarter and future quarter t to $t+4$ (columns 4-6). Column 5 indicates a marginally significant positive relation between increased discretionary ownership of ESG funds and the difference in MSCI key issue ESG score between the current quarter t and the future quarter $t+4$. In column 6, we note a negative relation between an increased discretionary ownership of conventional funds and a change in industry-weighted MSCI ESG score. ESG funds in quarter t increase their discretionary ownership in firms that, after one year, see significant absolute improvements in ESG behavior. Conventional funds, on the other hand, increase their discretionary ownership in stocks that have lower industry-adjusted ESG scores in $t+4$.

Next, we utilize the RepRisk database to examine the relationship between discretionary trades and actual environmental and social incidents observed in subsequent quarters. We follow Cohn et al. (2022) and do not log-transform our RepRisk incidents data, which is measured in the quarterly number of environmental and social incidents. In a Poisson model, we can still include a wide range of fixed effects without introducing bias to our estimation of the count-like dependent variable. The Distribution of # ES Incidents is skewed, with the largest mass of values being at 0[24].

In Table 6, we report the Poisson regressions[25] that relate quarterly trades to the cumulative number of environmental and social incidents that a firm exhibits over the next quarter and over the next two, three and four quarters:

$$\begin{aligned}\#\text{ES Incidents}_{j,t+s} = \exp(&\beta_0 + \beta_1 DiscretTrades_{j,t} + \beta_2 ExpectedTrades_{j,t} \\ &+ \gamma^{'}\mathbf{X}_{j,t} + \theta_j + \theta_t + \varepsilon_{j,t+s})\end{aligned} \tag{7}$$

[24] As reported in Table 2, the median number of firm ES RepRisk incidents within our firm-quarter sample is 0.

[25] When including fixed effects in a Poisson estimation, the model limits itself to observations that within the specified fixed effects groups have at least one non-zero value for the dependent variable. We additionally remove singletons where fixed effects, such as year-quarter fixed effects in our specification, are nested within clusters (here standard errors are clustered at the firm level).

where #ES Incidents$_{j,t+s}$ reflects the firm-level (cumulative) number of environmental and social RepRisk incidents, measured between the end of quarter t and $t+s$, where quarter $s \in \{1,2,3,4\}$. Similar to Equation (6) we control for the unrelated component of $DiscretTrades_{j,t}$, $ExpectedTrades_{j,t}$. We further control for time-varying firm and stock-level characteristics such as described in Section 2.2.1 and control for firm and year-quarter fixed effects. We find that ESG funds' net discretionary buys in a given quarter negatively relate to the cumulative number of ESG incidents that occur up to three quarters later. The negative coefficients on net discretionary buys are significant at either 5% (columns 2 and 4) or 10% (column 3)

Similar to Hoepner et al. (2024), we find that by including firm fixed effects, we lose about 30% of our total sample as we lose observations that do not have non-zero values for #ES Incidents$_{j,t+s}$ within the firm fixed effects. Nevertheless, this specification is desirable for our research question, as it restricts the sample to groups that are informative about the direction of discretionary ownership on # ES incidents. However, in Table 13 we report an alternative specification in which we substitute the fixed effects in Equation (6) for (main exchange) country and Fama-French 49 industry $\times$ year-quarter fixed effects[26]. While the main effects of Table 6 for $t+2$ (column 2) remain, especially noteworthy is that the coefficients of $ExpectedTrades_{j,t}$ flip sign. This is because the specification now also includes firms that never have a non-zero ES incident throughout our time series from March 2015 to December 2022[27]. Accordingly, we find that the expected trades of ESG Funds in Table 13 go toward stocks that never experience a non-zero incident. In 6, we impose firm and year-quarter fixed effects to control for time-invariant unobservables on the firm level, such as stable investment (e.g., style) preferences for specific stocks. As we focus on changes in discretionary ownership of firms that have at least one non-zero ES incident, we note that ESG funds increase their discretionary ownership in firms that see fewer cumulative ES incidents within two to four quarters in the future.

In contrast, conventional funds' net discretionary buys do not relate to the future number of incidents, regardless of the performance horizon we investigate or the fixed effects specification we apply. As conventional funds on average may have less non-pecuniary preferences than ESG funds, we additionally run the analyses of Tables 6 and 13 for governance incidents only: In Table 16 while we see a consistent pattern of ESG funds increasing their discretionary ownership in firms that see fewer governance-related incidents in the future, the coefficients for conventional funds' net buys

[26] We adjust Equation (7) to #ES Incidents$_{j,t+s} = \exp(\beta_0 + \beta_1 DiscretTrades_{j,t} + \beta_2 ExpectedTrades_{j,t} + \gamma' \mathbf{X}_{j,t} + \theta_c + \theta_k \times \theta_t + \varepsilon_{j,t+1})$ where $\theta_k \times \theta_t$ denote Fama-French 49 industry $\times$ year-quarter fixed effects amd θ_c denote main exchange counry of the stock fixed effects.

[27] In Table 13 we make a balanced panel of all firms in the RepRisk universe. Hence, while facing zero ES incidents, these firms can still be subjected to a governance-related incident or be subjected outside the time series of our paper.

remain statistically insignificant.

In Table 7, we delve deeper into ESG incidents that are labeled more 'severe' by RepRisk. Although the coefficients on discretionary trades of ESG funds are negative across all columns, they are only marginally significant (at 10% level) in column 2. Overall, the results on future Reprisk incidents partially support the idea that discretionary trades of ESG funds are informative about future developments in firms' ESG performance.

3.2 Exploring portfolio concentration and firm-level ESG volatility as moderators

According to a large body of literature, it can be expected that skilled fund managers are more likely to hold concentrated portfolios. For example, fund managers may choose to prioritize assets over which they likely enjoy a competitive informational advantage; see e.g. Van Nieuwerburgh and Veldkamp (2010) or have non-pecuniary preferences for (Ferreira and Matos, 2008; Hong and Kostovetsky, 2012; Pastor et al., 2023). In addition, several studies document that greater portfolio concentration is associated with better risk-adjusted fund performance, consistent with the idea that skilled portfolio managers hold fewer assets (see e.g., Kacperczyk et al., 2005). We explore in Table 8 first whether discretionary trades of fund managers are more informative about firms' future ESG performance compared to discretionary trades of more diversified funds. There is little evidence that portfolio concentration as such moderates the informativeness of discretionary trades in our sample. In fact, Table 8 reports that firms with more net buys by less concentrated funds subsequently experience stronger declines in carbon intensity (coefficient = -0.007; significant at 10%).

Similarly, examining portfolio concentration for ESG and conventional funds separately in Table 9 and Table 14, we find that only the changes in discretionary ownership of less concentrated ESG funds are consistently followed by decreases in future ES incidents: a one standard deviation increase in discretionary ownership by unconcentrated ESG funds is directed toward firms that see a reduction in the expected number of future ES incidents between 0.1-0.2% (Table 9)[28].

However, the effectiveness of portfolio concentration may depend on the potential for skilled fund managers to trade in stocks that are likely to exhibit greater improvements or declines in ESG performance. Kacperczyk et al. (2025) model learning from assets by institutional investors as an increasing function of the assets' fundamental volatility. Therefore, we also split our sample into,

[28]In 14 we note that the magntude of ESG skill increases to a reduction of 0.29-1.29%.

respectively, firms that experience past volatility in RepRisk ESG incidents above and below the median volatility (Table 10 Panel A), and into samples with above- and below-median volatility in MSCI Industry-Adjusted ESG score (Panel B).

Using total future RepRisk ES incidents as our dependent variable, we find that, particularly among firms with higher ESG volatility, there is a negative relation between discretionary ownership by ESG funds and future ES incidents. Andrei et al. (2023), through an equilibrium model, show that during increased economic uncertainty, investors shift their attention toward (among other) firms with a higher idiosyncratic volatility of earnings, less informative prices, and lower information acquisition costs. Similar to firm earnings announcements, investors may learn valuable information from historical ESG incidents[29].

3.3 Alternative ESG fund classification: U.S. versus Europe and SFDR labels

Our main tests compared ESG funds with conventional mutual funds using the Sustainable Mutual Fund Classification from Morningstar, which broadly reflects a fund's stated objective in prospectuses and regulatory filings. We explore two alternative ways to identify mutual funds that are more likely to integrate ESG issues in investment analysis from funds that are less likely. First, we compare discretionary trades of European and U.S.-domiciled funds. Studies on firm ownership as well as investors' surveys indicate that European institutional investors have a stronger ESG orientation than U.S. investors (Gibbon et al., 2023; Gibson Brandon et al., 2022; Dyck et al., 2019). We test how discretionary ownership changes by European funds and U.S. funds relate to firm-level changes in carbon intensity and ESG score (Table 11), and future RepRisk incidents (Tables 12 and 15).

Contrary to what the literature suggests, we find that European mutual funds' discretionary trades do not appear to anticipate developments in firms' future ESG performance. U.S. funds' discretionary ownership changes are also unrelated to future environmental and social incidents, but negatively related to changes in future carbon intensity. Hence, it is not evident that European mutual funds make trades that are more informed when it comes to firms' future ESG performance.

However, even within Europe, there is variation in the extent to which mutual funds incorporate ESG issues in investment decisions. The recently introduced Sustainable Finance Disclosure Regu-

[29]Derrien et al. (2022) shows that negative ESG incidents are deemed financially material and lower analysts' firm cash flow expectations, and Gantchev et al. (2022) notes that the incidents identified by RepRisk primarily reflect idiosyncratic events.

lation (SFDR) requires EU-regulated financial market participants to disclose how ESG issues are considered at the entity and product level; see Spaans et al. (2024) for a discussion. Based on funds' self-reported SFDR labels, we identify those that "promote environment and social characteristics" (Article 8) through integration of ESG issues, and funds that have sustainability investment as their core objective (Article 9). We compare these to "Article 6" funds in the EU that do not report consideration of ESG issues explicitly. For Article 6 mutual funds, columns 4-6 of Table 11 and columns 5-8 of Table 12 jointly indicate that their discretionary trades are not informative about firms' future ESG performance.

For Article 8/9 mutual funds, the results are mixed, but they demonstrate a pattern that is consistent with our main analysis of ESG mutual funds in Table 5: increased discretionary ownership by Article 8/9 funds has no significant relation with future changes in carbon intensity. It shows a marginally positive significant relation with the MSCI Key Issue ESG score in four quarters in the future (columns 4-6 of Table 11), but a negative relation with ES incidents that occur in the next two, three, and four quarters (columns 5-8 of Table 12). Overall, these results provide partial evidence that the discretionary trades of ESG-oriented funds, identified through SFDR labels, are skilled in anticipating future ESG-related outcomes: a one standard deviation increase in discretionary ownership by Article 8/9 funds go towards firms that, on average, see a 0.1-0.2% reduction in the expected future number of ES incidents[30].

3.4 Alternative definition of discretionary ownership

In section 2.3, we define discretionary trades as the net buys of firm shares (scaled by the total number of shares outstanding) that are net of changes we can expect to occur when a fund trades purely due to fund flows. Following Coval and Stafford (2007) and Huang et al. (2023) in our methodology, we assume that discretionary trades are the result of differences in buying (selling) behavior following fund dollar inflows (outflows). Specifically, sales after inflows are set to be 0; buys after outflows are set equal to 0. However, Coval and Stafford (2007) reports that even during the most extreme outflow decile, funds still chose to expand 19% of their positions.

[30]We re-estimate Equation (7) for the SFDR discretionary ownership in Table 15 replacing firm and year-quarter fixed effects with country and industry × year-quarter fixed effects. This also allows us to retain observations that do not have non-zero values for ES incidents within the firm fixed effects groups. We note that Article 8/9 funds see a negative relation in their expected trades and future ES incidents: a one standard deviation increase in expected ownership by Article 8/9 funds is directed toward firms that, on average, see a 0.4-1.39% reduction in the expected future number of ES incidents. This seems to be driven by Article 8/9 funds' portfolio composition that has selected firms that never count non-zero ES incidents. Instead, in Table 12—where we focus on the skill component of discretionary ownership—we see that Article 8/9 funds have a *positive* relation between their expected trades and the expected future number of firm ES incidents.

We define an alternative discretionary ownership measure, estimating the buying behavior of funds after they are faced with net outflows. We follow two lines of reasoning: (1) The fire-sale literature reports strategic decision making of mutual funds is most prominent when facing redemptions through investor outflows (e.g., Giannetti and Jotikasthira, 2024; Ma et al., 2022; Huang et al., 2023), deciding by how much and which holdings to sell/ buy; (2) Mutual funds can show discrepancies in skill behavior between their buying and selling decisions due to limits in the attention of the fund manager (Hartzmark, 2015). Akepanidtaworn et al. (2023) reports that mutual fund managers show most return-based stock-picking skill resulting from their buying behavior: buying decisions are known to require costly considerations and "in-depth research" as mutual funds tend to hold positions for a longer period. As such, for ESG funds, this may mean picking stocks that do better in terms of sustainability outcomes.

In Table 17 we estimate Equation (7) with our adjusted $DiscretTrades_{j,t}$ measure[31]. We test whether ESG funds show ESG skill in their buying decisions after facing outflows, defying the direction of expected changes in ownership. Only in the Poisson estimations for which we do not impose stringent firm fixed effects—hence allowing for firm observations that never have a non-zero value for # ES incidents in the firm fixed effect groups—we see a statistically significant negative relation between increased discretionary buying of ESG funds and future ES incidents. This brings about two possible lines of reasoning: (1) after facing investor outflows, ESG funds can select stocks for their portfolios that have not in the past, and will not face ES incidents in the future. Here ESG funds select firms that will perform without ES incidents in the future; (2) or, after facing investor outflows, ESG funds extrapolate on firms' ES risk track records and move ownership towards stocks that have performed well in the past (Akepanidtaworn et al., 2023). Indeed, in Table 17, the coefficients reduce in size for later quarters (columns 6 and 8).

3.5 Discretionary trades and firm-level stock return

The results of Sections 3.1 to 3.4 suggest that the discretionary trades of ESG funds—and those of European Article 8/9 funds—anticipate ESG incidents that firms experience in the future. A sizable number of studies relate firm-level ESG data to measures of corporate financial performance, although evidence on the direction of this relation is mixed. If these future incidents are financially

[31] We adjust the discretionary sell measure as explained in Section 2.3 to $DiscretionarySell_{j,t} = -\frac{\sum_i(min(0,-\Delta Position_{i,j,t}|flow_{i,t}<0)}{ShareOutstanding_{j,t-1}} - \frac{\sum_i(Position_{i,j,t-1}\times flow_{i,t}|flow_{i,t}<0)}{ShareOutstanding_{i,t-1}}$. Instead of taking the maximum value of $(0, -\Delta Position_{i,j,t})$ conditional on outflows, we now take the minimum value. We control for expected fund sales $\frac{\sum_i(Position_{i,j,t-1}\times flow_{i,t}|flow_{i,t}<0)}{ShareOutstanding_{i,t-1}}$

material and not yet reflected in current stock prices, it is conceivable that discretionary trades relate to future stock returns. Regarding ESG incidents, Lin et al. (2025) relate supply-chain ESG incidents to weaker profitability and future stock returns. Yet, analysts do appear to respond to ESG incidents in their forecasts and target prices according to Derrien et al. (2022) and Park et al. (2025).

In Table 18, column 1, we regress firm-level stock returns, measured over the next quarter, on changes in the discretionary ownership of ESG and conventional funds in conjunction with a host of controls[32]. We find that the change in discretionary ESG fund ownership positively predicts future stock returns (significant at 5% level), which is consistent with the idea that ESG funds' discretionary trades are informative about future firm-level ESG events that can affect returns eventually. In contrast, the change in conventional funds' discretionary ownership negatively relates to future stock return (significant at 10%). In terms of economic significance, the effect sizes predicted a 0.2 percentage-point (or 20 basis points) within-firm increase in next quarter's stock return for a one standard-deviation increase in discretionary ESG ownership. Furthermore, column 2 shows a positive relation between discretionary trades of European Article 8/9 funds and stock returns[33].

To see whether these returns revert over time, in Table 19 we impose additional future leads for our regression of future firm-level stock returns on changes in the discretionary ownership. In columns 2-4, we find that the positive relation between ESG discretionary ownership and future returns (column 1) do not hold up after one subsequent quarter. For Article 8/9 funds, returns following changes in discretionary ownership in quarter t, to some extent, revert in quarter $t+2$ (column 6) before becoming statistically insignificant.

In Table 10 (Section 3.2), we found evidence that ESG funds learn valuable information from historical ESG incidents and use this to make predictions for increasing discretionary ownership in firms that see fewer future incidents. Similarly, in Table 20 we also split, for our future stock-return analysis, our sample into, respectively, firms that experience past volatility in RepRisk ESG incidents above and below the median volatility (Table 20 columns 1a and 1b), and into samples with above- and below-median volatility in MSCI Industry-Adjusted ESG score (columns 2a and 2b). In column 1b, we find that, particularly among firms with higher ESG volatility, there is a

[32]In Table 18, we also control for the MSCI ACWI in line with Bolton and Kacperczyk (2021). Results are unchanged when we omit that control in Table 35.

[33]Huang et al. (2023) highlight that discretionary trades can induce price pressure. When we perform a similar analysis (following extreme fund flows, following Equation (3)), we indeed see evidence that ESG funds can exert price pressure on stocks.

positive relation between discretionary ownership by ESG funds and returns of 10 basis points per standard deviation.

Taken together, by focusing on the discretionary trades of mutual funds, we obtain some evidence that is consistent with ESG fund managers possessing financially material ESG skills.

4 Current ESG information and mutual funds trading

The relationships between discretionary ESG ownership changes and firms' future ESG incidents that we find are economically modest. This may imply that ESG funds have only a partial focus on the anticipation of future ESG-related events. Nevertheless, we could also expect that ESG-skilled mutual funds rely differently on ESG data. Literature on financial skill reports that indeed some investors have skill in investing in high-value assets, but that their attention may move away from individual stocks depending on macro-level trends.

On the one hand, it is conceivable that ESG-driven trades partly follow standard ESG metrics that are relatively easy to obtain. Earlier evidence suggests that mutual funds, especially those that are ESG-oriented, significantly trade on historic firm-level ESG data. For example, Berg et al. (2024) report that corporate ownership by U.S. ESG mutual funds mainly responds to changes in MSCI's ESG ratings. This raises the question of how much trades by ESG-skilled managers react to contemporaneous ESG information. On the other hand, we expect that ESG-skilled discretionary trades arise from proprietary ESG analysis (see Akepanidtaworn et al., 2023). We undertake two different analyses to shed more light on ESG and conventional funds' use of ESG data in trading. We first quantify the degree to which changes in discretionary ownership can be explained by changes in benchmark indices. Next, we analyze how mutual funds' quarterly position changes vary with recent (changes in) ESG scores and ESG incidents.

4.1 Responding to changes in index

As funds tabulate their historical returns alongside that of a self-designated passive benchmark index, it could be that our discretionary trades measure merely picks up changes made to the underlying constituents of these indices. Kacperczyk et al. (2021) find significant increases in foreign institutional ownership in firms that are added to the MSCI All Country World Index. We test whether our measure of discretionary trades are driven by changes in the MSCI All Country World Index (ACWI) and its sub-index, the MSCI All Country ESG Leaders Index.

For the former, MSCI uses exclusion criteria on the constituents of the MSCI ACWI based on firms' involvement in specific business activities, ESG ratings (in terms of levels, historical trends, and industry-adjusted ESG score), and their exposure to ESG controversies. Like its parent index, the MSCI ACWI ESG Leaders weights its constituents on their market capitalization[34]. As ESG funds screen their portfolios on ESG scores, we additionally measure the response of ESG discretionary ownership to changes made in the underlying constituents of the MSCI All Country ESG Leaders Index, the sub-index of the MSCI ACWI.

We employ an event study design following De Chaisemartin and d'Haultfoeuille (2024) as their approach allows for distinguishing treatments that turn on and off. Hence, we estimate the treatment effects of the firms that enter the MSCI indices over time on our measures of ESG and conventional discretionary ownership:

$$DiscretTrades_{j,t} = \sum_{\tau=-4,\tau\neq 0}^{4} \beta_\tau MSCI\ index_{j,t}^{\tau} + \gamma_j + \delta_t + \epsilon_{j,t} \tag{8}$$

where $MSCI\ index_{j,t}^{\tau}$ indicates that a firm enters the MSCI ACWI at time τ. T_j^* denotes the quarter in which the firm first enters the MSCI index in our panel. In this intertemporal treatment specification, we control for the firms' baseline treatment and hence only compare groups that have the same period-one treatment (i.e., firms that in period-one are all excluded from the MSCI ACWI: treatment is zero at baseline). Our control group consists of firms that have not-yet entered the MSCI ACWI[35]

We initially set $MSCI\ index_{j,t}^{\tau}$ equal to 1 for firms that are included in the MSCI ACWI in quarters $t \geq T_j^*$. For now, we neglect whether firm j is also included in the MSCI ACWI ESG Leaders index[36]. In Equation (8) we estimate β_τ for the period $T_j^* - 1$ to $T_j^* - 1 + k$ for the maximum post-treatment periods observed $k \in \{1, ..., 4\}$[37]. De Chaisemartin and d'Haultfoeuille (2024) set the reference period to $\tau = 0$ as the last quarter before the first treatment.

Tables 21 (Figure 1 and 22 (Figure 22) display the dynamic effects of MSCI ACWI index inclusion on the discretionary trades of ESG and conventional funds, respectively. Column 1 in

[34]In 2025, MSCI ACWI consisted of 2,647 holdings, while the MSCI ACWI ESG Leaders was made up of 1,157 holdings. In our sample, funds that enter MSCI ACWI ESG Leaders do so when, at that same moment, they are also added to the parent index MSCI ACWI. Hence, after having entered the MSCI ACWI, a firm will never enter the screened ESG Leaders index in a subsequent quarter.

[35]We additionally estimate the event study specification using only the 'never-treated' group. This does not change our results.

[36]We estimate placebo estimates.

[37]The specification stays stable when we extend the maximum post-treatment periods observed. However, we purposefully chose k so that we were able to limit the possible treatment paths for columns 2 and 3 in 21 and 22. By increasing k, one increases the likelihood of firms exiting the MSCI indices, creating additional treatment paths.

both tables initially indicates that MSCI ACWI inclusions positively drive discretionary ownership for both ESG and conventional funds during the first treatment quarter T_j^*. The coefficients for ESG discretionary ownership are marginally significant at 10%, while for conventional funds, the coefficients turn negative at $\tau \geq 2$ and remain highly significant.

However, De Chaisemartin and d'Haultfoeuille (2024) can distinguish different treatment trajectories, which allows us to differentiate the treatment effects of firms that are only included in the MSCI ACWI and firms that are included in both the MSCI ACWI and MSCI ACWI ESG Leaders indices: $\textit{MSCI index}^{\tau}_{j,t,d}$ where d indicates the treatment type of firm j. To do this, we create separate event study regressions for each treatment type d. For example, in column 2, the treatment indicator is set to 1 only for firms that enter the MSCI ACWI but not the MSCI ACWI ESG Leaders index ($d = 1$), and remains at 0 for all other firms, including those that are in both indices. The third column does the opposite, setting the treatment indicator to 1 only for firms that enter both indices, $d = 2$[38].

Tables 21 and 22 show that the event study estimations for ESG discretionary ownership turn insignificant when we distinguish firms that enter the MSCI AWCI from firms that enter both MSCI AWCI ESG Leaders (columns 2 and 3). This suggests that changes to benchmark indices do not fully dictate ESG discretionary ownership, reinforcing the results of Section 3[39].

Noteworthy is that conventional funds initially increase their discretionary ownership for firms that simultaneously join the MSCI ACWI and its sub-index MSCI ACWI ESG Leaders, but sell these holdings more than expected a quarter later. While an economically similar pattern occurs for firms that only enter the MSCI ACWI index, this is statistically less significant.

4.2 Responding to ESG information

To shed light on the extent to which mutual funds integrate specific past ESG information in their trading behavior, we estimate, using a fund–firm-time panel, how a fund's trading behavior depends on a stock's ESG score from MSCI as well as on recent ESG incidents. To evaluate this we investigate the position change of the fund: $PositionChange_{i,j,t}$ is the change in the position of fund i in stock j in quarter t estimated as $\frac{Price_{j,t-1}(NumberShares_{i,j,t} - NumberShares_{i,j,t-1})}{AUM_{i,t-1}}$ where $NumberShares_{i,j,t}$ as the number of shares held by fund i in stock j at time t. It describes the dollar

[38] $\forall j$, $\textit{MSCI index}_{j,1} \in \{0, 1, 2\}$. Hence, we restrict the sample such that $t < T_j^*$, or $T_j^* \leq t \leq T_j^* - 1 + k$, for the maximum post-treatment periods observed $k \in \{1, ..., 4\}$ and **MSCI Index ACWI** $= (0, 1, 1, 1, 1)$ and **MSCI Index ACWI ESG Leaders** $= (0, 2, 2, 2, 2)$

[39] In 32 we re-estimate Equation (7) and note that the negative relation between ESG discretionary ownership and future ES incidents is consistent for two and four subsequent quarters.

volume traded scaled by the fund's total net assets at the end of the previous quarter (Gantchev et al., 2023; Giannetti and Jotikasthira, 2024; Ceccarelli et al., 2024).

We expect that especially ESG funds have incentives to rebalance their portfolios towards stocks that (1) have high ESG scores and (2) see increases in ESG scores.

$$\begin{aligned} PositionChange_{i,j,t} = \beta \mathbb{1}[ESGFund]_{i,t} \times MSCIESG_{j,t} \\ + \gamma' \mathbf{X}_{j,t} + \theta_{i,t} + \varepsilon_{i,j,t} \end{aligned} \tag{9}$$

where we regress fund i's position changes of holding j between quarters $t-1$ and t on the firm's ESG scores (unweighted key issue MSCI ESG Score and the industry-weighted MSCI ESG Score), interacting this with an indicator of whether the fund making the position change is classified as an ESG fund as defined in Section 2.1.

We include fund × year-quarter fixed effects to control for funds' propensity to trade in a given quarter. Additionally, we control for time-varying stock characteristics that could be correlated with the firm's ESG scores.

In columns 1a and 1b in Table 23, we find that compared to conventional funds, ESG funds positively increase their positions that have a higher ESG score (0.13-0.25%) per increase in ESG score. Additionally, in columns 2a we report that ESG funds statistically significantly respond to changes in industry-weighted MSCI ESG scores, but do not respond more or less to the changes in the absolute ESG behavior of firms based on the MSCI Key Issue Score (column 2a).

In Table 24, we further introduce RepRisk ES incidents, which we expect to trigger investor response because of their salience. Moreover, several studies conclude that sell-side analysts incorporate ESG incidents in their firm-level forecasts of future cash flows and discount rates; see Park et al. (2025). We regress the Position Change on the industry-weighted MSCI score from the most recent quarter, the total number of RepRisk ES incidents in the respective quarter, and their interaction. Each column in Table 24 represents a regression based on a specific (sub)sample of mutual funds. We continue to find that ESG scores matter for position updates taken by ESG funds, European funds, and Article 8/9 mutual funds (columns 2, 4, and 6). Interestingly, while we find that these groups of funds, as expected, respond negatively in terms of trading to stocks with more ES incidents, we also notice that the interaction effect between ES incidents and MSCI ESG scores is positive.

We explore this finding further in Table 25 in which we split our fund-holding-quarter panel into

ESG (Panel A) and conventional funds (Panel B). Realizing that funds may change their positions with a lag (Berg et al., 2024), we re-estimate the model of Table 24 using various lags in stock ESG information. In columns 1-4 of Panel A, we see that the interaction coefficient remains significant, which would suggest that the effect of # ES Incidents varies by levels of stocks' ESG scores. In Panel B, instead, we find that conventional funds negatively trade on current ESG scores and the same quarter's ES incidents (A decrease in positions bought by 0.20% per standard deviation higher number of ES incidents).

We display the margin plot of column 2 in Table 25 in Figure 3. Indeed, we note that for stocks with higher values of (lagged) stock ESG scores (in our sample, the minimum ESG score is 0, maximum is 10), ESG funds seem less distressed by ES incidents, even moving their holdings *towards* stocks that faced ES incidents if they also have a high ESG score.

However, $PositionChange_{i,j,t}$ by definition picks up both discretionary as well as expected fund trades. In the case that ESG funds allocate their portfolios towards high ESG stocks (i.e., green tilting), we can expect that incoming fund flows will—at least to some extent—be distributed to these holdings. In columns 5-8 of 25 we substitute $PositionChange_{i,j,t}$ for discretionary ownership, $DiscretTrades_{i,j,t}$, by fund i of stock j[40].

Striking are the negative interactions of lagged MSCI ESG scores and # ES incidents for ESG funds in Panel A (columns 5-8). The margin plot of column 6 in Figure 4 visualizes the moderating effects of stocks' lagged ESG scores. Noticeable are the negative slopes visualizing the predictive margins of lagged ES incidents on discretionary trades. Slopes are steeper for stocks with higher lagged ESG scores. This result indicates that funds increasingly move away from stocks that are confronted with ES incidents when these stocks have higher ESG scores.

Although it at first seems that ESG funds direct their holdings towards higher ESG stocks, our analysis of discretionary trading—which separates the discretionary from the expected trading component from the funds' total trading behavior—shows evidence that ESG funds collect sustainability or ESG information for their portfolio holdings and actively make use of this in their discretionary trading behavior.

[40]We change Equation (2) and (4) so we do not sum the discretionary trades over all funds.

5 Fund level outcomes

In Section 3.5 we found evidence that the ESG skill of ESG fund managers may be financially material and might predict, on the stock level, in the short term, positive returns[41]. However, the economic significance of our stock-level ESG skill measures is moderate. As this is an *average* effect of all mutual fund discretionary trades, our analysis may not effectively pick up the effects of *individually* skilled mutual funds. In this section, for each fund, we aim to quantify their usage of forward- and backward ESG information and link this to various fund performance measures. Furthermore, we analyze the relation between fund ESG integration and fund performance—in terms of risk-adjusted returns and fund flows.

5.1 Fund use of forward-looking ES information

To determine funds' propensity to invest in stocks that see fewer future ES incidents, we follow Fang et al. (2014) and Chen et al. (2024) and estimate the propensity of funds to increase their discretionary ownership in stocks that see fewer ES incidents in the future. For each fund i in quarter t we estimate for each distinct eight-quarter window for each fund:

$$DiscretTrades_{i,j,t} = \beta_0 + \beta_1 \times ES\ Incidents_{j,t+1} + \gamma^{'}\mathbf{X}_{j,t} + \theta_t + \varepsilon_{i,j,t} \tag{10}$$

where $ES\ Incidents_{j,t+1} = -1 \times ln(1 + \#ES\ incidents_{j,t+1})$ to ensure that $\hat{\beta}_1$ indicates the relation between fewer future ES incidents and discretionary ownership (This follows Fang et al., 2014). We control for lagged stock characteristics (stock turnover rate, book-over-market ratio, and the natural logarithm of firm size) and year-quarter dummies. We cluster the standard errors at the firm level. For the propensity measure indicating the extent to which funds invest in stocks that see fewer ES incidents in the future quarter, we use the OLS regression results of four quarters:

$$Propensity_{i,t} = \frac{1}{\left(\frac{1}{\sigma^2_{i,t}} + \frac{1}{\sigma^2_{i,t-1}} + \frac{1}{\sigma^2_{i,t-2}} + \frac{1}{\sigma^2_{i,t-3}}\right)} \times \left(\frac{\beta_{i,t}}{\sigma^2_{i,t}} + \frac{\beta_{i,t-1}}{\sigma^2_{i,t-1}} + \frac{\beta_{i,t-2}}{\sigma^2_{i,t-2}} + \frac{\beta_{i,t-3}}{\sigma^2_{i,t-3}}\right) \tag{11}$$

where $\beta_{i,t-s}$ denotes the key beta coefficient for quarter $t-s$ and $\sigma^2_{i,t-s}$ denotes its corresponding variance. $\frac{1}{\sigma^2_{i,t-s}}$ therefore indicates the precision of the estimated beta $\hat{\beta}_{i,t-s}$. We calculate the standardized coefficients for Equation (10). A higher propensity for fund i in quarter t means that the fund has a stronger association between its discretionary trades and fewer future ES incidents,

[41] From Table 19 it might even seem that conventional funds 'leave money on the table'.

indicating the extent to which mutual funds in our sample trade with future ES risk in mind.

The mean (median) of the standardized propensity measure for our sample is -0.0005 (0.0002) with a standard deviation of 0.1146. For every quarter, we sort the one-quarter lagged propensity scores into quintiles. Funds with a Quintile 1 rating have the lowest propensity to invest in firms that are expected to experience fewer future ES incidents. Quintile 5 funds have the highest propensity to invest in firms with fewer future ES incidents.

In Table 26 we present the time series averages of cross-sectional return measures for the five propensity quintiles: excess returns, Fama-French three-Factors risk-adjusted returns, and Carhart four-Factors risk-adjusted returns. Excess returns are defined as the quarterly fund returns in t minus the quarterly risk-free rate. For each fund in each quarter, Fama-French three-factor and Carhart's four-factor returns are calculated using fund returns of the past 36 months.

For our time series averages in Table 26, we compute Newey and West standard errors with eight lags. We assign quintiles separately for sub-sets of funds: all funds (Panel A), ESG funds (Panel B), and conventional funds (Panel C). Column 1 reports the average propensity score for the respective quintile.

Columns 3 and 4 of Table 26 indicate, on average, statistically significant negative abnormal returns (alphas). However, funds that exhibit a higher propensity to invest in firms with lower numbers of future ES incidents, on average, do not outperform funds that have the lowest propensity scores.

Within propensity quintiles, we do not note significant differences between propensity scores for ESG and conventional funds (Table 27). Regardless, within the propensity quintile, ESG and conventional funds can still invest in different firms (e.g., conventional funds may invest in low ESG firms while complementarily considering their future ES risks). When we compare the time series average returns of ESG to those of conventional funds in Table 27, we find that ESG funds in the highest propensity quintile show significantly lower risk-adjusted returns than conventional funds that have the highest propensity to invest in firms with fewer future ES incidents (underperformance of -6.8 to -5.9 basis points).

5.2 Funds use of public ESG information

In this section, we further quantify the fund-level tradeoff between public and private ESG information. Traditional stock-picking literature has shown in the past that mutual fund managers

who rely on public information tend to underperform those who rely less on public information. A reliance on public information in the traditional sense indicates that the fund manager is less skilled in handling private signals (Kacperczyk and Seru, 2007), or is subjected to limited attention in their choice set of financial assets (Fang et al., 2014; Akepanidtaworn et al., 2023).

Several studies discuss the role of ESG trading on price informativeness. Chen et al. (2024) reasons that fund managers' trading on TruValueLabs Pulse ESG scores enhances the price informativeness of their portfolio firms. However, ESG information is known to be less transparent[42]. Goldstein et al. (2022) describe how trading on private ESG signals may reduce the price informativeness about the stock's financial payoff, which in turn raises its cost of capital[43].

In Sections 3.5 and 5.1, we find evidence that funds may possess forward-looking ESG-skill and trade on future ESG risks of their portfolio firms. On a stock level, we note that this skill may be financially material: discretionary ownership by ESG funds has predictive power of future stock returns. However, Section 4 demonstrates that ESG funds are more inclined to make trading decisions based on the current ESG information set.

To analyze funds' tradeoff between public and proprietary ESG information, we modify Kacperczyk and Seru (2007)'s funds' reliance on public information (RPI) measure, substituting the lagged quarterly changes in analysts' recommendations for (i) lagged changes in MSCI ESG scores, and (ii) lagged number of ES incidents. To estimate funds' reliance on the two sources of ESG information, we run two pooled regressions and predict for every fund-quarter the unadjusted R^2[44]:

$$\begin{aligned} PositionChange_{i,j,t} = \beta_0 + \beta_1 \Delta ESG_{j,t-1} + \beta_2 \Delta ESG_{j,t-2} + \\ \beta_3 \Delta ESG_{j,t-3} + \beta_4 \Delta ESG_{j,t-4} + \varepsilon_{i,j,t} \end{aligned} \tag{12}$$

where $\Delta ESG_{j,t-s}$ indicates the change in MSCI indusytry-adjusted ESG score between $t-s-1$ and $t-s$ for $s \in \{1,2,3,4\}$. In case the ESG score of stock j does not change between $t-s-1$ and $t-s$, $\Delta ESG_{j,t-s} = 0$ And

$$\begin{aligned} PositionChange_{i,j,t} = \beta_0 + \beta_1 \#ES\ Incidents_{j,t-1} + \beta_2 \#ES\ Incidents_{j,t-2} \\ + \beta_3 \#ES\ Incidents_{j,t-3} + \beta_4 \#ES\ Incidents_{j,t-4} + \varepsilon_{i,j,t} \end{aligned} \tag{13}$$

[42] Berg et al. (2022), for example, find that ESG ratings diverge.

[43] In their general equilibrium model, Goldstein and Yang (2017) explain that 'ESG' and 'traditional' investors may trade on ESG information in opposite directions.

[44] $RPI_{i,t-1} = 1 - \frac{\sigma^2(\varepsilon_{i,t})}{\sigma^2(PositionChange_{i,t})}$ where $\sigma^2(\varepsilon_{i,t})$ denotes the unexplained variance of residuals from Equations (12) and (13), and $\sigma^2(PositionChange_{i,t})$ is the overall fund-level variance in the change in stock positions j held by fund i of all between $t-1$ and t.

where $\#ES\ Incidents_{j,t-s}$ indicates the number of ES incidents in quarter $t-s$ for $s \in \{1,2,3,4\}$[45]. As in Kacperczyk and Seru (2007)s, the values of $RPI_{i,t-1}^{ESG}$ and $RPI_{i,t-1}^{incident}$ range between 0.001 and 0.999, with means (standard deviations) of 0.114 (0.146) and 0.140 (0.158), respectively. $RPI_{i,t-1}^{ESG}$ and $RPI_{i,t-1}^{incident}$ have a correlation of 31.70%, indicating that the public information on ESG scores and ES incidents is not the same. Funds with smaller values of $RPI_{i,t-1}^{ESG}$ and $RPI_{i,t-1}^{incident}$ are less dependent on public ESG or incident information[46].

Using public information on stocks' financial performance is expected to have a negative relationship with fund performance (Kacperczyk and Seru, 2007; Fang et al., 2014). In columns 1 and 2 of Table 28, we find that fund excess returns are indeed negatively related to funds' reliance on changes to MSCI ESG scores[47]. However, when controlling for both fund and year-quarter fixed effects in column 3, the coefficients lose statistical power. Controlling for fund fixed is desirable to control for time-invariant unobservables such as fund-family-specific ESG strategies[48].

In Table 29, columns 2 and 5 show complementary evidence for a negative relationship between fund reliance on ESG rating information and Fama-French three-factors and Carhart four-factors abnormal returns. The results, however, seem to be driven by fund unobservables and low statistical power after we control for fund fixed effects in columns 3 and 6.

Interestingly, our forward-looking skill measure (i.e., the one-quarter lagged propensity of funds to invest more in firms with lower degrees of future ES risk.) does not show a significant relation to fund returns. Hence, we see little evidence that our measures of ESG skill—fund managers' use of backward- and forward-looking private ESG information—has convincing fund return implications when controlling for time-invariant fund unobservables.

5.3 Fund flows

Previous academic work documents that investors chase fund performance in terms of historical returns. Similar trends are recorded for sustainable investing. Investors with sustainability preferences direct their wealth into sustainable assets after funds receive 'green' sustainability signals. Hartzmark and Sussman (2019) find that investors significantly move their investments to funds

[45] RepRisk retrieves all its incident data from public sources such as news or (social) media.

[46] Kacperczyk and Seru (2007) argue that fund managers that are less reliant on public information are more skilled.

[47] Results are consistent to including the $RPI_{i,t-1}^{ESG}$ and $RPI_{i,t-1}^{incident}$ variables separately or simultaneously in our models (Table 37).

[48] Kacperczyk and Seru (2007)'s main model specifications only include year-quarter fixed effects. However, they state that their findings are robust to the inclusion of fund fixed effects. They do not report regression results in which they include fund fixed effects separately or simultaneously.

that have a maximum Morningstar Globe ESG rating. Recent literature discusses the implications of investor flows into ESG funds. Van der Beck (2021) argues that positive ESG returns are the result of the buying pressure of ESG funds' flow-driven demand for sustainable assets. We indeed find evidence of this price effect for both ESG expected and discretionary ownership on stock returns in section 3.4[49].

Investors with non-pecuniary preferences have been shown to be inclined to invest in assets with known high ESG ratings (Rzeźnik et al., 2022; Hartzmark and Shue, 2023) and may hence seek mutual funds that cater to their 'top-ESG' preferences (Solomon et al., 2014)[50]. We argue that ESG funds are rational in buying stocks with high ESG ratings to cater to investor demands to profit from additional fund flows.

In Table 31, we regress fund flows of quarter t on our lagged fund ESG skill measures. $Propensity_{i,t-1}$ approximates the propensity that individual funds trade away from future ES risky stocks. $RPI^{ESG}_{i,t-1}$ and $RPI^{incident}_{i,t-1}$ proxy the reliance on public ESG scores and news on firm incidents, respectively.

We initially do not find a significant effect of any of our skill measures on fund flows in columns 1 and 3. However, as ESG funds cater to a different investor base than conventional funds, we interact the skill measures with a (time-invariant) ESG fund indicator. ESG funds that increasingly relied on public ESG scores see an increase in net investor flows of 1.5% per quarter (-0.9 + 2.4%). Investors with non-financial preferences thus allocate their wealth into ESG funds that have historically utilized ESG ratings more extensively in their portfolio trading decisions.

Next to this, in columns 4 and 5, we consider fund reliance on public ES incidents news. ESG funds whose trades have been informed to a greater degree by historical ES incident news see a reduction in net investor flows of 1.2-1.3% in quarter t. A plausible reason could be that investors do not *see* the extent to which funds trade in low incident stocks. Instead, they may only pay attention to the particular holdings of ESG funds *after* a firm's ES incident gets media attention Fang et al. (2014)[51].

Interestingly, investors do not reward funds that have more forward-looking ESG skill; in all columns of Table 31 $Propensity_{i,t-1}$ shows a positive sign, but its coefficients are not statistically

[49] In Table 30 (columns 1 and 3, and 5) we note that ESG funds that rely more on public ESG scores for their portfolios may underperform less in terms of excess returns than non-ESG funds.

[50] Trading platforms often prominently showcase asset-specific sustainability ratings of well-known raters for their assets.

[51] We offer three non-mutually exclusive interpretations: i) investors retract funds from investors that actively buy stocks that faced ES incidents in the past (i.e., the fund trades against its mandate), ii) ESG investors may 'punish' ESG for selling stocks *after* they faced ES incidents (i.e., ESG funds are punished for not having forward-looking ES risk skill), or iii) ESG investors may retract their wealth after ESG funds buy low incident firms (for example when that stock does not have a high ESG score).

significant.

In summary, we see that ESG funds are rewarded for more extensively following public (MSCI) ESG scores. Flow-chasing behavior by ESG funds may consequently induce them to overweight high ESG-scoring stocks[52].

6 Discussion and conclusion

The typical actively managed mutual fund is expected to incorporate financially relevant information into security analysis and investments to enhance its subsequent returns—sometimes described as stock-picking skill. For those mutual funds that additionally target ESG-related objectives (e.g., by following an ESG mandate), the question arises how informative their trades are about the future development in the ESG performance of their portfolio firms. We address this relatively underexplored question in this paper by analyzing mutual funds' discretionary trades, which we measure for each firm by the shares that funds trade beyond what can be expected if new capital flows were invested proportionally. Since ESG mutual funds are expected to incorporate ESG information more actively than their conventional counterparts, we investigate how the discretionary trades of ESG and non-ESG funds relate to firms' future ESG performance, carbon intensity, and ESG incidents. In other words, do ESG mutual funds, in aggregate, pick (drop) stocks that exhibit ESG performance improvement (decline) in the future?

Our first set of findings focuses on stock-level analyses. Based on quarterly fund holdings matched with firm-level ESG metrics over the period 2014-12 to 2022-12, we provide partial evidence that ESG mutual funds incorporate forward-looking information about firms' ESG performance. First, firms that experience increased discretionary ownership by ESG funds experience fewer negative environmental and social events in subsequent quarters, but exhibit neither more reductions in carbon intensity nor greater improvements in their corporate ESG scores. Expected trades of ESG funds tend to be directed to stocks that have never experienced environmental or social incidents. Discretionary trades of conventional funds are mostly unrelated to firms' future ESG performance. Second, contrary to popular belief, we do not find that funds with more concentrated (ESG) portfolios (fewer holdings) exhibit more informative discretionary trades: concentrated conventional portfolios' discretionary ownership is directed from firms that never experience negative incidents

[52]We additionally perform the regression models of Table 31 in which we replace our ESG fund indicator for an SFDR Article 8/9 indicator (takes on value 0 for Article 6 funds). None of our ESG skill measures or interactions are statistically significant.

to stocks that in the future see more ES incidents. However, more ESG discretionary ownership is associated with fewer future ESG incidents among stocks with more volatile ESG scores and ESG incidents, respectively. Third, firms with greater discretionary ownership by ESG funds exhibit higher returns in the quarter thereafter.

Although we present some evidence that future ESG events and stock returns trail discretionary trades of ESG-oriented mutual funds, we note that generally this relation appears to be economically small. Therefore, we also verify and substantiate earlier studies that document a significant response in ESG mutual fund ownership to MSCI's contemporaneous corporate ESG scores. Interestingly, we identify that ESG funds exhibit discrepancies in trading on information about ESG scores and firm incidents. On the one hand, these funds lowered their discretionary ownership in stocks that saw ES incidents, regardless of the stock's ESG score. On the other hand, the overall trades of ESG funds seem to overshadow this: ESG funds trade increasingly positively towards higher ESG stocks (Figures 4 and 3). ESG funds trade with ESG-skill by deviating from their expected trading, the latter following last quarter's portfolio allocation. However, this effect is economically small compared to the total quarterly position changes of ESG funds. ESG funds predominantly trade towards higher ESG scoring firms, but marginally move away from firms with past ES incidents. Thus, we conclude that trades by ESG mutual funds are both backward- and forward-looking.

Following these two sets of analyses, an important question still left unexplained is what makes some fund managers more ESG-informed than others. Some recent work expresses concern that professional (ESG) investors lack the sustainability-related competencies that are needed to make genuinely sustainable investment decisions[53]. To obtain a more complete picture of fund managers' use of ESG information and the informativeness of their trades, for every fund in our sample, we estimate a propensity measure based on their recorded changes in stock holdings that estimates their propensity to increase their discretionary ownership in stocks that see fewer ES incidents in the future. In our cross-section of funds, we indeed note significant differences between funds in the highest and lowest quintiles of forward-looking ESG trading skill. Literature on (ESG) skill discusses that less skilled funds should see lower abnormal performance (Chen et al., 2024; Kacperczyk and Seru, 2007, e.g.,). Our results concerning forward-looking ESG skills do not support this. Instead, we find that most skilled funds in their discretionary trading do not outperform or underperform the least skilled funds: skilled discretionary trades do not contribute positively to fund performance. A possible explanation could be that skilled discretionary trades are, on average, too small in

[53]Schumacher (2023) introduces the terminology of "competence greenwashing: intentional or negligent misrepresentation of knowledge or skills relating to sustainability or ESG." https://www.ft.com/content/9c02baa2-447d-4742-beb9-8c83bc3ecc88.

magnitude to be financially material to quarterly fund performance. Consequently, the significant positive relation of stock-level discretionary ownership by ESG funds and future returns may instead be driven by short-term price-pressure effects of green assets (Pástor et al., 2022).

We further complement our analysis on funds' forward-looking ESG expertise by quantifying (ESG) funds' reliance on public ESG information, such as responding to updates of stocks' ESG scores or ES incidents. In our analyses on fund position trades, we find that ESG funds essentially trade on MSCI ESG scores while their consideration of past ES incidents is economically small. Hence, we develop two proxies that quantify funds' reliance on public ESG scores and ES incident information. In line with the traditional skill literature, we find some evidence that funds that rely more extensively on historical changes of ESG scores experience a negative relation with risk-adjusted fund returns.

Funds are not rewarded for more skillful discretionary trading, and ESG funds may even be punished for relying on public signals on environmental or social firm incidents. Instead, we find evidence that ESG funds that rely more on historical ESG scores for their trading decisions are rewarded by investors with increased quarterly inflows. Conventional funds, on the other hand, see a negative relation between ESG score reliance and flows.

Moreover, if skillful discretionary ESG trading does not create a credible signal on the financial market, nor does its magnitude translate into financially material fund returns (see Section 5.1), investors may thus not be urged to seek skillful ESG funds. These findings spark the argument that ESG funds partake in flow-chasing behavior by catering to an investor base whose non-pecuniary preferences may be translated into a preference for top-ESG stocks.

Investor preference for high ESG stocks has been well documented. Hence, ESG funds are induced to partake in flow-chasing behavior by increasingly overweighting high ESG-scoring stocks. This may, in turn, diminish the portfolio heterogeneity across ESG funds. In a theoretical framework applied to the market of ESG rating agencies, Azarmsa and Shapiro (2023) argue that in a market where investors place a higher value on multiple components of ESG performance may induce generalization of ESG products. Indeed, our results point to a similar phenomenon in the ESG mutual fund market. The financial market has recorded exponential demand for green or high-ESG assets. If investors who prioritize sustainability seek out high-performing ESG assets across various categories—such as those that align with both environmental and social attributes—funds may be incentivized to focus their investment strategies on stocks that achieve high overall ESG scores to set their investment universe to stocks that score high on 'general' ESG scores.

References

Addoum, J. M., Ng, D. T., and Ortiz-Bobea, A. (2023). Temperature shocks and industry earnings news. *Journal of Financial Economics*, 150(1):1–45.

Akepanidtaworn, K., Mascio, R. d., Imas, A., and Schmidt, L. D. (2023). Selling fast and buying slow: Heuristics and trading performance of institutional investors. *The Journal of Finance*, 78(6):3055–3098.

Alves, R., Krueger, P., and van Dijk, M. (2022). *Drawing Up the Bill: Does Sustainable Investing Affect Stock Returns Around the World?* Netspar, Network for Studies on Pensions, Aging and Retirement.

Andrei, D., Friedman, H., and Ozel, N. B. (2023). Economic uncertainty and investor attention. *Journal of Financial Economics*, 149(2):179–217.

Ardia, D., Bluteau, K., Boudt, K., and Inghelbrecht, K. (2023). Climate change concerns and the performance of green vs. brown stocks. *Management Science*, 69(12):7607–7632.

Azarmsa, E. and Shapiro, J. D. (2023). The market for esg ratings. *Available at SSRN 4236912*.

Barber, B. M., Morse, A., and Yasuda, A. (2021). Impact investing. *Journal of Financial Economics*, 139(1):162–185.

Berg, F., Heeb, F., and Kölbel, J. (2024). The economic impact of esg ratings. Technical report, SAFE Working Paper.

Berg, F., Kölbel, J. F., and Rigobon, R. (2022). Aggregate confusion: The divergence of esg ratings. *Review of Finance*, 26(6):1315–1344.

Bolton, P., Eskildsen, M., and Kacperczyk, M. T. (2024). Carbon home bias. *Available at SSRN 4708844*.

Bolton, P. and Kacperczyk, M. (2021). Do investors care about carbon risk? *Journal of financial economics*, 142(2):517–549.

Bolton, P. and Kacperczyk, M. (2023). Global pricing of carbon-transition risk. *The Journal of Finance*, 78(6):3677–3754.

Borgers, A., Derwall, J., Koedijk, K., and Ter Horst, J. (2013). Stakeholder relations and stock returns: On errors in investors' expectations and learning. *Journal of Empirical Finance*, 22:159–175.

Busch, D. (2023). Eu sustainable finance disclosure regulation. *Capital Markets Law Journal*, 18(3):303–328.

Ceccarelli, M., Evans, R. B., Glossner, S., Homanen, M., and Luu, E. (2023). Esg skill of mutual fund managers. *Available at SSRN*.

Ceccarelli, M., Ramelli, S., and Wagner, A. F. (2024). Low carbon mutual funds. *Review of Finance*, 28(1):45–74.

Chen, L., Chen, Y., Kumar, A., and Leung, W. S. (2024). Firm-level esg information and active fund management. *Journal of Financial Intermediation*, 60:101122.

Cohn, J. B., Liu, Z., and Wardlaw, M. I. (2022). Count (and count-like) data in finance. *Journal of Financial Economics*, 146(2):529–551.

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

Coval, J. D. and Moskowitz, T. J. (1999). Home bias at home: Local equity preference in domestic portfolios. *The Journal of Finance*, 54(6):2045–2073.

Cremers, M., Riley, T. B., and Zambrana, R. (2024). The complex materiality of proprietary esg information: Evidence from actively managed funds. *Available at SSRN: https://ssrn.com/abstract=4335688*.

De Chaisemartin, C. and d'Haultfoeuille, X. (2024). Difference-in-differences estimators of intertemporal treatment effects. *Review of Economics and Statistics*, pages 1–45.

Derrien, F., Krueger, P., Landier, A., and Yao, T. (2022). Esg news, future cash flows, and firm value. *Swiss finance institute research paper*, .(21-84).

Derwall, J., Koedijk, K., and Ter Horst, J. (2011). A tale of values-driven and profit-seeking social investors. *Journal of Banking & Finance*, 35(8):2137–2147.

Dyck, A., Lins, K. V., Roth, L., and Wagner, H. F. (2019). Do institutional investors drive corporate social responsibility? international evidence. *Journal of financial economics*, 131(3):693–714.

Eccles, R. G., Ioannou, I., and Serafeim, G. (2014). The impact of corporate sustainability on organizational processes and performance. *Management science*, 60(11):2835–2857.

Edmans, A. (2011). Does the stock market fully value intangibles? employee satisfaction and equity prices. *Journal of Financial economics*, 101(3):621–640.

Edmans, A., Pu, D., Zhang, C., and Li, L. (2024). Employee satisfaction, labor market flexibility, and stock returns around the world. *Management Science*, 70(7):4357–4380.

Falato, A., Hortacsu, A., Li, D., and Shin, C. (2021). Fire-sale spillovers in debt markets. *The Journal of Finance*, 76(6):3055–3102.

Fang, L. H., Peress, J., and Zheng, L. (2014). Does media coverage of stocks affect mutual funds' trading and performance? *The Review of Financial Studies*, 27(12):3441–3466.

Ferreira, M. A. and Matos, P. (2008). The colors of investors' money: The role of institutional investors around the world. *Journal of financial economics*, 88(3):499–533.

Galema, R. and Gerritsen, D. (2025). Esg rating changes and stock returns. *Journal of International Money and Finance*, 154:103309.

Gantchev, N., Giannetti, M., and Li, R. (2022). Does money talk? divestitures and corporate environmental and social policies. *Review of Finance*, 26(6):1469–1508.

Gantchev, N., Giannetti, M., and Li, R. (2023). Sustainability or performance? ratings and fund managers' incentives. Finance Working Paper No. 747/2021, European Corporate Governance Institute.

Geczy, C., Jeffers, J. S., Musto, D. K., and Tucker, A. M. (2021). Contracts with (social) benefits: The implementation of impact investing. *Journal of Financial Economics*, 142(2):697–718.

Giannetti, M. and Jotikasthira, C. (2024). Bond Price Fragility and the Structure of the Mutual Fund Industry. *The Review of Financial Studies*, pages 1–47.

Gibbon, K., Derwall, J., Gerritsen, D., and Koedijk, K. (2023). Renaming with purpose: Investor response and fund manager behaviour after fund esg-renaming. *Available at SSRN: https://ssrn.com/abstract=4614978*.

Gibson Brandon, R., Glossner, S., Krueger, P., Matos, P., and Steffen, T. (2022). Do responsible investors invest responsibly? *Review of Finance*, 26(6):1389–1432.

Goldstein, I., Kopytov, A., Shen, L., and Xiang, H. (2022). On esg investing: Heterogeneous preferences, information, and asset prices. Technical report, National Bureau of Economic Research.

Goldstein, I. and Yang, L. (2017). Information disclosure in financial markets. *Annual Review of Financial Economics*, 9:101–125.

Hartzmark, S. M. (2015). The worst, the best, ignoring all the rest: The rank effect and trading behavior. *The Review of Financial Studies*, 28(4):1024–1059.

Hartzmark, S. M. and Shue, K. (2023). Counterproductive sustainable investing: The impact elasticity of brown and green firms. *SSRN Electronic Journal. Starks, LT (2023):"Presidential Address: Sustainable Finance and ESG Issuesâ¿" Value versus Values," The Journal of Finance*, 78(4):1837–1872.

Hartzmark, S. M. and Sussman, A. B. (2019). Do investors value sustainability? a natural experiment examining ranking and fund flows. *The Journal of Finance*, 74(6):2789–2837.

He, Y. E., Kahraman, B., and Lowry, M. (2023). Es risks and shareholder voice. *The Review of Financial Studies*, 36(12):4824–4863.

Heath, D., Macciocchi, D., Michaely, R., and C. Ringgenberg, M. (2023). Does socially responsible investing change firm behavior? *Review of Finance*, 27(6):2057–2083.

Hoepner, A. G., Oikonomou, I., Sautner, Z., Starks, L. T., and Zhou, X. Y. (2024). Esg shareholder engagement and downside risk. *Review of Finance*, 28(2):483–510.

Hong, H. and Kostovetsky, L. (2012). Red and blue investing: Values and finance. *Journal of financial economics*, 103(1):1–19.

Hong, H., Li, F. W., and Xu, J. (2019). Climate risks and market efficiency. *Journal of econometrics*, 208(1):265–281.

Huang, S., Ringgenberg, M. C., and Zhang, Z. (2023). The information in asset fire sales. *Management Science*, 69(9):5066–5086.

Jensen, T. I., Kelly, B. T., and Pedersen, L. H. (2022). Is there a replication crisis in finance? *Journal of Finance, Forthcoming*.

Kacperczyk, M., Nieuwerburgh, S. V., and Veldkamp, L. (2014). Time-varying fund manager skill. *The Journal of Finance*, 69(4):1455–1484.

Kacperczyk, M., Nosal, J., and Wang, T. (2025). Global volatility and firm-level capital flows. *Journal of Financial Economics*, 169:104078.

Kacperczyk, M. and Seru, A. (2007). Fund manager use of public information: New evidence on managerial skills. *The Journal of Finance*, 62(2):485–528.

Kacperczyk, M., Sialm, C., and Zheng, L. (2005). On the industry concentration of actively managed equity mutual funds. *The Journal of finance*, 60(4):1983–2011.

Kacperczyk, M., Sundaresan, S., and Wang, T. (2021). Do foreign institutional investors improve price efficiency? *The Review of Financial Studies*, 34(3):1317–1367.

Karolyi, G. A., Wu, Y., and Xiong, W. W. (2023). Understanding the global equity greenium. *Unpublished working paper*.

Khan, M., Serafeim, G., and Yoon, A. (2016). Corporate sustainability: First evidence on materiality. *The Accounting Review*, 91(6):1697–1724.

Kim, S. and Yoon, A. (2023). Analyzing active fund managers' commitment to esg: Evidence from the united nations principles for responsible investment. *Management Science*, 69(2):741–758.

Krüger, P. (2015). Corporate goodness and shareholder wealth. *Journal of financial economics*, 115(2):304–329.

Lin, X., She, G., Yoon, A., and Zhu, H. (2025). Shareholder value implications of supply chain esg: Evidence from negative incidents. *Review of Accounting Studies*, pages 1–33.

Ma, Y., Xiao, K., and Zeng, Y. (2022). Mutual fund liquidity transformation and reverse flight to liquidity. *The Review of Financial Studies*, 35(10):4674–4711.

Morgan Stanley Institute for Sustainable Investing (2024). Sustainable signals: Understanding individual investors' interests and priorities. Tech. Rep. 5th Edition, Morgan Stanley. Survey conducted in October 2023; published January 2024.

Pankratz, N., Bauer, R., and Derwall, J. (2023). Climate change, firm performance, and investor surprises. *Management science*, 69(12):7352–7398.

Park, M., Yoon, A., and Zach, T. (2025). Sell-side analysts' assessment of esg risk. *Journal of Accounting and Economics*, 79(2):101759.

Pástor, L., Stambaugh, R. F., and Taylor, L. A. (2021). Sustainable investing in equilibrium. *Journal of financial economics*, 142(2):550–571.

Pástor, L., Stambaugh, R. F., and Taylor, L. A. (2022). Dissecting green returns. *Journal of Financial Economics*, 146(2):403–424.

Pastor, L., Stambaugh, R. F., and Taylor, L. A. (2023). Green tilts. Technical report, National Bureau of Economic Research.

Pedersen, L. H., Fitzgibbons, S., and Pomorski, L. (2021). Responsible investing: The esg-efficient frontier. *Journal of financial economics*, 142(2):572–597.

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

Rzeźnik, A., Hanley, K. W., and Pelizzon, L. (2022). Investor reliance on esg ratings and stock price performance. Technical report, SAFE Working Paper.

Sautner, Z., Van Lent, L., Vilkov, G., and Zhang, R. (2023). Pricing climate change exposure. *Management Science*, 69(12):7540–7561.

Serafeim, G. and Yoon, A. (2023). Stock price reactions to esg news: The role of esg ratings and disagreement. *Review of accounting studies*, 28(3):1500–1530.

Sirri, E. R. and Tufano, P. (1998). Costly search and mutual fund flows. *The journal of finance*, 53(5):1589–1622.

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

Spaans, L., Derwall, J., Huij, J., and Koedijk, K. (2024). Sustainable finance disclosure regulation: Voluntary signaling or mandatory disclosure? *Available at SSRN 4722820*.

Starks, L. T. (2023). Presidential address: Sustainable finance and esg issues—value versus values. *The Journal of Finance*, 78(4):1837–1872.

Van der Beck, P. (2021). Flow-driven esg returns. Technical Report 21-71, Swiss Finance Institute Research Paper.

Van Nieuwerburgh, S. and Veldkamp, L. (2010). Information acquisition and under-diversification. *The Review of Economic Studies*, 77(2):779–805.

Wang, P. (2024). Portfolio pumping in mutual fund families. *Journal of Financial Economics*, 156:103839.

Wardlaw, M. (2020). Measuring mutual fund flow pressure as shock to stock returns. *The Journal of Finance*, 75(6):3221–3243.

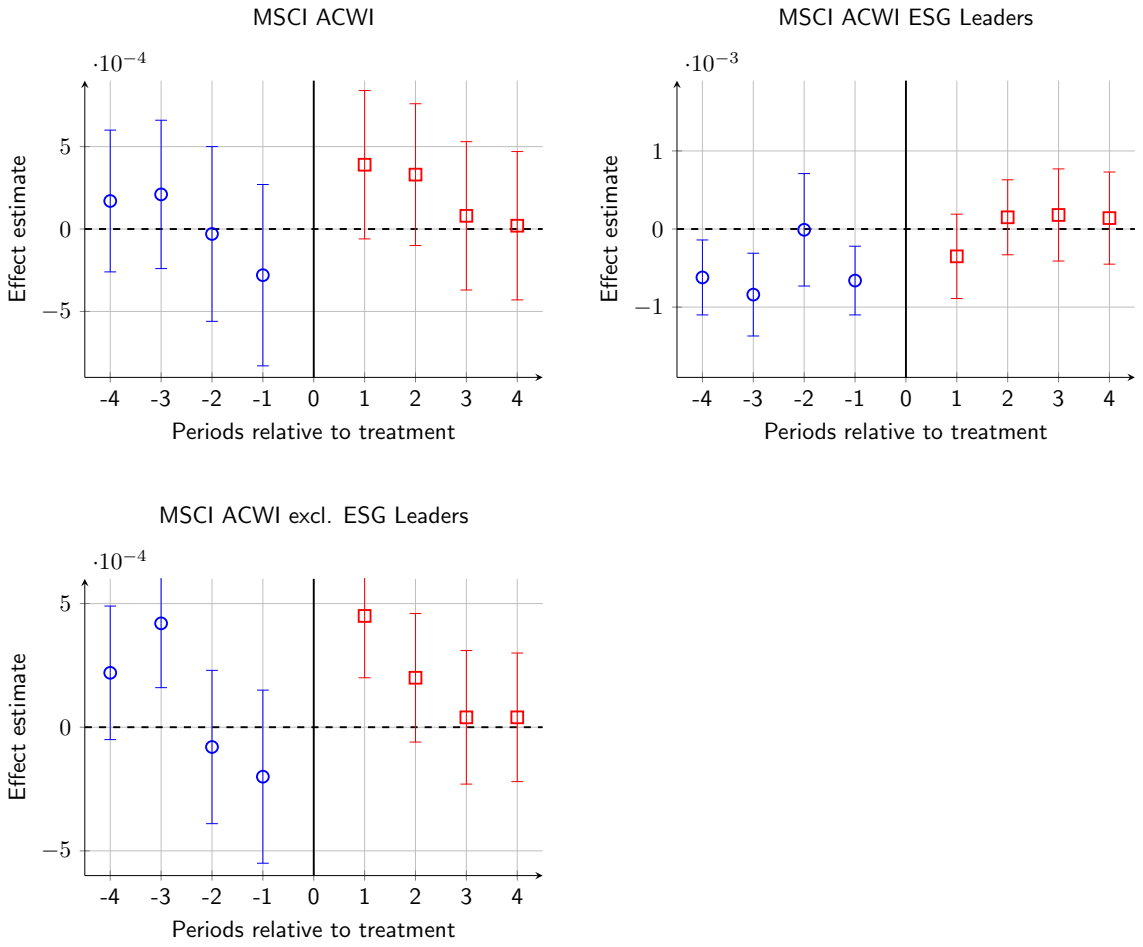
Zambrana, R. and Zapatero, F. (2021). A tale of two types: Generalists vs. specialists in asset management. *Journal of Financial Economics*, 142(2):844–861.

Zhang, S. (2025). Carbon returns across the globe. *The Journal of Finance*, 80(1):615–645.

Appendices

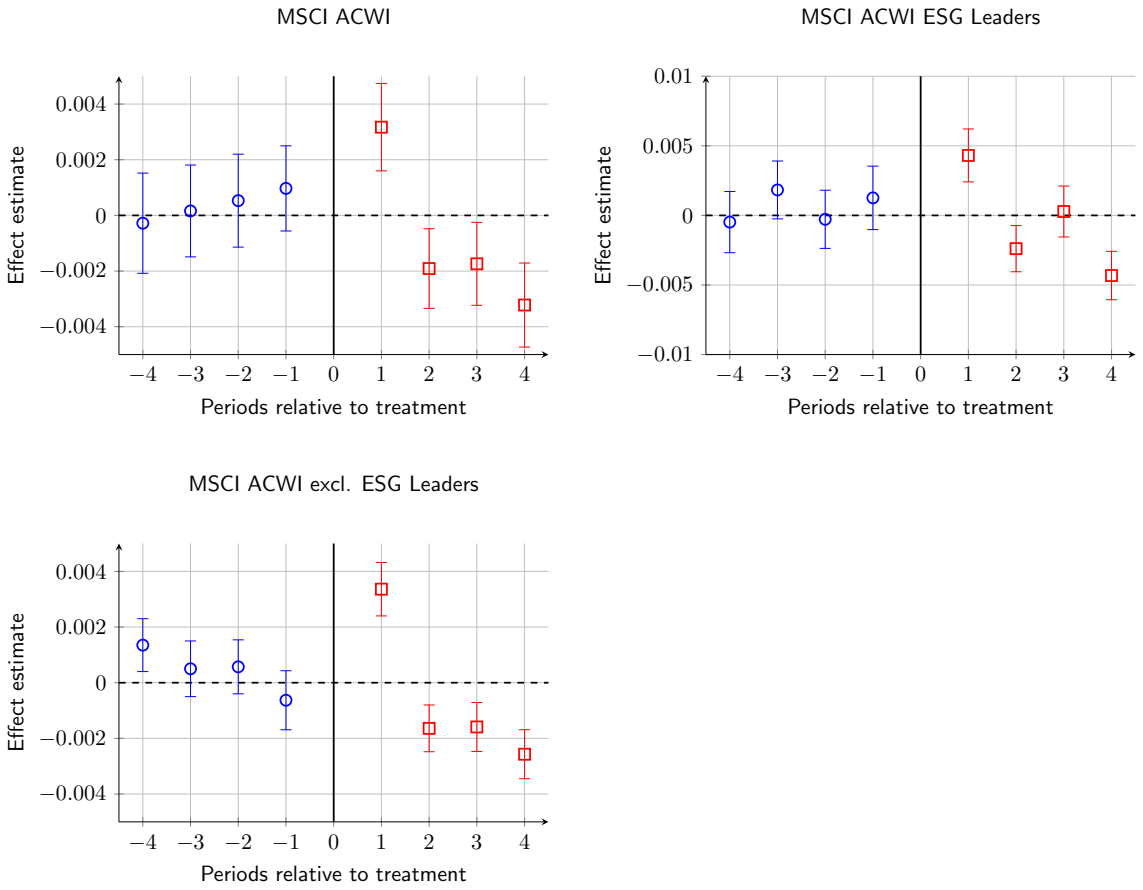
A Figures

Figure 1: MSCI Index Inclusion on ESG Discretionary Trades



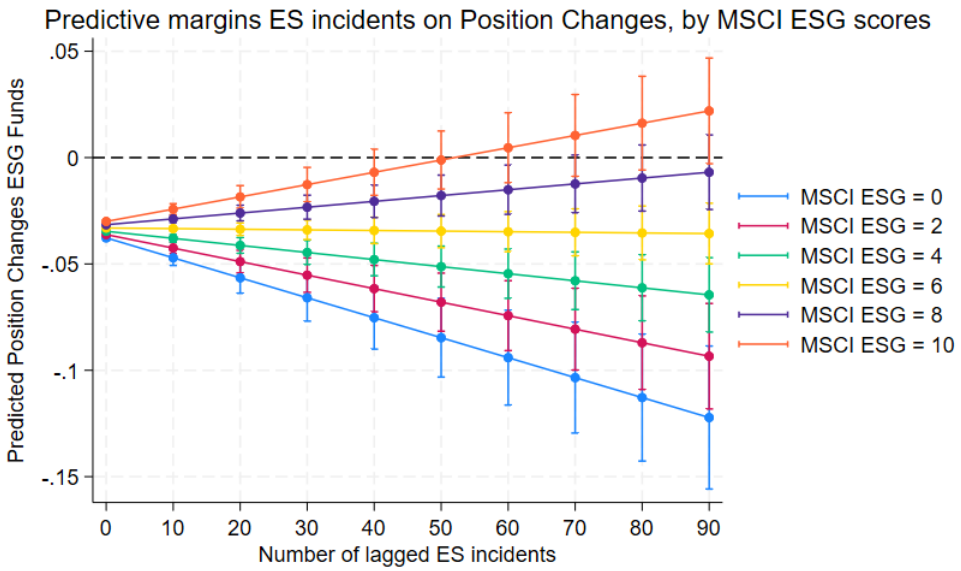
Notes: Event study results by treatment path. The left panel shows results for firms entering the MSCI All Country World Index (ACWI) with a total of 3,327 switchers compared to firms that have not switched yet. The right panel shows results for all firms entering both the MSCI ACWI and the MSCI ACWI ESG Leaders simultaneously, with 160 switchers. The bottom panel shows results for firms entering the MSCI ACWI, excluding those that also enter the ESG Leaders, with 602 switchers. Blue circles are placebo (pre-treatment) effects, and red squares are treatment (post-treatment) effects. Error bars represent 95% confidence intervals.

Figure 2: MSCI Index Inclusion on Conventional Discretionary Trades



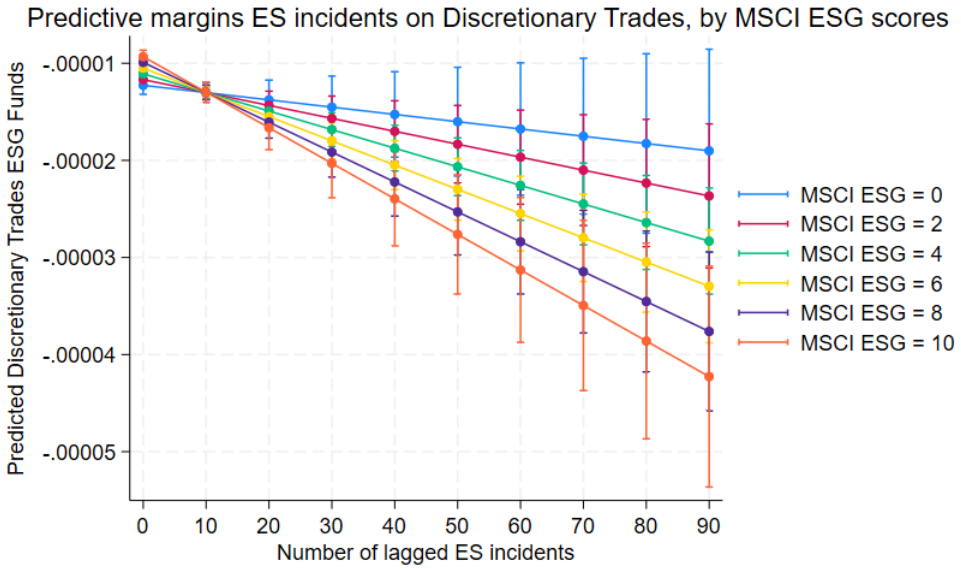
Notes: Event study results by treatment path. The left panel shows results for firms entering the MSCI All Country World Index (ACWI) with a total of 3,327 switchers compared to firms that have not switched yet. The right panel shows results for all firms entering both the MSCI ACWI and the MSCI ACWI ESG Leaders simultaneously, with 160 switchers. The bottom panel shows results for firms entering the MSCI ACWI, excluding those that also enter the ESG Leaders, with 602 switchers. Blue circles are placebo (pre-treatment) effects, and red squares are treatment (post-treatment) effects. Error bars represent 95% confidence intervals.

Figure 3: Margin plot ES incidents on Position Changes of ESG Funds



Notes: Margin plot predicting the margins of 1-quarter lagged ES incidents on position changes by ESG funds. Position Changes is the change in the position of fund i in stock j in quarter t estimated according to (Gantchev et al., 2023; Giannetti and Jotikasthira, 2024) and is trimmed at the 0.5 and 99.5 percentiles. Lagged ES Incidents denotes the number of environmental and social RepRisk incidents in quarter $t-1$ by firm j. Lagged Industry-weighted MSCI ESG score is set as the moderator and denotes the stock's industry-weighted MSCI ESG score in quarter $t-1$. Error bars represent 95% confidence intervals.

Figure 4: Margin plot ES incidents on Discretionary Trades of ESG Funds



Notes: Margin plot predicting the margins of 1-quarter lagged ES incidents on discretionary trades by ESG funds. Discretionary trades are defined according to Huang et al. (2023): Sales after inflows are assumed to be 0; buys after outflows are assumed to be equal to 0. Discretionary Trades are the share of fund trades that are not Expected Trades and is trimmed at the 0.5 and 99.5 percentiles. Lagged ES Incidents denotes the number of environmental and social RepRisk incidents in quarter $t-1$ by firm j. Lagged Industry-weighted MSCI ESG score is set as the moderator and denotes the stock's industry-weighted MSCI ESG score in quarter $t-1$. Error bars represent 95% confidence intervals.

B Tables

Table 1: Summary statistics - Fund-level variables (quarterly)

	N	Mean	1st pct	Median	99th pct	Std Dev
Total net assets (TNA) (USD mil.)	230,262	1.52e+09	2.87e+06	2.13e+08	1.88e+10	1.20e+10
Quarterly returns ($\times 100\%$)	230,262	0.0175	-0.2712	0.0283	0.2556	0.1018
Fama French 3-Factors α	165,972	-0.1413	-1.0119	-0.1256	0.7315	0.3555
Carhart 4-Factors α	165,972	-0.1378	-1.0083	-0.1264	0.7546	0.3583
Quarterly flow ($\times 100\%$)	230,262	0.0052	-0.3028	-0.0092	0.5768	0.1439
Change in TNA ($\times 100\%$)	230,262	0.0226	-0.3658	0.0163	0.6471	0.1794
Fund turnover ($\times 100\%$)	228,548	1.1037	0	0.4432	14.5982	2.6981
Age	230,262	15.0965	1.2457	13.2621	56.9829	11.5893
Cash/ short term investments as % of portfolio	230,262	2.6072	-2.3114	1.3192	19.7761	4.1715
Number of holdings	230,262	178.3999	20	64	2021	450.6580
ESG Fund	230,262	0.2857	0.0000	0.0000	1.0000	0.4517
European Fund	230,262	0.6878	0.0000	1.0000	1.0000	0.4634
SFDR Article 8/9 Fund	117,323	0.5955	0.0000	1.0000	1.0000	0.4908

Notes: The sample includes all European and US-domiciled open-end equity funds from December 2014 to December 2022. The mean, median, 1st percentile, 99th percentile, and standard deviation of various quarterly fund-level characteristics are reported. The data is recorded on a fund-quarter level. *Total net assets* denotes the level of total assets under management at the quarter-end in USD. *Quarterly returns* are the quarterly net returns of a fund. *Fama French 3-Factors* α is the fund's average quarterly alpha estimated using Fama-French three-factor model on a monthly rolling-window between month $t-36$ and t. *Carhart 4-Factors* α is the fund's average quarterly alpha estimated using Fama-French-Carhart four-factor model on a monthly rolling-window between month $t-36$ and t. *Quarterly flow* is defined as the dollar flows normalized by the fund's previous quarter's TNA. *Change in TNA* is the percentage change in total net assets between t and $t-1$. This is bound between -0.5 and 2. *Fund turnover* is the fund's quarterly portfolio turnover calculated following Gantchev et al. (2023): the aggregate absolute value of the position change between quarters $t-1$ and t across all primary stock holdings, computed using the stock price at $t-1$, divided by the fund's TNA at the end of quarter $t-1$, multiplied by 2. The values are trimmed at the 0.5th and 99.5h percentiles. *Age* is the number of years between the inception date of the oldest share class of the fund and the date of observation. *Cash/ short term investments as % of portfolio* indicates the weight in the fund's portfolio that is indicated by FactSet's generic position 'CASH'. CASH represents the as-reported market value of cash and short-term investments of the fund in quarter t. We trim fund-quarter observations for which *Cash/ short term investments as % of portfolio* surpasses the 0.5-99.5 percentiles. *Number of holdings* is a counter of the equity holdings that funds report they manage at the end of the quarter. *ESG Fund* takes on the value 1 if the fund is denoted by Morningstar to be a "General ESG Investment", 0 otherwise. *European Fund* takes on a value of 1 if the fund is domiciled countries part of the European Union including Norway, Switzerland, and the United Kingdom. It takes on the value of 0 for funds that are domiciled in the United States. *SFDR Article 8/9 Fund* applies to the sample funds that are domiciled in European countries to which the Sustainable Finance Disclosure Regulation (SFDR) applies. Morningstar indicates whether a fund reports in its prospectus that it aligns with Article 9, 8, or 6. *SFDR Article 8/9 Fund* is set to 1 for funds that align with Article 9 or 8, and 0 for funds that align with Article 6.

Table 2: Summary statistics - Stock-level variables (quarterly)

	N	Mean	1st pct	Median	99th pct	Std Dev
Log Market Cap.$_{j,t}$	757,692	5.9821	1.6013	5.8718	10.7672	1.9421
# Shares$_{j,t-1}$	757,715	1985.6171	1.5592	106.2001	1.58e+04	8.80e+04
Quarterly stock returns$_{j,t+1}$	744,484	0.0303	-0.5456	0.0009	1.0097	0.7208
Book/ Market$_{j,t}$	716,840	0.9686	0.0319	0.6427	7.0934	1.1071
Momentum$_{j,t}$	723,628	0.0966	-0.7761	-0.0029	2.6783	0.5416
CAPEX/ Assets$_{j,t}$	627,996	0.0411	0.0000	0.0256	0.2601	0.0476
Beta$_{j,t}$	707,520	0.9261	-0.0097	0.9135	2.1644	0.4201
Return volatility$_{j,t}$	707,520	0.0285	0.0085	0.0251	0.0906	0.0148
ROE$_{j,t}$	617,759	0.0012	-0.6519	0.0177	0.2627	0.1083
Leverage$_{j,t}$	724,310	0.2246	0.0000	0.1893	0.8705	0.1984
MSCI ACWI$_{j,t}$	757,715	0.0972	0.0000	0.0000	1.0000	0.2962
MSCI ACWI ESG Leaders$_{j,t}$	757,715	0.0354	0.0000	0.0000	1.0000	0.1847
# Environmental and social incidents$_{j,t+1}$	356,346	0.2825	0.0000	0.0000	5.0000	1.5474
# Severe environmental and social incidents$_{j,t+1}$	356,346	0.0931	0.0000	0.0000	2.0000	0.5757
Incident volatility$_{j,t}$	356,346	0.0316	0.0000	0.0000	0.2708	0.0580
Δ*Raw MSCI ESG*$_{j,t+1}$	195,087	0.0205	-0.7000	0.0000	0.8000	0.2610
Δ*Raw MSCI ESG*$_{j,t+4}$	184,615	0.0885	-1.1000	0.1000	1.3000	0.4656
Δ*MSCI ESG IVA*$_{j,t+1}$	194,773	0.0405	-1.4000	0.0000	1.9000	0.4645
Δ*MSCI ESG IVA*$_{j,t+4}$	184,353	0.1793	-2.2000	0.0000	2.6000	0.9263
Δ*Carbon Intensity*$_{j,t+1}$	127,698	-0.0051	-0.4670	0.0000	0.7321	0.1260
Δ*Carbon Intensity*$_{j,t+4}$	111,841	0.0237	-0.7680	-0.0571	3.5837	0.5258

Notes: The sample includes all firms for which the primary share was held by our sample of European and US domiciled funds from December 2014 to December 2022. The mean, median, 1st percentile, 99th percentile, and standard deviation of various quarterly firm-level characteristics are reported. *Log Market Cap.*$_{j,t}$ is the natural logarithm of the company j's market capitalization in quarter t. *# Shares*$_{j,t-1}$ denote the firm's j number of shares in the previous quarter $t-1$ in millions of shares. *Quarterly stock returns*$_{j,t+1}$ are the quarterly stock returns of stock j in future quarter $t+1$ (/100%). *Book/ Market*$_{j,t}$ is the firm j's book value over its most recent market capitalization. *Momentum*$_{j,t}$ is stock j's most recent 12 month stock return, omitting month $t-1$. *CAPEX/ Assets*$_{j,t}$ is the capital expenditure of firm j over its assets' book value. *Beta*$_{j,t}$ is the firm's primary stock j market beta calculated over the daily returns of the last 12 months. *Return volatility*$_{j,t}$ is the annualized standard deviation of stock j's daily returns over the previous 12 months. *ROE*$_{j,t}$ is the firm j's quarterly income scale by the book value of equity. *Leverage*$_{j,t}$ denotes the ratio of firm j's gross debt to the book value of assets in quarter t. *MSCI ACWI*$_{j,t}$ takes on 1 if stock j in quarter t is included in the MSCI All Country World Index, 0 otherwise. *MSCI ACWI ESG Leaders* takes on 1 if stock j in quarter t is included in the MSCI All Country World ESG Leaders Index, 0 otherwise. *# environmental and social incidents*$_{t+s}$ denotes the number of all RepRisk incidents of firm j that are characterized as an environmental or social issue in quarter(s) $t+s$ with $s \in \{1,2,3,4\}$. *# severe environmental and social incidents*$_{t+s}$ denotes the number of all RepRisk incidents of firm j that are characterized as an environmental or social issue with severity rank two or three in quarter(s) $t+s$ with $s \in \{1,2,3,4\}$. *Incident volatility*$_{j,t}$ is the firm j's 4-quarter rolling standard deviation of daily RepRisk incidents (environment, social, and governance). We estimate the percentage change in firm j's carbon intensity between current quarter t and future quarter $t+s$ as $\Delta CarbonIntensity_{j,t+s} = \frac{CarbonIntensity_{j,t+s} - CarbonIntensity_{j,t}}{CarbonIntensity_{j,t}}$. We calculate the absolute change in the raw and industry-adjusted (IVA) MSCI ESG scores between current quarter t and future quarter $t+s$ with $s \in \{1,4\}$ as $\Delta MSCI_{j,t+s} = MSCI_{j,t+s} - MSCI_{j,t}$.

Table 3: Summary statistics of discretionary and expected trades

	N	Mean	Min	Median	Max	Std Dev
Panel A: Trades Following All Flows (Quarterly)						
DiscretionaryTrades	757,715	-0.0000	-0.0888	0.0000	0.1032	0.0140
Expected_trades	757,715	-0.0003	-0.0157	0.0000	0.0146	0.0027
ESG DiscretionaryTrades	757,715	-0.0001	-0.0274	0.0000	0.0233	0.0035
ESG ExpectedTrades	757,715	0.0000	-0.0052	0.0000	0.0066	0.0009
Conv. DiscretionaryTrades	757,715	0.0000	-0.0685	0.0000	0.0842	0.0113
Conv. ExpectedTrades	757,715	-0.0003	-0.0138	0.0000	0.0111	0.0023
ESG Concentrated DiscretionaryTrades	757,715	-0.0001	-0.0155	0.0000	0.0101	0.0017
ESG Concentrated ExpectedTrades	757,715	0.0000	-0.0036	0.0000	0.0042	0.0006
ESG Unconcentrated DiscretionaryTrades	757,715	-0.0000	-0.0137	0.0000	0.0143	0.0020
ESG Unconcentrated ExpectedTrades	757,715	0.0000	-0.0026	0.0000	0.0033	0.0005
Conv. Concentrated DiscretionaryTrades	757,715	-0.0002	-0.0221	0.0000	0.0145	0.0027
Conv. Concentrated ExpectedTrades	757,715	-0.0001	-0.0075	0.0000	0.0057	0.0010
Conv. Unconcentrated DiscretionaryTrades	757,715	0.0002	-0.0539	0.0000	0.0755	0.0095
Conv. Unconcentrated ExpectedTrades	757,715	-0.0002	-0.0104	0.0000	0.0080	0.0017
European DiscretionaryTrades	757,715	-0.0003	-0.0525	0.0000	0.0410	0.0066
European ExpectedTrades	757,715	-0.0001	-0.0117	0.0000	0.0114	0.0018
US DiscretionaryTrades	757,715	0.0002	-0.0490	0.0000	0.0688	0.0087
US ExpectedTrades	757,715	-0.0002	-0.0107	0.0000	0.0070	0.0017
Article8/9 DiscretionaryTrades	757,715	-0.0001	-0.0308	0.0000	0.0248	0.0038
Article8/9 ExpectedTrades	757,715	0.0000	-0.0062	0.0000	0.0077	0.0010
Article6 DiscretionaryTrades	757,715	-0.0001	-0.0133	0.0000	0.0097	0.0016
Article6 ExpectedTrades	757,715	-0.0000	-0.0040	0.0000	0.0029	0.0005
Panel B: Trades Following Extreme Flows (Quarterly)						
DiscretionaryTrades	757,715	0.0000	-0.0260	0.0000	0.0231	0.0037
ExpectedTrades	757,715	-0.0001	-0.0107	0.0000	0.0108	0.0018
ESG DiscretionaryTrades	757,715	-0.0000	-0.0076	0.0000	0.0066	0.0010
ESG ExpectedTrades	757,715	0.0000	-0.0034	0.0000	0.0045	0.0006
Conv. DiscretionaryTrades	757,715	0.0001	-0.0204	0.0000	0.0187	0.0029
Conv. ExpectedTrades	757,715	-0.0001	-0.0094	0.0000	0.0082	0.0015
ESG Concentrated DiscretionaryTrades	757,715	-0.0000	-0.0040	0.0000	0.0032	0.0005
ESG Concentrated ExpectedTrades	757,715	0.0000	-0.0022	0.0000	0.0027	0.0003
ESG Unconcentrated DiscretionaryTrades	757,715	-0.0000	-0.0038	0.0000	0.0037	0.0005
ESG Unconcentrated ExpectedTrades	757,715	0.0000	-0.0017	0.0000	0.0023	0.0003
Conv. Concentrated DiscretionaryTrades	757,715	-0.0000	-0.0062	0.0000	0.0059	0.0008
Conv. Concentrated ExpectedTrades	757,715	-0.0000	-0.0049	0.0000	0.0039	0.0006
Conv. Unconcentrated DiscretionaryTrades	757,715	0.0001	-0.0161	0.0000	0.0154	0.0024
Conv. Unconcentrated ExpectedTrades	757,715	-0.0001	-0.0071	0.0000	0.0059	0.0011
European DiscretionaryTrades	757,715	-0.0000	-0.0145	0.0000	0.0126	0.0019
European ExpectedTrades	757,715	0.0000	-0.0072	0.0000	0.0085	0.0012
US DiscretionaryTrades	757,715	0.0001	-0.0144	0.0000	0.0143	0.0021
US ExpectedTrades	757,715	-0.0001	-0.0073	0.0000	0.0051	0.0011
Article8/9 DiscretionaryTrades	757,715	-0.0000	-0.0085	0.0000	0.0072	0.0011
Article8/9 ExpectedTrades	757,715	0.0000	-0.0040	0.0000	0.0054	0.0007
Article6 DiscretionaryTrades	757,715	-0.0002	-0.0137	0.0000	0.0040	0.0014
Article6 ExpectedTrades	757,715	-0.0000	-0.0022	0.0000	0.0021	0.0003

Notes: The sample includes all mutual fund holdings that are primary common stocks as defined by Jensen et al. (2022) from December 2014 to December 2022. The mean, median, minimum, maximum, and standard deviation of the following variables are reported: the discretionary and expected trades of all funds and various subsamples of funds are reported: ESG funds, conventional funds, ESG (un)concentrated funds, conventional (un)concentrated funds, European funds, US funds, SFDR abiding Article 8/9 funds, and SFDR abiding Article 6 funds. Discretionary trades are defined conform the pressure trading measure of Coval and Stafford (2007) and Huang et al. (2023): Sales after inflows are assumed to be 0; buys after outflows are assumed to be equal to 0. ExpectedTrading is the portion of fund trading that is equal to fund flows prorated to the lagged holding weight in the fund portfolio. They are winsorized at the 0.5th and 99.5th percentiles. DiscretionaryTrading is the share of fund trades that are not ExpectedTrades, and is winsorized at the 0.5th and 99.5th percentiles.

Table 4: Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
(1) DiscretionaryTrades	1.000																					
(2) ExpectedTrades	0.114*	1.000																				
(3) ESG DiscretionaryTrades	0.420*	0.038*	1.000																			
(4) ESG ExpectedTrades	0.076*	0.484*	0.066*	1.000																		
(5) Conv. DiscretionaryTrades	0.879*	0.092*	0.043*	0.029*	1.000																	
(6) Conv. ExpectedTrades	0.105*	0.897*	0.028*	0.110*	0.102*	1.000																
(7) ESG Concentrated DiscretionaryTrades	0.261*	0.006*	0.652*	-0.002	0.026*	0.018*	1.000															
(8) ESG Concentrated ExpectedTrades	0.064*	0.368*	0.069*	0.757*	0.020*	0.088*	0.017*	1.000														
(9) ESG Unconcentrated DiscretionaryTrades	0.281*	0.023*	0.697*	0.038*	0.043*	0.021*	0.038*	0.035*	1.000													
(10) ESG Unconcentrated ExpectedTrades	0.060*	0.327*	0.069*	0.674*	0.024*	0.089*	0.001	0.127*	0.063*	1.000												
(11) Conv. Concentrated DiscretionaryTrades	0.330*	0.004*	0.052*	0.013*	0.381*	0.007*	0.062*	0.017*	0.026*	0.005*	1.000											
(12) Conv. Concentrated ExpectedTrades	0.057*	0.553*	0.031*	0.114*	0.051*	0.599*	0.025*	0.107*	0.020*	0.074*	0.010*	1.000										
(13) Conv. Unconcentrated DiscretionaryTrades	0.795*	0.086*	0.032*	0.023*	0.907*	0.094*	0.011*	0.013*	0.041*	0.022*	0.044*	0.032*	1.000									
(14) Conv. Unconcentrated ExpectedTrades	0.108*	0.744*	0.018*	0.070*	0.113*	0.843*	0.010*	0.045*	0.015*	0.067*	0.030*	0.129*	0.109*	1.000								
(15) European DiscretionaryTrades	0.613*	0.044*	0.623*	0.080*	0.384*	0.024*	0.425*	0.080*	0.390*	0.059*	0.421*	0.046*	0.224*	0.015*	1.000							
(16) European ExpectedTrades	0.063*	0.729*	0.048*	0.586*	0.026*	0.540*	0.007*	0.468*	0.026*	0.365*	-0.012*	0.527*	0.017*	0.319*	0.067*	1.000						
(17) US DiscretionaryTrades	0.745*	0.091*	0.075*	0.021*	0.832*	0.103*	0.025*	0.009*	0.085*	0.025*	0.140*	0.036*	0.872*	0.117*	0.020*	0.008*	1.000					
(18) US ExpectedTrades	0.117*	0.683*	0.017*	0.112*	0.126*	0.753*	0.009*	0.063*	0.014*	0.115*	0.034*	0.269*	0.124*	0.784*	0.007*	0.041*	0.143*	1.000				
(19) Article8/9 DiscretionaryTrades	0.435*	0.038*	0.773*	0.069*	0.140*	0.023*	0.505*	0.073*	0.526*	0.060*	0.218*	0.040*	0.062*	0.010*	0.730*	0.059*	0.015*	0.005*	1.000			
(20) Article8/9 ExpectedTrades	0.069*	0.521*	0.056*	0.756*	0.028*	0.243*	0.002	0.593*	0.033*	0.486*	0.013*	0.275*	0.018*	0.131*	0.085*	0.720*	0.009*	0.031*	0.070*	1.000		
(21) Article6 DiscretionaryTrades	0.246*	-0.008*	0.084*	0.005*	0.265*	-0.009*	0.089*	0.010*	0.050*	0.002	0.318*	0.006*	0.178*	-0.002	0.423*	-0.013*	0.024*	0.007*	0.052*	0.019*	1.000	
(22) Article6 ExpectedTrades	0.047*	0.364*	0.029*	0.131*	0.039*	0.372*	0.020*	0.119*	0.020*	0.086*	0.025*	0.367*	0.025*	0.238*	0.062*	0.482*	0.008*	0.052*	0.034*	0.119*	-0.009*	1.000

Notes: Pearson correlation matrix of all mutual fund holdings expected and discretionary trades as defined conform to the pressure trading measure of Coval and Stafford (2007) and Huang et al. (2023): Sales after inflows are assumed to be 0; buys after outflows are assumed to be equal to 0. ExpectedTrading is the portion of fund trading that is equal to fund flows prorated to the lagged holding weight in the fund portfolio. They are winsorized at the 0.5th and 99.5th percentiles. DiscretionaryTrading is the share of fund trades that are not ExpectedTrades, and is winsorized at the 0.5th and 99.5th percentiles. * p¡0.05.

Table 5: OLS Regression Results: ESG and Conventional Discretionary Trades on Changes in Future Firm Carbon Emissions and MSCI ESG Score

	Short term: $t+1$ compared to t			Long term: $t+4$ compared to t		
	(1) ΔCarbon Intensity$_{t+1}$	(2) ΔRaw MSCI ESG$_{t+1}$	(3) ΔMSCI ESG IVA$_{t+1}$	(4) ΔCarbon Intensity$_{t+4}$	(5) ΔRaw MSCI ESG$_{t+4}$	(6) ΔMSCI ESG IVA$_{t+4}$
ESG DiscretTrades	0.001	0.004	-0.000	0.003	0.004*	0.000
	(0.307)	(1.265)	(-0.138)	(0.890)	(1.647)	(0.115)
ESG ExpectedTrades	0.005	-0.006**	-0.009***	0.005	-0.000	-0.012***
	(1.194)	(-2.280)	(-3.204)	(1.177)	(-0.001)	(-3.163)
conv. DiscretTrades	-0.002	-0.000	0.001	-0.004	-0.002	-0.005*
	(-0.600)	(-0.151)	(0.449)	(-1.286)	(-0.928)	(-1.699)
conv. ExpectedTrades	0.015***	0.001	0.006*	0.007	0.001	0.002
	(3.648)	(0.337)	(1.757)	(1.293)	(0.220)	(0.548)
logsize	0.164***	0.032***	0.049***	0.339***	0.032	0.096***
	(7.698)	(2.665)	(3.633)	(8.350)	(1.460)	(4.038)
be_me	0.041***	-0.003	-0.001	0.036**	-0.002	0.007
	(4.620)	(-0.512)	(-0.208)	(2.311)	(-0.216)	(0.639)
ret_12_1	-0.024***	0.007*	-0.013***	-0.032***	0.023***	-0.001
	(-4.817)	(1.844)	(-3.343)	(-4.097)	(4.262)	(-0.147)
capx_at	-0.003	0.003	-0.008	-0.039***	0.010	-0.013
	(-0.355)	(0.572)	(-1.371)	(-2.607)	(1.076)	(-1.240)
beta_252d	0.010	-0.004	-0.005	0.014	0.013*	-0.005
	(1.449)	(-0.994)	(-1.069)	(1.263)	(1.764)	(-0.599)
rvol_252d	-0.046***	-0.004	0.002	-0.048***	0.004	0.001
	(-5.078)	(-0.660)	(0.365)	(-3.319)	(0.394)	(0.130)
niq_be	0.027***	-0.000	0.009**	0.026***	-0.008*	0.015***
	(5.873)	(-0.110)	(2.161)	(3.964)	(-1.872)	(2.984)
debt_at	-0.028***	0.011*	0.003	-0.032*	0.029***	0.029**
	(-2.830)	(1.834)	(0.456)	(-1.947)	(2.587)	(2.353)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	93,190	143,716	143,350	81,633	135,564	135,252
R-squared	0.073	0.059	0.046	0.288	0.164	0.162
Within R-squared	0.003	0.000	0.000	0.009	0.001	0.001
F-statistic	21.60***	2.80***	3.68***	14.51***	4.39***	4.00***

Notes: The table reports the relation between ESG and conventional mutual fund trading behavior and future changes in firm-level carbon intensity and MSCI ESG scores. Discretionary trades are defined according to Coval and Stafford (2007) and Huang et al. (2023): Sales after inflows are assumed to be 0; buys after outflows are assumed to be equal to 0. OLS regressions include firm and year-quarter fixed effects. Discretionary and expected trades are winsorized at the 0.5 and 99.5%. All continuous control variables are winsorized at the 1 and 99 percentiles. Δ Raw MSCI ESG is defined as the difference in firm-level key issue MSCI ESG score in t+s and t with s$\in \{1, 4\}$. ΔMSCI ESG IVA is defined as the difference in firm-level industry peer adjusted MSCI ESG score in t+s and t with s$\in \{1, 4\}$. ΔCarbon Intensity is defined as the percentage difference in firm-level carbon intensity in t+s and t with s$\in \{1, 4\}$. OLS regressions include firm and year-quarter fixed effects, and standard errors are clustered at the firm level. Coefficients are standardized and t-statistics are reported in parentheses. * p¡0.10, ** p¡0.05, *** p¡0.01.

Table 6: Poisson Regression Results: ESG and Conventional Discretionary Trades on Future Firm Environmental and Social Incidents.

Dependent variable: (Cumulative) Future Environmental and Social Incidents in t+s				
	1 quarter	2 quarters	3 quarters	4 quarters
	(1)	(2)	(3)	(4)
ESG DiscretTrades	-0.002	-0.001**	-0.001*	-0.001**
	(-1.101)	(-2.068)	(-1.645)	(-2.207)
ESG ExpectedTrades	0.011***	0.005***	0.003***	0.002***
	(3.826)	(3.706)	(3.943)	(3.384)
conv. DiscretTrades	0.000	0.000	0.000	0.000
	(0.081)	(0.053)	(0.154)	(0.051)
conv. ExpectedTrades	-0.008***	-0.001	-0.000	0.000
	(-2.593)	(-0.974)	(-0.289)	(0.117)
logsize	0.276***	0.141***	0.094***	0.070***
	(9.549)	(9.826)	(9.806)	(9.867)
be_me	0.067***	0.033***	0.022***	0.016***
	(7.002)	(6.818)	(6.898)	(6.886)
ret_12_1	-0.032***	-0.017***	-0.011***	-0.008***
	(-7.025)	(-7.602)	(-7.497)	(-7.104)
capx_at	0.001	-0.000	-0.001	-0.001
	(0.063)	(-0.107)	(-0.262)	(-0.408)
beta_252d	-0.008	-0.004	-0.001	-0.000
	(-1.567)	(-1.371)	(-0.432)	(-0.049)
rvol_252d	0.030***	0.013***	0.006**	0.003*
	(4.150)	(3.486)	(2.508)	(1.931)
niq_be	-0.002	0.001	0.001	0.001
	(-0.863)	(0.896)	(1.073)	(1.273)
debt_at	0.041***	0.021***	0.013***	0.010***
	(4.216)	(4.115)	(3.945)	(3.807)
Firm FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Observations	161,423	164,214	167,338	169,843
Pseudo R-squared	0.591	0.669	0.714	0.745
χ^2-statistic	126.44***	125.66***	120.43***	119.77***

Notes: The table reports the relation between ESG and conventional mutual fund trading behavior and future changes in firm-level (cumulative) number of environmental and social RepRisk incidents, measured at t+s, where quarter s $\in \{1, 2, 3, 4\}$. Discretionary trades are defined according to Coval and Stafford (2007) and Huang et al. (2023): Sales after inflows are assumed to be 0; buys after outflows are assumed to be equal to 0. Discretionary and expected trades are winsorized at the 0.5 and 99.5%. Poisson regressions include firm and year-quarter fixed effects, and standard errors are clustered at the firm level. Regressions include firm and year-quarter fixed effects. All continuous control variables are winsorized at the 1 and 99 percentiles. Coefficients are standardized and z-statistics are reported in parentheses. * p¡0.10, ** p¡0.05, *** p¡0.01

Table 7: Poisson Regression Results: ESG and Conventional Discretionary Trades on Future Severe Firm Environmental and Social Incidents.

Dependent variable: (Cumulative) Severe Future Environmental and Social Incidents in t+s				
	1 quarter	2 quarters	3 quarters	4 quarters
	(1)	(2)	(3)	(4)
ESG DiscretTrades	-0.003	-0.005*	-0.002	-0.002
	(-0.394)	(-1.836)	(-1.324)	(-1.432)
ESG ExpectedTrades	0.034***	0.015***	0.011***	0.007***
	(3.615)	(3.433)	(3.551)	(3.244)
conv. DiscretTrades	0.004	0.001	-0.000	0.000
	(0.526)	(0.267)	(-0.125)	(0.045)
conv. ExpectedTrades	-0.029***	-0.006	-0.001	-0.001
	(-2.886)	(-1.116)	(-0.343)	(-0.632)
logsize	0.551***	0.316***	0.218***	0.166***
	(6.520)	(6.966)	(6.958)	(6.797)
be_me	0.166***	0.091***	0.060***	0.044***
	(5.886)	(5.978)	(5.793)	(5.495)
ret_12_1	-0.053***	-0.029***	-0.019***	-0.014***
	(-3.812)	(-3.889)	(-3.957)	(-3.832)
capx_at	0.018	0.002	-0.003	-0.003
	(0.712)	(0.137)	(-0.298)	(-0.474)
beta_252d	-0.024	-0.018**	-0.011*	-0.009**
	(-1.466)	(-2.122)	(-1.902)	(-2.066)
rvol_252d	0.064***	0.033***	0.022***	0.016***
	(2.827)	(2.756)	(2.670)	(2.623)
niq_be	0.012	0.008*	0.006*	0.005**
	(1.263)	(1.683)	(1.857)	(2.191)
debt_at	0.086***	0.049***	0.034***	0.027***
	(3.225)	(3.391)	(3.398)	(3.488)
Firm FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Observations	95,250	96,772	98,524	100,144
Pseudo R-squared	0.431	0.507	0.556	0.594
χ^2-statistic	95.29***	91.48***	90.53***	84.24***

Notes: The table reports the relation between ESG and conventional mutual fund trading behavior and future changes in firm-level (cumulative) number of severe environmental and social RepRisk incidents, measured at t+s, where quarter s $\in \{1, 2, 3, 4\}$. Discretionary trades are defined according to Coval and Stafford (2007) and Huang et al. (2023): Sales after inflows are assumed to be 0; buys after outflows are assumed to be equal to 0. Discretionary and expected trades are winsorized at the 0.5 and 99.5%. Poisson regressions include firm and year-quarter fixed effects, and standard errors are clustered at the firm level. Regressions include firm and year-quarter fixed effects. All continuous control variables are winsorized at the 1 and 99 percentiles. Coefficients are standardized and z-statistics are reported in parentheses. * p¡0.10, ** p¡0.05, *** p¡0.01

Table 8: OLS Regression Results: Unconcentrated and Concentrated ESG and conventional Discretionary Trades on Changes in Future Firm Carbon Emissions and MSCI ESG Score

	ESG Funds		Conventional Funds	
	(1) ΔCarbon Intensity	(2) ΔMSCI ESG	(3) ΔCarbon Intensity	(4) ΔMSCI ESG
Concentrated DiscretionaryTrades	0.001	0.003	0.004	0.002
	(0.227)	(1.227)	(1.239)	(0.732)
Concentrated ExpectedTrades	0.001	-0.009***	0.002	0.003
	(0.173)	(-3.400)	(0.416)	(0.913)
Unconcentrated DiscretionaryTrades	0.000	0.002	-0.007*	0.000
	(0.005)	(0.842)	(-1.825)	(0.124)
Unconcentrated ExpectedTrades	0.010***	0.001	0.019***	-0.001
	(2.697)	(0.435)	(4.508)	(-0.447)
logsize	0.163***	0.167***	0.031***	0.030**
	(7.660)	(7.824)	(2.648)	(2.559)
be_me	0.041***	0.041***	-0.003	-0.003
	(4.628)	(4.655)	(-0.506)	(-0.533)
ret_12_1	-0.023***	-0.023***	0.007*	0.006*
	(-4.553)	(-4.668)	(1.910)	(1.739)
capx_at	-0.003	-0.003	0.003	0.003
	(-0.376)	(-0.341)	(0.554)	(0.547)
beta_252d	0.009	0.009	-0.005	-0.004
	(1.332)	(1.379)	(-1.071)	(-0.908)
rvol_252d	-0.047***	-0.046***	-0.004	-0.004
	(-5.224)	(-5.068)	(-0.675)	(-0.657)
niq_be	0.027***	0.027***	-0.000	-0.000
	(5.869)	(5.880)	(-0.116)	(-0.124)
debt_at	-0.028***	-0.027***	0.011*	0.011*
	(-2.845)	(-2.781)	(1.833)	(1.789)
Firm FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Observations	93,190	93,190	143,716	143,716
R-squared	0.073	0.074	0.059	0.059
Within R-squared	0.003	0.003	0.000	0.000
F-statistic	20.71***	22.43***	3.38***	2.49***

Notes: The table reports the relation between concentrated and unconcentrated ESG mutual fund trading behavior (columns 1-2) and conventional mutual fund trading behavior (columns 3-4) and future changes in firm-level carbon intensity and MSCI ESG scores. Discretionary trades are defined according to Coval and Stafford (2007) and Huang et al. (2023): Sales after inflows are assumed to be 0; buys after outflows are assumed to be equal to 0. OLS regressions include firm and year-quarter fixed effects. Discretionary and expected trades are winsorized at the 0.5 and 99.5%. All continuous control variables are winsorized at the 1 and 99 percentiles. ΔMSCI is defined as the difference in firm-level MSCI ESG score in t+1 and t. ΔCarbon Intensity is defined as the percentage difference in firm-level carbon intensity in t+1 and t. OLS regressions include firm and year-quarter fixed effects, and standard errors are clustered at the firm level. Coefficients are standardized and t-statistics are reported in parentheses. * p¡0.10, ** p¡0.05, *** p¡0.01.

Table 9: Poisson Regression Results: Unconcentrated and Concentrated ESG and conventional Discretionary Trades on Future Firm Environmental and Social Incidents.

	Dependent variable: (Cumulative) Future Environmental and Social Incidents in t+s							
	ESG Funds				Conventional Funds			
	(1) 1 quarter	(2) 2 quarters	(3) 3 quarters	(4) 4 quarters	(5) 1 quarter	(6) 2 quarters	(7) 3 quarters	(8) 4 quarters
Concentrated DiscretionaryTrades	-0.001	-0.001	-0.000	-0.000	0.003	0.002	0.001	0.001
	(-0.688)	(-1.026)	(-0.817)	(-0.692)	(0.985)	(1.080)	(1.132)	(1.087)
Concentrated ExpectedTrades	0.005*	0.003**	0.002**	0.001**	-0.001	-0.001	-0.000	-0.000
	(1.732)	(2.136)	(2.343)	(2.399)	(-0.408)	(-0.671)	(-0.201)	(-0.302)
Unconcentrated DiscretionaryTrades	-0.002*	-0.001**	-0.001**	-0.001***	0.000	-0.000	-0.000	-0.000
	(-1.706)	(-2.173)	(-2.492)	(-3.534)	(0.073)	(-0.101)	(-0.036)	(-0.152)
Unconcentrated ExpectedTrades	0.007***	0.004**	0.002**	0.001**	-0.006**	-0.001	0.000	0.000
	(2.693)	(2.359)	(2.389)	(2.173)	(-2.080)	(-0.405)	(0.156)	(0.614)
logsize	0.276***	0.141***	0.094***	0.071***	0.282***	0.144***	0.096***	0.072***
	(9.554)	(9.800)	(9.768)	(9.808)	(9.361)	(9.579)	(9.613)	(9.627)
be_me	0.067***	0.033***	0.022***	0.016***	0.068***	0.034***	0.022***	0.016***
	(6.997)	(6.819)	(6.902)	(6.888)	(7.022)	(6.801)	(6.889)	(6.853)
ret_12_1	-0.033***	-0.017***	-0.011***	-0.008***	-0.032***	-0.017***	-0.011***	-0.007***
	(-7.107)	(-7.647)	(-7.494)	(-7.067)	(-6.895)	(-7.569)	(-7.394)	(-6.988)
capx_at	-0.000	-0.001	-0.001	-0.001	0.000	-0.001	-0.001	-0.001
	(-0.001)	(-0.156)	(-0.292)	(-0.426)	(0.023)	(-0.135)	(-0.294)	(-0.431)
beta_252d	-0.009*	-0.004	-0.001	-0.000	-0.009*	-0.004	-0.001	-0.000
	(-1.645)	(-1.409)	(-0.462)	(-0.070)	(-1.768)	(-1.589)	(-0.648)	(-0.249)
rvol_252d	0.031***	0.013***	0.006**	0.003*	0.031***	0.013***	0.006***	0.004**
	(4.212)	(3.508)	(2.518)	(1.935)	(4.201)	(3.555)	(2.581)	(2.005)
niq_be	-0.002	0.001	0.001	0.001	-0.002	0.001	0.001	0.001
	(-0.830)	(0.921)	(1.088)	(1.284)	(-0.794)	(0.967)	(1.139)	(1.328)
debt_at	0.042***	0.021***	0.014***	0.010***	0.043***	0.021***	0.014***	0.010***
	(4.301)	(4.160)	(3.978)	(3.830)	(4.313)	(4.202)	(4.038)	(3.881)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	161,423	164,214	167,338	169,843	161,423	164,214	167,338	169,843
Pseudo R-squared	0.591	0.669	0.714	0.745	0.591	0.669	0.714	0.745
χ^2-statistic	123.64***	139.05***	132.81***	131.35***	152.97***	143.25***	131.11***	124.67***

Notes: The table reports the relation between concentrated and unconcentrated ESG mutual fund trading behavior (columns 1-4) and conventional mutual fund trading behavior (columns 5-8) and future changes in firm-level (cumulative) number of environmental and social RepRisk incidents, measured at t+s, where quarter s $\in \{1, 2, 3, 4\}$. Discretionary trades are defined according to Coval and Stafford (2007) and Huang et al. (2023): Sales after inflows are assumed to be 0; buys after outflows are assumed to be equal to 0. Discretionary and expected trades are winsorized at the 0.5 and 99.5%. All continuous control variables are winsorized at the 1 and 99 percentiles. Poisson regressions include firm and year-quarter fixed effects, and standard errors are clustered at the firm level. Coefficients are standardized and z-statistics are reported in parentheses. * p¡0.10, ** p¡0.05, *** p¡0.01.

Table 10: Poisson Regression Results on Future Environmental and Social Incidents: heterogeneity across firms

Panel A: Sample split based on the median of the 4-quarter rolling volatility of firms' RepRisk incidences in quarter t-1

	Dependent variable: (Cumulative) Future Environmental and Social Incidents in t+s							
	1 quarter (1)		2 quarters (2)		3 quarters (3)		4 quarters (4)	
	(a) Below median	(b) Above median	(a) Below median	(b) Above median	(a) Below median	(b) Above median	(a) Below median	(b) Above median
ESG DiscretTrades	0.003	-0.001	-0.011	-0.001*	-0.003	-0.000	0.001	-0.000**
	(0.086)	(-0.994)	(-0.704)	(-1.821)	(-0.350)	(-1.487)	(0.093)	(-2.226)
ESG ExpectedTrades	0.019	0.009***	0.008	0.004***	0.004	0.003***	-0.002	0.002***
	(0.461)	(4.433)	(0.403)	(4.240)	(0.296)	(4.706)	(-0.188)	(4.313)
conv. DiscretTrades	0.039	0.000	0.014	0.000	0.008	0.000	0.001	0.000
	(1.124)	(0.056)	(0.852)	(0.074)	(0.802)	(0.216)	(0.089)	(0.207)
conv. ExpectedTrades	-0.068	-0.006***	-0.019	-0.001	-0.006	-0.000	-0.005	-0.000
	(-1.337)	(-2.751)	(-0.704)	(-1.300)	(-0.311)	(-0.700)	(-0.351)	(-0.298)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	76,291	65,413	79,908	67,241	83,535	68,834	86,634	70,065
Pseudo R-squared	0.136	0.554	0.164	0.650	0.193	0.705	0.220	0.743
χ^2-statistic	77.28***	85.49***	83.35***	81.61***	96.87***	76.15***	108.59***	69.17***

Panel B: Sample split based on the median of the 4-quarter rolling volatility of firms' MSCI's industry-weighted ESG scores in quarter t-1

	Dependent variable: (Cumulative) Future Environmental and Social Incidents in t+s							
	1 quarter (1)		2 quarters (2)		3 quarters (3)		4 quarters (4)	
	(a) Below median	(b) Above median	(a) Below median	(b) Above median	(a) Below median	(b) Above median	(a) Below median	(b) Above median
ESG DiscretTrades	-0.000	-0.004*	-0.001	-0.002**	-0.000	-0.001**	-0.000	-0.001**
	(-0.165)	(-1.647)	(-0.691)	(-2.351)	(-0.461)	(-2.140)	(-0.832)	(-2.238)
ESG ExpectedTrades	0.012***	0.007**	0.006***	0.004***	0.004***	0.003***	0.003***	0.002***
	(3.571)	(2.342)	(3.699)	(2.771)	(3.674)	(3.301)	(3.584)	(2.828)
conv. DiscretTrades	0.001	-0.002	0.001	-0.000	0.001*	-0.000	0.000	-0.000
	(0.680)	(-0.737)	(0.805)	(-0.302)	(1.896)	(-0.680)	(1.274)	(-0.045)
conv. ExpectedTrades	-0.009**	-0.005	-0.002	-0.001	-0.001	-0.000	-0.000	-0.000
	(-2.327)	(-1.271)	(-1.087)	(-0.591)	(-0.660)	(-0.209)	(-0.466)	(-0.167)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	29,980	30,675	32,708	33,008	34,647	34,349	36,416	35,424
Pseudo R-squared	0.591	0.587	0.687	0.684	0.739	0.738	0.775	0.773
χ^2-statistic	72.86***	64.22***	80.73***	61.95***	75.85***	65.01***	70.81***	54.86***

Notes: The table reports the relation between ESG and conventional mutual fund trading behavior and future changes in firm-level (cumulative) number of environmental and social RepRisk incidents, measured at t+s, where quarter s $\in \{1, 2, 3, 4\}$. Panel A divides the sample of firms into those that, in quarter t-1, have an above- or below-median 4-quarter standard deviation of RepRisk total incidents. Panel B divides the sample of firms into those that, in quarter t-1, have an above- or below-median 4-quarter standard deviation of MSCI industry-weighted ESG scores. Discretionary trades are defined according to Coval and Stafford (2007) and Huang et al. (2023): Sales after inflows are assumed to be 0; buys after outflows are assumed to be equal to 0. Discretionary and expected trades are winsorized at the 0.5 and 99.5%. Poisson regressions include firm and year-quarter fixed effects, and standard errors are clustered at the firm level. Regressions include firm and year-quarter fixed effects. Controls are added to the model one by one. All continuous control variables are winsorized at the 1 and 99 percentiles. Coefficients are standardized, and z-statistics are reported in parentheses. * p¡0.10, ** p¡0.05, *** p¡0.01.

Table 11: OLS Regression Results: Discretionary Trades per domicile and SFDR label on Changes in Future Firm Carbon Emissions and MSCI ESG Score

	European & US Funds			Article 8/9 & Article 6 Funds		
	(1)	(2)	(3)	(4)	(5)	(6)
	ΔCarbon Intensity $t+1$	ΔMSCI ESG $t+1$	ΔMSCI ESG $t+4$	ΔCarbon Intensity $t+1$	ΔMSCI ESG $t+1$	ΔMSCI ESG $t+4$
Europe DiscretTrades	0.004	-0.000	0.003			
	(1.199)	(-0.019)	(1.046)			
Europe ExpectedTrades	0.006	-0.008***	-0.005			
	(1.510)	(-2.877)	(-1.309)			
US DiscretTrades	-0.006*	0.001	-0.002			
	(-1.768)	(0.494)	(-0.761)			
US ExpectedTrades	0.019***	0.008**	0.008*			
	(4.251)	(2.223)	(1.740)			
Article 8/9 DiscretTrades				0.001	0.001	0.005*
				(0.146)	(0.392)	(1.900)
Article 8/9 ExpectedTrades				0.007*	-0.010***	-0.012***
				(1.730)	(-3.521)	(-3.305)
Article 6 DiscretTrades				0.005	0.004	0.001
				(1.423)	(1.591)	(0.432)
Article 6 ExpectedTrades				0.002	0.001	0.001
				(0.464)	(0.297)	(0.319)
logsize	0.165***	0.032***	0.033	0.164***	0.032***	0.034
	(7.735)	(2.713)	(1.505)	(7.693)	(2.696)	(1.554)
be_me	0.041***	-0.004	-0.002	0.042***	-0.003	-0.002
	(4.585)	(-0.543)	(-0.228)	(4.676)	(-0.483)	(-0.159)
ret_12_1	-0.024***	0.006*	0.022***	-0.023***	0.007**	0.023***
	(-4.805)	(1.736)	(4.214)	(-4.574)	(1.976)	(4.422)
capx_at	-0.003	0.003	0.010	-0.003	0.003	0.010
	(-0.352)	(0.578)	(1.083)	(-0.368)	(0.568)	(1.077)
beta_252d	0.009	-0.005	0.013*	0.009	-0.005	0.012*
	(1.403)	(-1.091)	(1.716)	(1.380)	(-1.109)	(1.656)
rvol_252d	-0.045***	-0.003	0.005	-0.047***	-0.004	0.004
	(-5.000)	(-0.542)	(0.457)	(-5.223)	(-0.654)	(0.391)
niq_be	0.027***	-0.000	-0.008*	0.027***	-0.000	-0.008*
	(5.864)	(-0.099)	(-1.862)	(5.876)	(-0.123)	(-1.881)
debt_at	-0.027***	0.011*	0.029***	-0.028***	0.011*	0.029***
	(-2.795)	(1.837)	(2.595)	(-2.851)	(1.847)	(2.613)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	93,190	143,716	135,564	93,190	143,716	135,564
R-squared	0.074	0.059	0.164	0.073	0.059	0.164
Within R-squared	0.003	0.000	0.001	0.003	0.000	0.001
F-statistic	22.31***	3.31***	4.59***	20.59***	3.41***	5.15***

Notes: The table reports the relation between European and US domiciled mutual fund trading behavior (columns 1-3) and SFDR Article 8/9 and Article 6 mutual fund trading behavior (columns 4-6) and future changes in firm-level carbon intensity and MSCI ESG scores. Discretionary trades are defined according to Coval and Stafford (2007) and Huang et al. (2023): Sales after inflows are assumed to be 0; buys after outflows are assumed to be equal to 0. OLS regressions include firm and year-quarter fixed effects. Discretionary and expected trades are winsorized at the 0.5 and 99.5%. All continuous control variables are winsorized at the 1 and 99 percentiles. ΔMSCI is defined as the difference in firm-level MSCI ESG score in t+1 and t. ΔCarbon Intensity is defined as the percentage difference in firm-level carbon intensity in t+1 and t. OLS regressions include firm and year-quarter fixed effects, and standard errors are clustered at the firm level. Coefficients are standardized and t-statistics are reported in parentheses. * p¡0.10, ** p¡0.05, *** p¡0.01.

Table 12: Discretionary Trades per domicile and SFDR label on Future Firm Environmental and Social Incidents.

	Dependent variable: (Cumulative) Future Environmental and Social Incidents in t+s							
	European & US Funds				Article 8/9 & Article 6 Funds			
	(1) 1 quarter	(2) 2 quarters	(3) 3 quarters	(4) 4 quarters	(5) 1 quarter	(6) 2 quarters	(7) 3 quarters	(8) 4 quarters
Europe DiscretTrades	0.001	-0.001	-0.000	-0.000				
	(0.596)	(-1.242)	(-0.430)	(-1.273)				
Europe ExpectedTrades	0.004	0.003**	0.002**	0.001**				
	(1.543)	(2.178)	(2.177)	(1.996)				
US DiscretTrades	-0.000	0.000	0.000	0.000				
	(-0.046)	(0.144)	(0.205)	(0.356)				
US ExpectedTrades	-0.006*	-0.000	0.001	0.001				
	(-1.847)	(-0.189)	(0.678)	(1.134)				
Article 8/9 DiscretTrades					-0.002	-0.002**	-0.001*	-0.001***
					(-1.198)	(-2.092)	(-1.739)	(-2.944)
Article 8/9 ExpectedTrades					0.007**	0.004***	0.002**	0.001**
					(2.523)	(2.583)	(2.270)	(2.295)
Article 6 DiscretTrades					0.002	0.001	0.001	0.000
					(0.902)	(0.789)	(0.918)	(0.572)
Article 6 ExpectedTrades					-0.001	-0.001	0.000	0.000
					(-0.483)	(-0.355)	(0.269)	(0.168)
logsize	0.281***	0.144***	0.096***	0.071***	0.281***	0.144***	0.096***	0.071***
	(9.172)	(9.458)	(9.485)	(9.584)	(9.304)	(9.532)	(9.580)	(9.660)
be_me	0.068***	0.033***	0.022***	0.016***	0.068***	0.033***	0.022***	0.016***
	(6.965)	(6.772)	(6.854)	(6.840)	(7.033)	(6.855)	(6.939)	(6.927)
ret_12_1	-0.032***	-0.017***	-0.011***	-0.008***	-0.033***	-0.017***	-0.011***	-0.008***
	(-6.810)	(-7.396)	(-7.316)	(-6.964)	(-6.890)	(-7.398)	(-7.292)	(-6.902)
capx_at	0.000	-0.001	-0.001	-0.001	0.000	-0.001	-0.001	-0.001
	(0.047)	(-0.111)	(-0.269)	(-0.408)	(0.016)	(-0.140)	(-0.288)	(-0.428)
beta_252d	-0.009*	-0.004	-0.001	-0.000	-0.009*	-0.004	-0.001	-0.000
	(-1.713)	(-1.493)	(-0.550)	(-0.149)	(-1.721)	(-1.484)	(-0.528)	(-0.122)
rvol_252d	0.031***	0.013***	0.006**	0.004**	0.031***	0.013***	0.006**	0.004*
	(4.184)	(3.531)	(2.572)	(1.995)	(4.227)	(3.525)	(2.541)	(1.952)
niq_be	-0.002	0.001	0.001	0.001	-0.002	0.001	0.001	0.001
	(-0.793)	(0.960)	(1.132)	(1.322)	(-0.786)	(0.974)	(1.144)	(1.333)
debt_at	0.042***	0.021***	0.014***	0.010***	0.043***	0.021***	0.014***	0.010***
	(4.263)	(4.176)	(4.022)	(3.886)	(4.326)	(4.186)	(4.001)	(3.851)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	161,423	164,214	167,338	169,843	161,423	164,214	167,338	169,843
Pseudo R-squared	0.591	0.669	0.714	0.745	0.591	0.669	0.714	0.745
χ^2-statistic	119.79***	118.77***	114.14***	113.01***	141.83***	146.77***	134.28***	129.92***

Notes: The table reports the relation between European and US domiciled mutual fund trading behavior (columns 1-4) and SFDR Article 8/9 and Article 6 mutual fund trading behavior (columns 5-8) and future changes in firm-level (cumulative) number of environmental and social RepRisk incidents, measured at t+s, where quarter s $\in \{1, 2, 3, 4\}$. Discretionary trades are defined according to Coval and Stafford (2007) and Huang et al. (2023): Sales after inflows are assumed to be 0; buys after outflows are assumed to be equal to 0. Discretionary and expected trades are winsorized at the 0.5 and 99.5%. All continuous control variables are winsorized at the 1 and 99 percentiles. Poisson regressions include firm and year-quarter fixed effects, and standard errors are clustered at the firm level. Coefficients are standardized and z-statistics are reported in parentheses. * p¡0.10, ** p¡0.05, *** p¡0.01.

Table 13: Alternative Poisson Regression Results: ESG and Conventional Discretionary Trades on Future Firm Environmental and Social Incidents.

Dependent variable: (Cumulative) Future Environmental and Social Incidents in t+s				
	1 quarter (1)	2 quarters (2)	3 quarters (3)	4 quarters (4)
ESG DiscretTrades	-0.003	-0.002*	-0.001	-0.001
	(-1.318)	(-1.856)	(-1.432)	(-1.483)
ESG ExpectedTrades	-0.017***	-0.008***	-0.006***	-0.004***
	(-3.123)	(-2.833)	(-2.870)	(-3.030)
conv. DiscretTrades	0.001	-0.000	-0.000	-0.000
	(0.271)	(-0.040)	(-0.062)	(-0.191)
conv. ExpectedTrades	0.001	0.002	0.002	0.002
	(0.067)	(0.508)	(0.623)	(0.644)
logsize	0.987***	0.510***	0.343***	0.259***
	(56.210)	(55.926)	(55.564)	(55.319)
be_me	0.243***	0.126***	0.085***	0.064***
	(18.915)	(18.798)	(18.697)	(18.517)
ret_12_1	-0.087***	-0.045***	-0.029***	-0.021***
	(-8.084)	(-8.384)	(-8.286)	(-8.023)
capx_at	0.012	0.007	0.005	0.004
	(0.674)	(0.779)	(0.870)	(0.946)
beta_252d	-0.027**	-0.013*	-0.007*	-0.005
	(-2.154)	(-1.939)	(-1.679)	(-1.550)
rvol_252d	0.148***	0.074***	0.048***	0.036***
	(10.081)	(9.828)	(9.519)	(9.316)
niq_be	-0.064***	-0.031***	-0.021***	-0.015***
	(-7.392)	(-7.083)	(-7.062)	(-6.967)
debt_at	0.065***	0.034***	0.023***	0.017***
	(3.681)	(3.709)	(3.724)	(3.737)
Firm FE	No	No	No	No
Year-quarter FE	No	No	No	No
Country FE	Yes	Yes	Yes	Yes
Industry × Year-quarter FE	Yes	Yes	Yes	Yes
Observations	239,435	240,641	240,792	240,980
Pseudo R-squared	0.503	0.553	0.582	0.602
χ^2-statistic	4097.36***	4052.45***	4054.07***	4045.15***

Notes: The table reports the relation between ESG and conventional mutual fund trading behavior and future changes in firm-level (cumulative) number of environmental and social RepRisk incidents, measured at t+s, where quarter s $\in \{1, 2, 3, 4\}$. Discretionary trades are defined according to Coval and Stafford (2007) and Huang et al. (2023): Sales after inflows are assumed to be 0; buys after outflows are assumed to be equal to 0. Discretionary and expected trades are winsorized at the 0.5 and 99.5 percentiles. Poisson regressions include country and industry × year-quarter fixed effects, and standard errors are clustered at the firm level. All continuous control variables are winsorized at the 1 and 99 percentiles. We control for singletons and observations that are separated by the fixed effects. Coefficients are standardized and z-statistics are reported in parentheses. * p¡0.10, ** p¡0.05, *** p¡0.01

Table 14: Alternative Poisson Regression Results: Unconcentrated and Concentrated ESG and conventional Discretionary Trades on Future Firm Environmental and Social Incidents.

	Dependent variable: (Cumulative) Future Environmental and Social Incidents in t+s							
	ESG Funds				Conventional Funds			
	(1) 1 quarter	(2) 2 quarters	(3) 3 quarters	(4) 4 quarters	(5) 1 quarter	(6) 2 quarters	(7) 3 quarters	(8) 4 quarters
Concentrated DiscretionaryTrades	0.001	0.001	0.000	0.000	0.010***	0.005***	0.003***	0.002**
	(0.499)	(0.387)	(0.349)	(0.580)	(2.710)	(2.766)	(2.643)	(2.374)
Concentrated ExpectedTrades	-0.013***	-0.007**	-0.004**	-0.003**	-0.002	-0.001	-0.000	-0.000
	(-2.588)	(-2.547)	(-2.267)	(-2.256)	(-0.371)	(-0.303)	(-0.101)	(-0.155)
Unconcentrated DiscretionaryTrades	-0.009***	-0.004***	-0.002***	-0.002***	-0.003	-0.002	-0.001*	-0.001*
	(-3.496)	(-3.994)	(-3.565)	(-3.674)	(-1.083)	(-1.621)	(-1.645)	(-1.693)
Unconcentrated ExpectedTrades	-0.010***	-0.005***	-0.004***	-0.003***	0.000	0.002	0.002	0.001
	(-2.824)	(-2.734)	(-2.974)	(-3.216)	(0.060)	(0.692)	(0.745)	(0.830)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No	No	No	No
Year-quarter FE	No	No	No	No	No	No	No	No
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	239,435	240,641	240,792	240,980	239,435	240,641	240,792	240,980
Pseudo R-squared	0.503	0.553	0.582	0.602	0.503	0.553	0.582	0.602
χ^2-statistic	3984.43***	4035.48***	4028.35***	4070.31***	4124.65***	4085.45***	4098.75***	4084.95***

Notes: The table reports the relation between concentrated and unconcentrated ESG mutual fund trading behavior (columns 1-4) and conventional mutual fund trading behavior (columns 5-8) and future changes in firm-level (cumulative) number of environmental and social RepRisk incidents, measured at t+s, where quarter s $\in \{1, 2, 3, 4\}$. Discretionary trades are defined according to Coval and Stafford (2007) and Huang et al. (2023): Sales after inflows are assumed to be 0; buys after outflows are assumed to be equal to 0. Trades are winsorized at the 0.5 and 99.5 percentiles. All continuous control variables are winsorized at the 1 and 99 percentiles. Poisson regressions include country and industry × year-quarter fixed effects, and standard errors are clustered at the firm level. We control for singletons and observations that are separated by the fixed effects. Standardized beta coefficients are reported and z-statistics are reported in parentheses. * p¡0.10, ** p¡0.05, *** p¡0.01.

Table 15: Alternative Poisson Regression Results: Discretionary Trades per domicile and SFDR label on Future Firm Environmental and Social Incidents.

	Dependent variable: (Cumulative) Future Environmental and Social Incidents in t+1							
	European & US Funds				Article 8/9 & Article 6 Funds			
	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 1	(6) Model 2	(7) Model 3	(8) Model 4
Europe DiscretTrades	0.003	-0.000	0.000	-0.000				
	(0.936)	(-0.323)	(0.255)	(-0.198)				
Europe ExpectedTrades	-0.014***	-0.006**	-0.004**	-0.003**				
	(-2.715)	(-2.180)	(-2.056)	(-2.089)				
US DiscretTrades	-0.004	-0.002	-0.001	-0.001				
	(-1.153)	(-1.276)	(-1.287)	(-1.155)				
US ExpectedTrades	0.002	0.003	0.003	0.002				
	(0.233)	(0.675)	(0.821)	(0.834)				
Article 8/9 DiscretTrades					-0.002	-0.002	-0.001	-0.001
					(-0.854)	(-1.077)	(-0.765)	(-1.085)
Article 8/9 ExpectedTrades					-0.014**	-0.007**	-0.005**	-0.004**
					(-2.522)	(-2.381)	(-2.452)	(-2.466)
Article 6 DiscretTrades					0.001	-0.000	0.000	-0.000
					(0.339)	(-0.030)	(0.177)	(-0.112)
Article 6 ExpectedTrades					-0.005	-0.002	-0.000	-0.000
					(-1.143)	(-0.739)	(-0.320)	(-0.443)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No	No	No	No
Year-quarter FE	No	No	No	No	No	No	No	No
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	239,435	240,641	240,792	240,980	239,435	240,641	240,792	240,980
Pseudo R-squared	0.503	0.553	0.582	0.602	0.503	0.553	0.582	0.602
χ^2-statistic	4159.12***	4122.37***	4123.70***	4131.64***	4046.39***	4045.21***	4030.75***	4041.34***

Notes: The table reports the relation between European and US domiciled mutual fund trading behavior (columns 1-4) and SFDR Article 8/9 and Article 6 mutual fund trading behavior (columns 5-8) and future changes in firm-level (cumulative) number of environmental and social RepRisk incidents, measured at t+1. Discretionary trades are defined according to Coval and Stafford (2007) and Huang et al. (2023): Sales after inflows are assumed to be 0; buys after outflows are assumed to be equal to 0. Discretionary and expected trades are winsorized at the 0.5 and 99.5 percentiles. All continuous control variables are winsorized at the 1 and 99 percentiles. Poisson regressions include country fixed effects and industry × year-quarter fixed effects, and standard errors are clustered at the firm level. Coefficients are standardized and z-statistics are reported in parentheses. * p¡0.10, ** p¡0.05, *** p¡0.01.

Table 16: Poisson Regression Results: ESG and Conventional Discretionary Trades on Future Firm Governance Incidents.

	Dependent variable: (Cumulative) Future Governance Incidents in t+s							
	1 quarter		2 quarters		3 quarters		4 quarters	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ESG DiscretTrades	-0.000	-0.001	-0.002**	-0.003*	-0.002**	-0.002**	-0.002***	-0.002**
	(-0.007)	(-0.309)	(-2.062)	(-1.780)	(-2.401)	(-2.067)	(-2.716)	(-1.993)
ESG ExpectedTrades	0.009*	-0.013*	0.005**	-0.006*	0.003**	-0.004*	0.003**	-0.003**
	(1.753)	(-1.747)	(1.977)	(-1.699)	(2.031)	(-1.819)	(2.257)	(-1.977)
conv. DiscretTrades	0.002	-0.003	0.001	-0.001	0.000	-0.001	0.000	-0.000
	(0.760)	(-0.639)	(0.773)	(-0.444)	(0.348)	(-0.585)	(0.723)	(-0.329)
conv. ExpectedTrades	0.001	-0.006	0.001	-0.003	0.001	-0.003	-0.000	-0.003
	(0.129)	(-0.442)	(0.327)	(-0.479)	(0.269)	(-0.521)	(-0.181)	(-0.675)
logsize	0.214***	1.290***	0.121***	0.676***	0.089***	0.458***	0.072***	0.346***
	(3.946)	(48.762)	(4.508)	(48.408)	(5.074)	(48.289)	(5.604)	(48.079)
be_me	0.038**	0.345***	0.022**	0.181***	0.017***	0.122***	0.013***	0.092***
	(2.129)	(17.699)	(2.513)	(17.663)	(2.898)	(17.636)	(3.095)	(17.580)
ret_12_1	-0.050***	-0.161***	-0.024***	-0.082***	-0.016***	-0.055***	-0.011***	-0.040***
	(-5.649)	(-10.815)	(-5.665)	(-10.529)	(-5.614)	(-10.481)	(-5.540)	(-10.318)
capx_at	-0.009	-0.054*	-0.004	-0.028*	-0.002	-0.018*	-0.001	-0.014*
	(-0.499)	(-1.854)	(-0.419)	(-1.822)	(-0.336)	(-1.784)	(-0.301)	(-1.751)
beta_252d	0.000	-0.098***	0.003	-0.050***	0.003	-0.034***	0.002	-0.026***
	(0.038)	(-4.303)	(0.552)	(-4.195)	(0.691)	(-4.188)	(0.718)	(-4.229)
rvol_252d	0.039***	0.193***	0.015**	0.099***	0.007	0.066***	0.005	0.050***
	(2.640)	(8.431)	(2.032)	(8.238)	(1.467)	(8.069)	(1.247)	(8.070)
niq_be	-0.016***	-0.115***	-0.008***	-0.060***	-0.006***	-0.041***	-0.004***	-0.030***
	(-3.304)	(-9.076)	(-3.567)	(-9.019)	(-3.847)	(-9.139)	(-3.695)	(-9.036)
debt_at	0.044**	0.147***	0.024***	0.077***	0.016***	0.052***	0.012***	0.039***
	(2.489)	(5.587)	(2.614)	(5.577)	(2.600)	(5.525)	(2.647)	(5.504)
Firm FE	Yes	No	Yes	No	Yes	No	Yes	No
Year-quarter FE	Yes	No	Yes	No	Yes	No	Yes	No
Country FE	No	Yes	No	Yes	No	Yes	No	Yes
Industry × Year-quarter FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	139,570	237,995	143,240	240,103	147,081	240,497	150,600	240,734
Pseudo R-squared	0.552	0.469	0.625	0.514	0.669	0.540	0.701	0.558
χ^2-statistic	93.96***	2758.78***	95.46***	2816.31***	90.89***	2854.52***	99.72***	2872.04***

Notes: The table reports the relation between ESG and conventional mutual fund trading behavior and future changes in firm-level (cumulative) number of governance RepRisk incidents, measured at t+s, where quarter s $\in \{1, 2, 3, 4\}$. Discretionary trades are defined according to Coval and Stafford (2007) and Huang et al. (2023): Sales after inflows are assumed to be 0; buys after outflows are assumed to be equal to 0. Discretionary and expected trades are winsorized at the 0.5 and 99.5 percentiles. Poisson regressions include firm and year-quarter (uneven columns), or country and industry × year-quarter fixed effects (even columns), and standard errors are clustered at the firm level. All continuous control variables are winsorized at the 1 and 99 percentiles. We control for singletons and observations that are separated by the fixed effects. Coefficients are standardized and z-statistics are reported in parentheses. * p¡0.10, ** p¡0.05, *** p¡0.01

Table 17: Poisson Regression Results: Alternative ESG and Conventional Discretionary Buys on Future Firm Environmental and Social Incidents.

	Dependent variable: (Cumulative) Future Environmental and Social Incidents in t+s							
	1 quarter		2 quarters		3 quarters		4 quarters	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ESG DiscretTrades	0.002	-0.010*	0.002	-0.005*	0.001*	-0.003	0.001	-0.003*
	(0.537)	(-1.792)	(1.248)	(-1.916)	(1.911)	(-1.639)	(1.450)	(-1.872)
ESG ExpectedTrades	0.005	0.015	0.002	0.006	0.001	0.004	0.000	0.003
	(1.112)	(1.238)	(1.021)	(1.075)	(0.994)	(1.049)	(0.390)	(0.808)
conv. DiscretTrades	0.000	0.000	0.002	0.002	0.002*	0.002	0.001*	0.001
	(0.094)	(0.038)	(1.239)	(0.456)	(1.823)	(0.747)	(1.662)	(0.769)
conv. ExpectedTrades	-0.009	0.005	-0.001	0.006	0.001	0.005	0.001	0.004
	(-1.542)	(0.439)	(-0.202)	(0.920)	(0.507)	(1.224)	(0.786)	(1.310)
logsize	0.285***	0.990***	0.145***	0.512***	0.097***	0.344***	0.072***	0.259***
	(8.940)	(53.301)	(9.185)	(53.048)	(9.223)	(52.657)	(9.326)	(52.507)
be_me	0.069***	0.243***	0.034***	0.126***	0.022***	0.085***	0.016***	0.064***
	(6.955)	(18.918)	(6.775)	(18.805)	(6.860)	(18.711)	(6.846)	(18.538)
ret_12_1	-0.032***	-0.088***	-0.017***	-0.045***	-0.011***	-0.030***	-0.008***	-0.022***
	(-7.009)	(-8.406)	(-7.532)	(-8.714)	(-7.385)	(-8.649)	(-7.035)	(-8.386)
capx_at	0.000	0.016	-0.001	0.009	-0.001	0.007	-0.001	0.005
	(0.033)	(0.874)	(-0.117)	(0.944)	(-0.271)	(1.018)	(-0.408)	(1.074)
beta_252d	-0.009*	-0.024*	-0.004	-0.011*	-0.001	-0.006	-0.000	-0.004
	(-1.757)	(-1.911)	(-1.538)	(-1.694)	(-0.599)	(-1.429)	(-0.191)	(-1.295)
rvol_252d	0.031***	0.147***	0.013***	0.073***	0.006**	0.048***	0.003*	0.035***
	(4.193)	(10.123)	(3.500)	(9.830)	(2.514)	(9.493)	(1.947)	(9.285)
niq_be	-0.002	-0.064***	0.001	-0.031***	0.001	-0.021***	0.001	-0.015***
	(-0.838)	(-7.389)	(0.930)	(-7.071)	(1.104)	(-7.047)	(1.301)	(-6.951)
debt_at	0.043***	0.062***	0.022***	0.033***	0.014***	0.022***	0.010***	0.017***
	(4.231)	(3.528)	(4.118)	(3.557)	(3.957)	(3.569)	(3.814)	(3.578)
Firm FE	Yes	No	Yes	No	Yes	No	Yes	No
Year-quarter FE	Yes	No	Yes	No	Yes	No	Yes	No
Country FE	No	Yes	No	Yes	No	Yes	No	Yes
Industry × Year-quarter FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	161,423	239,435	164,214	240,641	167,338	240,792	169,843	240,980
Pseudo R-squared	0.591	0.503	0.669	0.554	0.714	0.582	0.745	0.602
χ^2-statistic	129.95***	3593.97***	132.61***	3654.18***	131.67***	3640.97***	122.46***	3652.53***

The table reports the relation between ESG and conventional mutual fund trading behavior and future changes in firm-level (cumulative) number of environmental and social RepRisk incidents, measured at t+s, where quarter s $\in \{1, 2, 3, 4\}$. We consider the discretionary trades omitted by Coval and Stafford (2007) and Huang et al. (2023) during outflows: Instead of assuming sales (buys) after outflows to be equal to 0, we estimate these discretionary share trades. Hence, we set sales after extreme inflows equal to 0. Poisson regressions include firm and year-quarter fixed effects. Discretionary and expected trades are winsorized at the 0.5 and 99.5%. All continuous control variables are winsorized at the 1 and 99 percentiles. Poisson regressions include firm and year-quarter (uneven columns), or country and industry × year-quarter fixed effects (even columns), and standard errors are clustered at the firm level. We control for singletons and observations that are separated by the fixed effects. Coefficients are standardized and z-statistics are reported in parentheses. * p¡0.10, ** p¡0.05, *** p¡0.01.

Table 18: OLS Regression Results: ESG and Conventional and SFDR Discretionary Trades on Future Stock Returns

	Dependent Variable: Quarterly Stock Returns in t+1	
	(1)	(2)
	ESG & Conventional Funds	Article 8/9 & Article 6 Funds
ESG DiscretTrades	0.002**	
	(2.339)	
ESG ExpectedTrades	0.002*	
	(1.710)	
conv. DiscretTrades	-0.002*	
	(-1.943)	
conv. ExpectedTrades	-0.005***	
	(-4.526)	
Article 8/9 DiscretTrades		0.002**
		(2.304)
Article 8/9 ExpectedTrades		-0.000
		(-0.327)
Article 6 DiscretTrades		0.001
		(1.123)
Article 6 ExpectedTrades		0.003***
		(2.869)
logsize	-0.655***	-0.655***
	(-29.459)	(-29.477)
be_me_win	-0.014**	-0.014**
	(-2.448)	(-2.446)
ret_12_1_win	0.034***	0.034***
	(15.506)	(15.345)
capx_at_win	0.001	0.001
	(0.239)	(0.259)
beta_252d_win	-0.022***	-0.022***
	(-4.938)	(-4.919)
rvol_252d_win	0.006	0.007
	(1.313)	(1.424)
niq_be_win	0.015***	0.016***
	(3.680)	(3.696)
debt_at_win	-0.003	-0.003
	(-0.743)	(-0.724)
MSCI ACWI	0.004	0.004
	(1.208)	(1.140)
Firm FE	Yes	Yes
Year-quarter FE	Yes	Yes
Observations	486,327	486,327
R-squared	0.173	0.173
Within R-squared	0.028	0.028
F-statistic	182.09***	181.24***

Notes: The table reports the relation between ESG and conventional mutual fund trading behavior and future quarterly stock returns. Discretionary trades are defined according to Coval and Stafford (2007) and Huang et al. (2023): Sales after inflows are assumed to be 0; buys after outflows are assumed to be equal to 0. Discretionary and expected trades are winsorized at the 0.5 and 99.5%. All continuous control variables are winsorized at the 1 and 99 percentiles. The dependent variable, future quarterly stock returns, is measured in quarter t+1. OLS regressions include firm and year-quarter fixed effects, and standard errors are clustered at the firm level. Coefficients are standardized and t-statistics are reported in parentheses. * p¡0.10, ** p¡0.05, *** p¡0.01.

Table 19: OLS Regression Results: ESG and Conventional and SFDR Discretionary Trades on Future Stock Returns

	Dependent Variable: Quarterly Stock Returns in t+s							
	ESG & Conventional Funds				Article 8/9 & Article 6 Funds			
	(1) $t+1$	(2) $t+2$	(3) $t+3$	(4) $t+4$	(5) $t+1$	(6) $t+2$	(7) $t+3$	(8) $t+4$
ESG DiscretTrades	0.002**	-0.000	-0.000	0.000				
	(2.339)	(-0.005)	(-0.834)	(0.809)				
ESG ExpectedTrades	0.002*	-0.002***	-0.000	-0.000				
	(1.710)	(-3.295)	(-0.641)	(-0.107)				
conv. DiscretTrades	-0.002*	-0.002***	-0.002***	0.000				
	(-1.943)	(-2.890)	(-2.819)	(0.627)				
conv. ExpectedTrades	-0.005***	-0.003***	-0.001	-0.002**				
	(-4.526)	(-4.557)	(-1.429)	(-2.414)				
Article 8/9 DiscretTrades					0.002**	-0.001*	0.000	-0.000
					(2.304)	(-1.820)	(0.038)	(-0.178)
Article 8/9 ExpectedTrades					-0.000	-0.002***	-0.001***	-0.001**
					(-0.327)	(-4.393)	(-2.743)	(-2.405)
Article 6 DiscretTrades					0.001	0.000	-0.002***	-0.000
					(1.123)	(0.322)	(-4.013)	(-0.719)
Article 6 ExpectedTrades					0.003***	0.000	0.000	-0.000
					(2.869)	(0.540)	(0.060)	(-0.066)
logsize	-0.655***	-0.349***	-0.316***	-0.293***	-0.655***	-0.349***	-0.316***	-0.293***
	(-29.459)	(-26.511)	(-20.870)	(-52.887)	(-29.477)	(-26.521)	(-20.884)	(-52.862)
be_me_win	-0.014**	-0.006**	0.001	0.003	-0.014**	-0.006**	0.001	0.003
	(-2.448)	(-2.082)	(0.280)	(1.255)	(-2.446)	(-2.082)	(0.290)	(1.256)
ret_12_1_win	0.034***	0.011***	-0.003	-0.007***	0.034***	0.011***	-0.003	-0.007***
	(15.506)	(3.690)	(-0.741)	(-6.200)	(15.345)	(3.602)	(-0.765)	(-6.273)
capx_at_win	0.001	-0.000	0.001	0.001	0.001	-0.000	0.001	0.001
	(0.239)	(-0.225)	(0.720)	(0.829)	(0.259)	(-0.213)	(0.728)	(0.833)
beta_252d_win	-0.022***	-0.010***	-0.004	0.006	-0.022***	-0.010***	-0.004	0.006
	(-4.938)	(-3.262)	(-1.169)	(1.054)	(-4.919)	(-3.257)	(-1.171)	(1.053)
rvol_252d_win	0.006	-0.003	-0.003	-0.013***	0.007	-0.003	-0.003	-0.013***
	(1.313)	(-0.985)	(-1.354)	(-6.889)	(1.424)	(-0.910)	(-1.309)	(-6.866)
niq_be_win	0.015***	0.007*	-0.000	0.004**	0.016***	0.007*	-0.000	0.004**
	(3.680)	(1.881)	(-0.077)	(2.503)	(3.696)	(1.890)	(-0.075)	(2.509)
debt_at_win	-0.003	0.002	0.001	-0.000	-0.003	0.002	0.001	-0.000
	(-0.743)	(0.658)	(0.257)	(-0.114)	(-0.724)	(0.671)	(0.265)	(-0.096)
MSCI ACWI	0.004	0.001	0.003	0.001	0.004	0.001	0.003	0.001
	(1.208)	(0.510)	(1.351)	(0.629)	(1.140)	(0.461)	(1.396)	(0.604)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	486,327	465,278	444,787	425,920	486,327	465,278	444,787	425,920
R-squared	0.173	0.229	0.228	0.238	0.173	0.229	0.228	0.238
Within R-squared	0.028	0.009	0.008	0.007	0.028	0.009	0.008	0.007
F-statistic	182.09***	291.40***	233.68***	444.20***	181.24***	289.88***	236.68***	444.94***

Notes: The table reports the relation between ESG and conventional mutual fund trading behavior and future quarterly stock returns. Discretionary trades are defined according to Coval and Stafford (2007) and Huang et al. (2023): Sales after inflows are assumed to be 0; buys after outflows are assumed to be equal to 0. Discretionary and expected trades are winsorized at the 0.5 and 99.5%. All continuous control variables are winsorized at the 1 and 99 percentiles. The dependent variable, future quarterly stock returns, is measured in quarter t+1. OLS regressions include firm and year-quarter fixed effects, and standard errors are clustered at the firm level. Coefficients are standardized and t-statistics are reported in parentheses. * pj0.10, ** pj0.05, *** pj0.01.

Table 20: ESG and Conventional Discretionary Trades on Future Stock Returns

	Dependent Variable: Quarterly Stock Returns in t+1			
	(1) RepRisk incident volatility		(2) MSCI ESG Score volatility	
	(a) Below median	(b) Above median	(a) Below median	(b) Above median
ESG DiscretTrades	-0.001	0.011***	0.007	0.004
	(-1.158)	(3.558)	(1.458)	(1.107)
ESG ExpectedTrades	0.002	0.008**	0.012**	0.006
	(1.300)	(2.207)	(2.416)	(1.527)
conv. DiscretTrades	-0.000	-0.002	0.004	-0.006
	(-0.165)	(-0.578)	(1.157)	(-1.514)
conv. ExpectedTrades	-0.007***	-0.013***	-0.015***	-0.014***
	(-4.317)	(-2.958)	(-2.975)	(-3.073)
logsize	-0.439***	-1.106***	-0.814***	-0.878***
	(-10.401)	(-28.887)	(-23.590)	(-25.891)
be_me	-0.000	-0.030*	0.036*	0.045**
	(-0.007)	(-1.664)	(1.645)	(2.064)
ret_12_1	0.021***	0.011	-0.001	0.022***
	(6.267)	(1.644)	(-0.087)	(3.058)
capx_at	0.003	-0.010	-0.008	-0.014
	(0.863)	(-1.133)	(-0.741)	(-1.216)
beta_252d	-0.029***	-0.052***	-0.053***	-0.044***
	(-2.829)	(-6.661)	(-5.583)	(-5.086)
rvol_252d	0.018***	0.038***	0.061***	0.071***
	(2.921)	(3.031)	(3.923)	(5.328)
niq_be	0.015*	0.002	-0.005	-0.016*
	(1.725)	(0.259)	(-0.653)	(-1.654)
debt_at	0.009	-0.027**	0.009	0.000
	(1.076)	(-2.089)	(0.653)	(0.035)
Firm FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Observations	160,074	89,779	60,322	59,331
R-squared	0.162	0.317	0.381	0.387
Within R-squared	0.018	0.060	0.066	0.072
F-statistic	75.85***	104.27***	90.81***	96.77***

Notes: The table reports the relation between ESG and conventional mutual fund trading behavior and future quarterly stock returns. Columns 1 and 2 divide the sample of firms into those that, in quarter t-1, have, respectively, a below- or above-median 4-quarter standard deviation of RepRisk total incidents. Columns 3 and 4 divide the sample of firms into those that, in quarter t-1, have, respectively, a below- or above-median 4-quarter standard deviation of MSCI industry-weighted ESG scores. Discretionary trades are defined according to Coval and Stafford (2007) and Huang et al. (2023): Sales after inflows are assumed to be 0; buys after outflows are assumed to be equal to 0. Discretionary and expected trades are winsorized at the 0.5 and 99.5%. All continuous control variables are winsorized at the 1 and 99 percentiles. The dependent variable, future quarterly stock returns, is measured in quarter t+1. OLS regressions include firm and year-quarter fixed effects, and standard errors are clustered at the firm level. Coefficients are standardized, and t-statistics are reported in parentheses. * p¡0.10, ** p¡0.05, *** p¡0.01.

Table 21: Event-Study MSCI Index Inclusion on Discretionary Trades by ESG Funds

	Dependent variable: Discretionary Trades by ESG Funds		
	Treatment: MSCI ACWI	Treatment: MSCI ACWI excl. ESG Leaders	Treatment: MSCI ACWI ESG Leaders
Treat_{t+1}	0.00039^{*}	0.00045	-0.00035
	(0.00023)	(0.00025)	(0.00054)
Treat_{t+2}	0.00033^{*}	0.00020	0.00015
	(0.00022)	(0.00026)	(0.00048)
Treat_{t+3}	0.00008	0.00004	0.00018
	(0.00023)	(0.00027)	(0.00059)
Treat_{t+4}	0.00002	0.00004	0.00014
	(0.00023)	(0.00026)	(0.00059)
Placebo_{t-1}	0.00017	0.00022	-0.00062
	(0.00022)	(0.00027)	(0.00048)
Placebo_{t-2}	0.00021	0.00042	-0.00084
	(0.00023)	(0.00026)	(0.00053)
Placebo_{t-3}	-0.00003	-0.00008	-0.00001
	(0.00027)	(0.00031)	(0.00072)
Placebo_{t-4}	-0.00028	-0.00020	-0.00066
	(0.00028)	(0.00035)	(0.00044)
Firm FE	YES	YES	YES
Year-Quarter FE	YES	YES	YES
Observations	647,399	644,661	642,653
# Switchers	3,327	2,408	640

Notes: Discretionary trades are defined according to Coval and Stafford (2007) and Huang et al. (2023): Sales after inflows are assumed to be 0; buys after outflows are assumed to be equal to 0. Discretionary trades are winsorized at the 0.5 and 99.5%. As in De Chaisemartin and d'Haultfoeuille (2024) $t = 0$ is the last period before treatment. Effects show the impact at different periods after treatment, while placebos test for pre-treatment trends. For column 1, treatment takes on a value of 1 if firms enter the MSCI All Country World Index (ACWI), 0 for firms that do not-yet switch. In column 2, treatment is assigned based on entry into MSCI ACWI excluding ESG Leaders. In column 3, treatment is defined by entry into both MSCI ACWI and MSCI ACWI ESG Leaders. We only estimate the treatment effect at the moment of entry, omitting exits. We assume the composition of switchers remains stable across periods. Standard errors are clustered at the appropriate level. * p¡0.10, ** p¡0.05, *** p¡0.01.

Table 22: Event-Study MSCI Index Inclusion on Discretionary Trades by Conventional Funds

	Dependent variable: Discretionary Trades by Conventional Funds		
	Treatment: MSCI ACWI	Treatment: MSCI ACWI excl. ESG Leaders	Treatment: MSCI ACWI ESG Leaders
Treat_{t+1}	0.00317^{***}	0.00336^{***}	0.00431^{**}
	(0.00080)	(0.00096)	(0.00190)
Treat_{t+2}	-0.00191^{***}	-0.00164^{**}	-0.00239
	(0.00073)	(0.00084)	(0.00166)
Treat_{t+3}	-0.00174^{***}	-0.00159^{*}	0.00028
	(0.00076)	(0.00088)	(0.00183)
Treat_{t+4}	-0.00322^{***}	-0.00257^{***}	-0.00432^{**}
	(0.00077)	(0.00088)	(0.00174)
Placebo_{t-1}	0.00097	0.00135	-0.00048
	(0.00078)	(0.00095)	(0.00220)
Placebo_{t-2}	0.00053	0.00050	0.00183
	(0.00085)	(0.00100)	(0.00208)
Placebo_{t-3}	0.00016	0.00057	-0.00028
	(0.00084)	(0.00097)	(0.00209)
Placebo_{t-4}	-0.00028	-0.00063	0.00126
	(0.00092)	(0.00106)	(0.00228)
Firm FE	YES	YES	YES
Year-Quarter FE	YES	YES	YES
Observations	647,399	644,661	642,653
# Switchers	$3,327$	$2,408$	640

Notes: Discretionary trades are defined according to Coval and Stafford (2007) and Huang et al. (2023): Sales after inflows are assumed to be 0; buys after outflows are assumed to be equal to 0. Discretionary trades are winsorized at the 0.5 and 99.5%. As in De Chaisemartin and d'Haultfoeuille (2024) $t = 0$ is the last period before treatment. Effects show the impact at different periods after treatment, while placebos test for pre-treatment trends. For column 1, treatment takes on a value of 1 if firms enter the MSCI All Country World Index (ACWI), 0 for firms that do not-yet switch. In column 2, treatment is assigned based on entry into MSCI ACWI excluding ESG Leaders. In column 3, treatment is defined by entry into both MSCI ACWI and MSCI ACWI ESG Leaders. We only estimate the treatment effect at the moment of entry, omitting exits. We assume the composition of switchers remains stable across periods. Standard errors are clustered at the appropriate level. * p¡0.10, ** p¡0.05, *** p¡0.01.

Table 23: OLS Regression Results: Mutual Funds Trading and Stocks' (future) MSCI ESG Scores

	Dependent variable: Position Changes			
	(1) MSCI ESG Score		(2) ΔMSCI ESG Score	
	(a) Raw	(b) Industry-weighted	(c) Raw	(d) Industry-weighted
MSCI ESG	-0.0004***	-0.0003***		
	(0.0001)	(0.0000)		
MSCI ESG × ESG Fund	0.0025***	0.0013***		
	(0.0002)	(0.0001)		
ΔMSCI ESG			0.0007**	0.0005***
			(0.0004)	(0.0002)
ΔMSCI ESG × ESG Fund			0.0015	0.0018***
			(0.0009)	(0.0005)
logsize	-0.0017***	-0.0017***	-0.0017***	-0.0016***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
be_me_1lag	-0.0026***	-0.0026***	-0.0026***	-0.0026***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
debt_at_1lag	-0.0022***	-0.0022***	-0.0021***	-0.0021***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
roa_1lag	-0.0757***	-0.0755***	-0.0728***	-0.0728***
	(0.0047)	(0.0047)	(0.0047)	(0.0047)
saleq_gr1_1lag	0.0047***	0.0047***	0.0045***	0.0046***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
QStock_ret_1lag	0.0001***	0.0001***	0.0001***	0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Constant	0.0174***	0.0179***	0.0177***	0.0176***
	(0.0025)	(0.0025)	(0.0024)	(0.0024)
Fund×Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	26,573,632	26,518,342	26,339,777	26,285,085
Adjusted R-squared	0.0889	0.0889	0.0892	0.0893
Within R-squared	0.0001	0.0001	0.0001	0.0001
F-statistic	65.75***	66.01***	54.54***	57.16***

Notes: OLS regressions on mutual fund (relative) position changes with standard errors are clustered at the fund level. Position Changes is the change in the position of fund i in stock j in quarter t estimated as $\frac{Price_{j,t-1}(NumberShares_{i,j,t}-NumberShares_{i,j,t-1})}{AUM_{i,t-1}}$(Gantchev et al., 2023; Giannetti and Jotikasthira, 2024). Position Changes is trimmed at the 0.5 and 99.5 percentiles. Raw MSCI ESG denotes the stock's MSCI raw key issue ESG score in quarter t. Industry-weighted MSCI ESG enotes the stock's industry-weighted MSCI ESG score in quarter t. ΔRaw MSCI ESG denotes the stock's change in its MSCI raw key issue ESG score between quarters $t-1$ and t. ΔIndustry-weighted MSCI ESG denotes the stock's change in its industry-weighted MSCI ESG between quarters $t-1$ and t. Regressions include fund × year-quarter fixed effects. ESG Fund takes on value 1 if the fund is denoted as an ESG fund following Morningstar's "General ESG Fund" indicator. All lagged continuous control variables are winsorized at the 1 and 99 percentiles. Standard errors are clustered on the fund level and are reported in parentheses. * p¡0.10, ** p¡0.05, *** p¡0.01.

Table 24: OLS Regression Results: Mutual Funds Trading on Stocks' MSCI ESG Scores and Environmental and Social Incidents

	Dependent variable: Position Changes							
	(1a) All Funds	(1b) All Funds	(2) ESG Funds	(3) Conventional Funds	(4) European Funds	(5) US Funds	(6) Article 8/9 funds	(7) Article 6 funds
MSCI ESG		0.0003	0.0041***	-0.0008***	0.0013***	-0.0013***	0.0032***	-0.0005
		(1.1731)	(7.3528)	(-3.4517)	(4.3987)	(-3.7684)	(5.7090)	(-1.0279)
# ES Incidents		-0.0022***	-0.0032***	-0.0020***	-0.0013***	-0.0043***	-0.0024***	-0.0003
		(-4.4266)	(-3.2330)	(-3.5265)	(-2.5840)	(-3.8132)	(-2.6899)	(-0.3629)
MSCI ESG × # ES Incidents		0.0016***	0.0046***	0.0004	0.0023***	-0.0003	0.0040***	-0.0003
		(4.5911)	(6.2130)	(0.9996)	(5.2806)	(-0.4166)	(5.6694)	(-0.3815)
logsize	-0.0063***	-0.0047***	0.0088***	-0.0090***	-0.0039***	-0.0056***	0.0062***	-0.0076***
	(-6.4993)	(-4.9368)	(5.4445)	(-7.7728)	(-3.3712)	(-3.5077)	(3.9340)	(-3.8255)
be_me_1lag	-0.0031***	-0.0027***	-0.0059***	-0.0020***	-0.0038***	-0.0010***	-0.0069***	-0.0027***
	(-12.9420)	(-11.0096)	(-9.8654)	(-7.3330)	(-10.8804)	(-3.1106)	(-10.9171)	(-4.5715)
debt_at_1lag	-0.0008***	-0.0008***	-0.0022***	-0.0004**	-0.0014***	0.0001	-0.0029***	-0.0012***
	(-4.9422)	(-4.4127)	(-5.0495)	(-2.0163)	(-5.4117)	(0.3273)	(-6.1209)	(-2.7237)
roa_1lag	-0.0043***	-0.0046***	-0.0035***	-0.0050***	-0.0035***	-0.0059***	-0.0042***	-0.0040***
	(-16.0204)	(-15.7557)	(-5.3597)	(-15.2261)	(-8.4257)	(-14.3693)	(-5.7101)	(-5.4591)
saleq_gr1_1lag	0.0033***	0.0034***	0.0060***	0.0028***	0.0052***	0.0014***	0.0060***	0.0043***
	(12.6583)	(12.2853)	(9.2851)	(9.0367)	(12.4255)	(3.8015)	(8.3359)	(5.8905)
QStock_ret_1lag	0.0034***	0.0035***	0.0105***	0.0016*	0.0046***	0.0022*	0.0099***	0.0026
	(4.3060)	(4.2301)	(5.8412)	(1.7334)	(4.0022)	(1.8662)	(4.9702)	(1.1708)
Firm×Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26,573,632	23,587,629	5,655,734	17,931,895	13,872,685	9,714,944	5,398,375	4,350,679
R-squared	0.097	0.099	0.101	0.098	0.102	0.090	0.098	0.095
Adjusted R-squared	0.089	0.090	0.089	0.090	0.092	0.084	0.086	0.085
Within R-squared	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F-statistic	74.18***	51.56***	36.05***	37.07***	36.85***	25.64***	34.33***	9.06***

Notes: OLS regressions on mutual fund (relative) position changes with standard errors are clustered at the fund level. Position Changes is the change in the position of fund i in stock j in quarter t estimated as $\frac{Price_{j,t-1}(NumberShares_{i,j,t}-NumberShares_{i,j,t-1})}{AUM_{i,t-1}}$(Gantchev et al., 2023; Giannetti and Jotikasthira, 2024). Position Changes is trimmed at the 0.5 and 99.5 percentiles. Industry-weighted MSCI ESG enotes the stock's industry-weighted MSCI ESG score in quarter t. # ES Incidents denotes the number of environmental and social RepRisk incidents in quarter t by firm j. Regressions include fund × year-quarter fixed effects. All lagged continuous control variables are winsorized at the 1 and 99 percentiles. Standard errors are clustered at the fund level. Coefficients are standardized and t-statistics are reported in parentheses. * p¡0.10, ** p¡0.05, *** p¡0.01.

Table 25: Mutual funds trading: discrepancies between ESG score and ES incidents in different lags

Panel A: Sample split for ESG Funds

	Dependent Variable: Position Changes				Dependent Variable: Discretionary Trades			
	(1) t	(2) $t-1$	(3) $t-2$	(4) $t-3$	(5) t	(6) $t-1$	(7) $t-2$	(8) $t-3$
MSCI ESG$_{t-s}$	0.0041***	0.0053***	0.0062***	0.0055***	0.0007	0.0019***	0.0030***	0.0028***
	(7.3528)	(9.2826)	(10.1275)	(8.5728)	(1.5190)	(3.5349)	(5.0267)	(4.6229)
# ES incidents$_{t-s}$	-0.0032***	-0.0012	-0.0023**	-0.0022**	-0.0004	-0.0035***	-0.0036***	-0.0033***
	(-3.2330)	(-1.3929)	(-2.4663)	(-2.1617)	(-0.9501)	(-7.3904)	(-7.5688)	(-6.8388)
MSCI ESG$_{t-s}$ × # ES incidents$_{t-s}$	0.0046***	0.0037***	0.0047***	0.0042***	-0.0002	-0.0010**	-0.0016***	-0.0020***
	(6.2130)	(5.2123)	(6.0000)	(4.8513)	(-0.6000)	(-2.5654)	(-3.7716)	(-4.7950)
Constant	0.0183***	-0.0826***	-0.0772***	-0.0624***	0.0043***	-0.0309***	-0.0296***	-0.0235***
	(34.6998)	(-143.9542)	(-124.5725)	(-94.8198)	(5.9647)	(-29.9400)	(-25.9212)	(-19.7019)
1 quarter lagged controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,655,734	4,550,670	3,841,410	3,259,402	5,568,391	4,487,555	3,792,714	3,219,513
R-squared	0.101	0.173	0.172	0.171	0.140	0.153	0.155	0.157
Within R-squared	0.000	0.000	0.000	0.000	0.000	0.002	0.002	0.001
F-statistic	36.05***	23.52***	28.26***	24.16***	18.40***	32.29***	27.86***	21.89***

Panel B: Sample split for Conventional funds

	Dependent Variable: Position Changes				Dependent Variable: Discretionary Trades			
	(1) t	(2) $t-1$	(3) $t-2$	(4) $t-3$	(5) t	(6) $t-1$	(7) $t-2$	(8) $t-3$
MSCI ESG$_{t-s}$	-0.0008***	-0.0002	0.0001	-0.0002	-0.0009***	-0.0003	-0.0003	-0.0004
	(-3.4517)	(-0.9037)	(0.4383)	(-0.7856)	(-2.7625)	(-0.9237)	(-0.8475)	(-1.0041)
# ES incidents$_{t-s}$	-0.0020***	0.0008	0.0011**	-0.0003	0.0003	-0.0013***	-0.0011**	-0.0008*
	(-3.5265)	(1.4225)	(1.9806)	(-0.4837)	(0.8720)	(-2.7006)	(-2.1339)	(-1.6731)
MSCI ESG$_{t-s}$ × # ES incidents$_{t-s}$	0.0004	0.0003	0.0002	-0.0003	0.0001	-0.0003	-0.0008***	-0.0012***
	(0.9996)	(0.7191)	(0.4198)	(-0.6563)	(0.5543)	(-1.1166)	(-3.1622)	(-4.6408)
Constant	-0.0067***	-0.0802***	-0.0730***	-0.0590***	-0.0042***	-0.0294***	-0.0273***	-0.0196***
	(-90.9479)	(-1.02e+03)	(-730.9652)	(-450.5880)	(-30.3384)	(-141.7267)	(-103.0090)	(-71.2315)
1 quarter lagged controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,931,895	14,882,648	12,862,971	11,173,154	17,604,611	14,637,781	12,664,023	11,008,398
R-squared	0.098	0.195	0.192	0.189	0.136	0.147	0.151	0.152
Within R-squared	0.000	0.000	0.000	0.000	0.000	0.001	0.001	0.001
F-statistic	37.07***	48.03***	52.44***	48.10***	35.72***	69.45***	62.25***	51.60***

Notes: The table reports the relation between mutual fund trading (Columns 1-4: total position changes, columns 5-8: discretionary trades). Discretionary trades are defined according to Coval and Stafford (2007) and Huang et al. (2023): Sales after inflows are assumed to be 0; buys after outflows are assumed to be equal to 0. Discretionary trades are trimmed at the 0.5 and 99.5%. Position Changes is the change in the position of fund i in stock j in quarter t estimated as $\frac{Price_{j,t-1}(NumberShares_{i,j,t}-NumberShares_{i,j,t-1})}{AUM_{i,t-1}}$(Gantchev et al., 2023; Giannetti and Jotikasthira, 2024). Position Changes is trimmed at the 0.5 and 99.5 percentiles. All lagged continuous control variables are winsorized at the 1 and 99 percentiles. Standard errors are clustered at the fund level. Coefficients are standardized and t-statistics are reported in parentheses. * p¡0.10, ** p¡0.05, *** p¡0.01.

Table 26: Integration of ES risks in discretionary ownership and risk-adjusted fund returns

Panel A: Integration of ES risks by all funds

	Propensity (1)	Excess Return (2)	α_{FF3} (3)	α_{C4} (4)
Quintile 1	-0.124484^{***}	0.0196947	-0.0009028^{***}	-0.000817^{***}
	(-19.54)	(1.27)	(-3.80)	(-3.22)
Quintile 2	-0.0080596^{***}	0.0182341	-0.0015927^{***}	-0.0015714^{***}
	(-8.64)	(1.37)	(-7.06)	(-6.88)
Quintile 3	0.0004481^{***}	0.0177224	-0.0017901^{***}	-0.001784^{***}
	(13.09)	(1.43)	(-11.92)	(-11.26)
Quintile 4	0.0105816^{***}	0.0182023	-0.0014963^{***}	-0.0014896^{***}
	(18.08)	(1.36)	(-10.23)	(-8.47)
Quintile 5	0.1191018^{***}	0.0197914	-0.0008059^{***}	-0.0007444^{***}
	(35.12)	(1.34)	(-4.45)	(-3.81)
5 – 1	0.2435858^{***}	0.0000967	0.0000969	0.0000726
	(33.75)	(0.00)	(0.32)	(0.23)

Panel B: Integration of ES risks by ESG funds

Quintile 1	-0.1240476^{***}	0.0197864	-0.00119^{***}	-0.0011365^{***}
	(-23.04)	(1.21)	(-3.98)	(-3.45)
Quintile 2	-0.0081075^{***}	0.0180543	-0.0018819^{***}	-0.0018525^{***}
	(-8.83)	(1.35)	(-6.85)	(-6.65)
Quintile 3	0.0004361^{***}	0.0178947	-0.0018288^{***}	-0.0018252^{***}
	(8.68)	(1.40)	(-9.13)	(-9.67)
Quintile 4	0.010922^{***}	0.0176625	-0.001739^{***}	-0.0017318^{***}
	(17.21)	(1.31)	(-8.13)	(-7.43)
Quintile 5	0.1158267^{***}	0.0201237	-0.0012202^{***}	-0.0012182^{***}
	(35.17)	(1.30)	(-6.48)	(-4.95)
5 – 1	0.2398743^{***}	0.0003373	-0.0000302	-0.0000817
	(37.99)	(0.02)	(-0.09)	(-0.20)

Panel C: Integration of ES risks by conventional funds

Quintile 1	-0.1246109^{***}	0.0196616	-0.0007853^{***}	-0.0006866^{***}
	(-17.87)	(1.30)	(-3.69)	(-3.06)
Quintile 2	-0.0080448^{***}	0.0182951	-0.0014708^{***}	-0.0014526^{***}
	(-8.50)	(1.38)	(-7.13)	(-6.99)
Quintile 3	0.0004537^{***}	0.0177314	-0.0017786^{***}	-0.0017708^{***}
	(15.64)	(1.45)	(-13.15)	(-11.75)
Quintile 4	0.0104424^{***}	0.0184301	-0.0014011^{***}	-0.0013943^{***}
	(18.36)	(1.39)	(-11.39)	(-8.95)
Quintile 5	0.1204826^{***}	0.0196661	-0.0006282^{***}	-0.0005419^{***}
	(32.41)	(1.36)	(-3.50)	(-3.04)
5 – 1	0.2450935^{***}	0.0000045	0.0001571	0.0001447
	(31.02)	(0.00)	(0.56)	(0.51)

Notes: This table reports average portfolio characteristics and risk-adjusted returns across quintiles sorted by lagged trading propensity on future ES risks (Methodology follows Fang et al., 2014; Chen et al., 2024). Propensity scores are trimmed on the 0.5 and 99.5 percentiles. We sort for every quarter funds into quintiles by their lagged propensity measures. Column 1 reports the equal-weighted propensity scores per quintile. Excess returns (column 2) are defined as the quarterly fund returns in t minus the risk-free rate. For each fund in each quarter, Fama-French three-factor returns (column 3) are calculated using fund returns of the past 36 months. Quarterly Carhart's 4-factor returns (column 4) are calculated using fund returns of the past 36 months. We denominate quarterly risk-adjusted returns per month ($\times$100%). For individual quintiles, using 8 lags, we indicate whether the average is significantly different from zero at the 10%, 5%, and 1% levels. The last row reports the difference between Quintile 5 and Quintile 1. Newey–West standard errors are computed with 8 lags. * p¡0.10, ** p¡0.05, *** p¡0.01.

Table 27: Difference in Time-Series Averages: ESG vs. Conventional Funds

Quintile	Propensity			Excess Return		
	Diff. Mean	Std. Err.	t-stat	Diff. Mean	Std. Err.	t-stat
1	0.00056	0.00881	0.064	0.00012	0.02226	0.006
2	-0.00006	0.00132	-0.048	-0.00024	0.01882	-0.013
3	-0.00002	0.00006	-0.303	0.00016	0.01769	0.009
4	0.00048	0.00085	0.563	-0.00077	0.01895	-0.041
5	-0.00466	0.00497	-0.937	0.00046	0.02119	0.022
Quintile	**Fama-French 3-Factors α**			**Carhart 4-Factors α**		
	Diff. Mean	Std. Err.	t-stat	Diff. Mean	Std. Err.	t-stat
1	-0.00040	0.00037	-1.103	-0.00045	0.00040	-1.129
2	-0.00041	0.00034	-1.197	-0.00040	0.00035	-1.150
3	-0.00005	0.00024	-0.208	-0.00005	0.00024	-0.225
4	-0.00034	0.00025	-1.369	-0.00034	0.00028	-1.205
5	-0.00059**	0.00026	-2.275	-0.00068**	0.00030	-2.225

Notes: The table presents the difference in time-series average returns of Table 26 between ESG and Conventional funds for each quintile. Returns are in $\times$ 100%. The values correspond to (ESG minus Conventional funds). The standard errors for the difference are calculated as $\sqrt{SE^2_{ESG} + SE^2_{Conv}}$. The t-statistics are the ratio of the difference in means to the standard error of the difference. Significant values at the 5% level ($|t| > 1.96$) are shown in with **.

Table 28: OLS Regression Results on Fund Excess Returns with Alternative Fixed Effects Specifications

Dependent Variable: Fund Excess Returns in t			
	(1)	(2)	(3)
Propensity$_{t-1}$	-0.395	-0.157	-0.164
	(0.415)	(0.162)	(0.217)
RPI ESG$_{t-1}$	-0.727**	-0.788***	-0.062
	(0.333)	(0.117)	(0.142)
RPI ES Incidents$_{t-1}$	0.338	-0.090	-0.085
	(0.264)	(0.096)	(0.114)
logsize$_{t-1}$	-4.702***	0.044***	-1.464***
	(0.112)	(0.008)	(0.045)
logage$_{t-1}$	-2.141***	0.024	0.812***
	(0.158)	(0.018)	(0.125)
Turnover$_{t-1}$	0.049**	0.015***	0.014*
	(0.021)	(0.005)	(0.008)
QFlow$_{t-1}$	-0.203	0.070	0.105
	(0.280)	(0.106)	(0.118)
Constant	99.759***	1.027***	28.394***
	(2.179)	(0.146)	(0.880)
Fund FE	Yes	No	Yes
Year-quarter FE	No	Yes	Yes
Observations	110,047	110,380	110,047
R-squared	0.063	0.844	0.855
Within R-squared	0.040	0.001	0.020
F-statistic	311.08***	18.71***	158.24***

Notes: The table reports the relation between the RPI (Reliance on Public Information) ratio, propensity to invest on future ES risks, and fund excess return. For each fund in each quarter, we calculate the difference between the quarterly fund return and the risk-free rate. Our propensity measure is defined as per Fang et al. (2014) and Chen et al. (2024) on discretionary ownership and is standardized. Standardized propensity scores are trimmed on the 0.5 and 99.5 percentiles. In a similar fashion to Kacperczyk and Seru (2007), we proxy for usage of public ESG information: RPI ESG is defined by the R^2 of a pooled OLS regression of fund holdings changes on changes in the MSCI ESG ratings during 4 lags. RPI ES Incidents is defined by the R^2 of a pooled OLS regression of holdings changes on ES incidents during 4 lags. Values of RPI are bound between 0.01% and 99.9%. Fund portfolio turnover is trimmed at the 0.5 and 99.5 percentiles. All other continuous control variables are winsorized at the 1 and 99 percentiles. Standard errors are clustered at the fund level and are reported in parentheses. * p¡0.10, ** p¡0.05, *** p¡0.01.

Table 29: OLS Regression Results on Fund Risk-Adjusted Returns with Alternative Fixed Effects Specifications

	Dependent Variable: Risk-Adjust Fund Returns in t					
	Fama-French 3-Factors α			Carhart 4-Factors α		
	(1)	(2)	(3)	(4)	(5)	(6)
Propensity$_{t-1}$	0.004	-0.003	0.005	0.001	-0.005	0.003
	(0.021)	(0.022)	(0.020)	(0.021)	(0.023)	(0.020)
RPI ESG$_{t-1}$	0.022**	-0.080***	0.005	0.007	-0.078***	-0.012
	(0.009)	(0.014)	(0.009)	(0.010)	(0.014)	(0.009)
RPI ES Incidents$_{t-1}$	-0.009	-0.022*	-0.005	-0.008	-0.022*	-0.004
	(0.007)	(0.012)	(0.007)	(0.008)	(0.012)	(0.007)
logsize$_{t-1}$	0.050***	0.049***	0.056***	0.064***	0.048***	0.069***
	(0.004)	(0.002)	(0.005)	(0.005)	(0.002)	(0.005)
logage$_{t-1}$	0.050***	-0.030***	-0.033	-0.039***	-0.025***	-0.048**
	(0.012)	(0.005)	(0.021)	(0.012)	(0.005)	(0.022)
Turnover$_{t-1}$	-0.002***	-0.002*	-0.002***	-0.002***	-0.002***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
QFlow$_{t-1}$	0.159***	0.256***	0.155***	0.156***	0.257***	0.154***
	(0.011)	(0.015)	(0.011)	(0.011)	(0.015)	(0.011)
Constant	-1.240***	-0.985***	-1.130***	-1.272***	-0.973***	-1.333***
	(0.090)	(0.035)	(0.104)	(0.091)	(0.034)	(0.106)
Fund FE	Yes	No	Yes	Yes	No	Yes
Year-quarter FE	No	Yes	Yes	No	Yes	Yes
Observations	106,391	106,723	106,391	106,391	106,723	106,391
R-squared	0.562	0.101	0.584	0.533	0.106	0.565
Within R-squared	0.018	0.082	0.018	0.020	0.079	0.022
F-statistic	53.46***	184.09***	54.10***	59.85***	182.38***	61.73***

Notes: The table reports the relation between the RPI (Reliance on Public Information) ratio, propensity to invest on future ES risks, and fund risk-adjusted return. For each fund in each quarter, Fama-French three-factor returns (columns 1-4) are calculated using fund returns of the past 36 months. Quarterly Carhart's 4-factor returns (columns 5-8) are calculated using fund returns of the past 36 months. We denominate quarterly risk-adjusted returns in basis points per month. Our propensity measure is defined as per Fang et al. (2014) and Chen et al. (2024) on discretionary ownership and is standardized. Standardized propensity scores are trimmed on the 0.5 and 99.5 percentiles. In a similar fashion to Kacperczyk and Seru (2007), we proxy for usage of public ESG information: RPI ESG is defined by the R^2 of a pooled OLS regression of fund holdings changes on changes in the MSCI ESG ratings during 4 lags. RPI ES Incidents is defined by the R^2 of a pooled OLS regression of holdings changes on ES incidents during 4 lags. Values of RPI are bound between 0.01% and 99.9%. Fund portfolio turnover is trimmed at the 0.5 and 99.5 percentiles. All other continuous control variables are winsorized at the 1 and 99 percentiles. Standard errors are clustered at the fund level and are reported in parentheses. * p¡0.10, ** p¡0.05, *** p¡0.01.

Table 30: OLS Regression Results on Fund Returns

	Dependent Variable: Fund Returns in t					
	Fund Excess Returns in t		Fama-French 3-Factors α		Carhart 4-Factors α	
	(1)	(2)	(3)	(4)	(5)	(6)
Propensity$_{t-1}$	-0.253	-0.213	0.002	0.001	0.007	0.007
	(0.193)	(0.253)	(0.026)	(0.023)	(0.026)	(0.023)
Propensity$_{t-1}$ × ESG Fund	0.331	0.177	-0.019	0.014	-0.045	-0.015
	(0.355)	(0.491)	(0.051)	(0.047)	(0.051)	(0.048)
ESG Fund	-0.151***		-0.072***		-0.069***	
	(0.039)		(0.008)		(0.008)	
RPI ESG$_{t-1}$	-1.046***	-0.239	-0.129***	0.004	-0.121***	-0.013
	(0.142)	(0.172)	(0.017)	(0.011)	(0.017)	(0.011)
RPI ESG$_{t-1}$ × ESG Fund	0.863***	0.571*	0.172***	0.006	0.153***	0.004
	(0.247)	(0.303)	(0.030)	(0.019)	(0.030)	(0.020)
RPI ES Incidents$_{t-1}$	-0.152	-0.042	-0.064***	0.001	-0.059***	0.004
	(0.115)	(0.137)	(0.015)	(0.009)	(0.015)	(0.009)
RPI ES Incidents$_{t-1}$ × ESG Fund	0.191	-0.150	0.143***	-0.019	0.127***	-0.024
	(0.209)	(0.248)	(0.025)	(0.016)	(0.025)	(0.016)
logsize$_{t-1}$	0.042***	-1.464***	0.048***	0.056***	0.047***	0.069***
	(0.008)	(0.045)	(0.002)	(0.005)	(0.002)	(0.005)
logage$_{t-1}$	0.021	0.809***	-0.032***	-0.033	-0.026***	-0.048**
	(0.018)	(0.125)	(0.005)	(0.021)	(0.005)	(0.022)
Turnover$_{t-1}$	0.015***	0.014*	-0.001	-0.002***	-0.002**	-0.003***
	(0.005)	(0.008)	(0.001)	(0.001)	(0.001)	(0.001)
QFlow$_{t-1}$	0.071	0.104	0.261***	0.155***	0.262***	0.154***
	(0.106)	(0.118)	(0.015)	(0.011)	(0.015)	(0.011)
Constant	1.115***	28.398***	-0.950***	-1.130***	-0.939***	-1.332***
	(0.149)	(0.881)	(0.035)	(0.104)	(0.035)	(0.106)
Fund FE	No	Yes	No	Yes	No	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	110,380	110,047	106,723	106,391	106,723	106,391
R-squared	0.844	0.855	0.105	0.584	0.110	0.565
Within R-squared	0.002	0.020	0.087	0.018	0.083	0.022
F-statistic	13.92***	110.87***	127.80***	38.23***	125.64***	43.52***

Notes: The table reports the relation between the RPI (Reliance on Public Information) ratio, propensity to invest on future ES risks, and fund excess and risk-adjusted return. Column 1 presents results from a time fixed effects model using quarterly excess returns. In column 2 for each fund in each quarter, we calculate the difference between the quarterly fund return and the risk-free rate. Column 3 presents results from a time fixed effects model using Fama-French three-factor alpha. For each fund in each quarter, Fama-French three-factor returns (column 4) are calculated using fund returns of the past 36 months. Column 5 presents results from a time fixed effects model using Fama-French-Momentum four-factor alpha. Quarterly Carhart's 4-factor returns (column 6) are calculated using fund returns of the past 36 months. We denominate quarterly risk-adjusted returns in basis points per month. Our propensity measure is defined as per Fang et al. (2014) and Chen et al. (2024) on discretionary ownership and is standardized. Standardized propensity scores are trimmed on the 0.5 and 99.5 percentiles. In a similar fashion to Kacperczyk and Seru (2007), we proxy for usage of public ESG information: RPI ESG is defined by the R^2 of a pooled OLS regression of fund holdings changes on changes in the MSCI ESG ratings during 4 lags. RPI ES Incidents is defined by the R^2 of a pooled OLS regression of holdings changes on ES incidents during 4 lags. Values of RPI are bound between 0.01% and 99.9%. ESG Fund takes on the value 1 if the fund is denoted by Morningstar to be a "General ESG Investment", 0 otherwise. Fund portfolio turnover is trimmed at the 0.5 and 99.5 percentiles. All other continuous control variables are winsorized at the 1 and 99 percentiles. Standard errors are clustered at the fund level and are reported in parentheses. * p¡0.10, ** p¡0.05, *** p¡0.01.

Table 31: Impact of ESG label, integrating ES risks, and RPI on Fund Flows

	Dependent Variable: Fund Flows in t (%)				
	(1)	(2)	(3)	(4)	(5)
Propensity$_{t-1}$	0.003	0.005	0.003	0.005	0.005
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Propensity$_{t-1}$ × ESG Fund		-0.007		-0.005	-0.005
		(0.011)		(0.011)	(0.011)
RPI ESG$_{t-1}$	-0.002	-0.009**			-0.009**
	(0.003)	(0.004)			(0.004)
RPI ESG$_{t-1}$ × ESG Fund		0.023***			0.025***
		(0.008)			(0.008)
RPI ES Incidents$_{t-1}$			0.001	0.005	0.005
			(0.003)	(0.003)	(0.003)
RPI ES Incidents$_{t-1}$ × ESG Fund				-0.012*	-0.013**
				(0.007)	(0.007)
logsize$_{t-1}$	-0.041***	-0.041***	-0.041***	-0.041***	-0.041***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
logage$_{t-1}$	-0.041***	-0.041***	-0.041***	-0.041***	-0.041***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
QReturn$_{t-1}$	0.270***	0.270***	0.268***	0.268***	0.271***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Turnover$_{t-1}$	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.905***	0.906***	0.907***	0.907***	0.904***
	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
Fund FE	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	111,372	111,372	111,668	111,668	110,047
R-squared	0.194	0.194	0.195	0.195	0.195
Within R-squared	0.036	0.036	0.036	0.036	0.036
F-statistic	190.59***	145.66***	191.30***	144.48***	116.48***

Notes: The table reports the relation between the RPI (Reliance on Public Information) ratio, propensity to invest on future ES risks, and fund flows. Our propensity measure is defined as per Fang et al. (2014) and Chen et al. (2024) on discretionary ownership and is standardized. Standardized propensity scores are trimmed on the 0.5 and 99.5 percentiles. In a similar fashion to Kacperczyk and Seru (2007), we proxy for usage of public ESG information: RPI ESG is defined by the R^2 of a pooled OLS regression of fund holdings changes on changes in the MSCI ESG ratings during 4 lags. RPI ES Incidents is defined by the R^2 of a pooled OLS regression of holdings changes on ES incidents during 4 lags. Values of RPI are bound between 0.01% and 99.9%. ESG Fund takes on the value 1 if the fund is denoted by Morningstar to be a "General ESG Investment", 0 otherwise. Fund portfolio turnover is trimmed at the 0.5 and 99.5 percentiles. All other continuous control variables are winsorized at the 1 and 99 percentiles. Standard errors are clustered at the fund level and are reported in parentheses. * p¡0.10, ** p¡0.05, *** p¡0.01.

Table 32: Poisson Regression Results, controlling for MSCI ACWI changes: Discretionary Trades on Future Firm Environmental and Social Incidents.

Dependent variable: (Cumulative) Future Environmental and Social Incidents in t+s				
	1 quarter (1)	2 quarters (2)	3 quarters (3)	4 quarters (4)
ESG DiscretTrades	-0.002	-0.001**	-0.001	-0.001**
	(-1.093)	(-2.056)	(-1.632)	(-2.195)
ESG ExpectedTrades	0.011***	0.005***	0.003***	0.002***
	(3.856)	(3.724)	(3.962)	(3.401)
conv. DiscretTrades	0.000	0.000	0.000	0.000
	(0.132)	(0.114)	(0.216)	(0.116)
conv. ExpectedTrades	-0.008***	-0.001	-0.000	0.000
	(-2.616)	(-1.001)	(-0.316)	(0.088)
MSCI ACWI	0.019**	0.010**	0.007**	0.005**
	(1.990)	(2.069)	(2.141)	(2.233)
logsize	0.267***	0.137***	0.091***	0.068***
	(8.862)	(9.139)	(9.116)	(9.160)
be_me_win	0.067***	0.033***	0.022***	0.016***
	(6.958)	(6.767)	(6.838)	(6.818)
ret_12_1_win	-0.031***	-0.017***	-0.011***	-0.007***
	(-6.722)	(-7.262)	(-7.135)	(-6.753)
capx_at_win	0.000	-0.001	-0.001	-0.001
	(0.055)	(-0.116)	(-0.272)	(-0.419)
beta_252d_win	-0.008	-0.004	-0.001	-0.000
	(-1.549)	(-1.354)	(-0.414)	(-0.031)
rvol_252d_win	0.031***	0.013***	0.006***	0.004**
	(4.270)	(3.596)	(2.626)	(2.057)
niq_be_win	-0.003	0.001	0.001	0.001
	(-0.882)	(0.870)	(1.046)	(1.244)
debt_at_win	0.042***	0.021***	0.014***	0.010***
	(4.237)	(4.135)	(3.964)	(3.827)
Firm FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Observations	161,423	164,214	167,338	169,843
Pseudo R-squared	0.591	0.669	0.714	0.745
χ^2-statistic	131.90***	128.24***	124.16***	122.99***

Notes: The table reports the relation between ESG and conventional mutual fund trading behavior and future changes in firm-level (cumulative) number of environmental and social RepRisk incidents, measured at t+s, where quarter s $\in \{1, 2, 3, 4\}$. We control for changes to the MSCI All Country World Index (ACWI). MSCI ACWI is an indicator that takes on the value 1 if the holding is included in the MSCI All Country World Index, and 0 otherwise. This indicator varies over time. Discretionary trades are defined according to Coval and Stafford (2007) and Huang et al. (2023): Sales after inflows are assumed to be 0; buys after outflows are assumed to be equal to 0. Discretionary and expected trades are winsorized at the 0.5 and 99.5%. Poisson regressions include firm and year-quarter fixed effects, and standard errors are clustered at the firm level. Regressions include firm and year-quarter fixed effects. All continuous control variables are winsorized at the 1 and 99 percentiles. Coefficients are standardized and z-statistics are reported in parentheses. * p¡0.10, ** p¡0.05, *** p¡0.01

C Internet Appendix

Table 33: Winsorizing Options: Poisson Regressions Results on Future Environmental and Social Incidents

Panel A: No winsorizing

	Dependent variable: (Cumulative) Future Environmental and Social Incidents in t+s							
	1 quarter (1)		2 quarters (2)		3 quarters (3)		4 quarters (4)	
	(a) All flows	(b) Extreme flows	(a) All flows	(b) Extreme flows	(a) All flows	(b) Extreme flows	(a) All flows	(b) Extreme flows
ESG Discretionary Trades	-0.010	-0.088	-0.011	-0.005	-0.004	0.063	0.003	0.045
	(0.012)	(0.109)	(0.009)	(0.097)	(0.005)	(0.077)	(0.003)	(0.060)
ESG Expected Trades	0.228	0.107	0.157	0.079	0.190	0.197	0.178	0.197
	(0.197)	(0.228)	(0.187)	(0.239)	(0.143)	(0.188)	(0.109)	(0.140)
Conv. Discretionary Trades	0.000	0.003	-0.003	-0.003	0.001	-0.000	0.001*	-0.000
	(0.001)	(0.006)	(0.002)	(0.008)	(0.001)	(0.006)	(0.001)	(0.006)
Conv. Expected Trades	-0.093	0.012	0.026	0.128	0.010	0.342	0.063	0.408
	(0.101)	(0.691)	(0.102)	(0.610)	(0.126)	(0.515)	(0.111)	(0.510)
Constant	-2.572***	-2.573***	-1.788***	-1.790***	-1.319***	-1.323***	-0.952***	-0.957***
	(0.385)	(0.385)	(0.369)	(0.369)	(0.361)	(0.361)	(0.350)	(0.350)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	161,423	161,423	164,214	164,214	167,338	167,338	169,843	169,843
Pseudo R-squared	0.591	0.591	0.669	0.669	0.714	0.714	0.745	0.745
χ^2-statistic	105.37***	114.79***	105.86***	117.86***	99.25***	123.09***	103.52***	128.70***

Notes: Discretionary trades are defined conform Coval and Stafford (2007) and Huang et al. (2023): Sales after inflows are assumed to be 0; buys after outflows are assumed to be equal to 0. The dependent variable, the (cumulative) number of Environmental and Social Incidents, is measured at t+s, where quarter s $\in \{1, 2, 3, 4\}$. Poisson regressions include firm and year-quarter fixed effects. All continuous control variables are winsorized at the 1 and 99 percentiles. Standard errors are clustered at the firm level. * p¡0.10, ** p¡0.05, *** p¡0.01.

Table 33: Cont. Winsorizing Options: Poisson Regressions Results on Future Environmental and Social Incidents

Panel B: Winsorize on 0.5-99.5%

	Dependent variable: (Cumulative) Future Environmental and Social Incidents in t+s							
	1 quarter (1)		2 quarters (2)		3 quarters (3)		4 quarters (4)	
	(a) All flows	(b) Extreme flows	(a) All flows	(b) Extreme flows	(a) All flows	(b) Extreme flows	(a) All flows	(b) Extreme flows
ESG Discretionary Trades	-0.797	-2.964	-1.233**	-0.960	-0.806*	-2.303	-0.976**	-2.808
	(0.724)	(2.964)	(0.596)	(2.005)	(0.490)	(1.745)	(0.443)	(1.768)
ESG Expected Trades	20.908***	14.495*	19.484***	16.452**	18.394***	14.859**	15.540***	11.321*
	(5.465)	(8.072)	(5.258)	(6.898)	(4.665)	(6.563)	(4.592)	(6.402)
Conv. Discretionary Trades	0.025	0.628	0.014	0.717	0.040	0.957	0.013	0.693
	(0.307)	(1.274)	(0.267)	(1.061)	(0.261)	(1.041)	(0.253)	(1.001)
Conv. Expected Trades	-5.754***	-8.295***	-1.987	-2.643	-0.583	-1.896	0.231	-1.480
	(2.219)	(3.192)	(2.039)	(3.409)	(2.017)	(3.364)	(1.975)	(2.949)
Constant	-2.499***	-2.530***	-1.711***	-1.769***	-1.237***	-1.308***	-0.883***	-0.945***
	(0.356)	(0.365)	(0.339)	(0.356)	(0.333)	(0.351)	(0.324)	(0.341)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	161,423	161,423	164,214	164,214	167,338	167,338	169,843	169,843
Pseudo R-squared	0.591	0.591	0.669	0.669	0.714	0.714	0.745	0.745
χ^2-statistic	126.44***	113.78***	125.66***	129.55***	120.43***	130.92***	119.77***	128.45***
Panel C: Winsorize on 1-99%								
ESG Discretionary Trades	-2.092*	-7.231	-2.130**	-2.768	-1.723**	-4.118	-1.902***	-4.672*
	(1.118)	(4.421)	(0.884)	(3.031)	(0.722)	(2.770)	(0.662)	(2.736)
ESG Expected Trades	25.067***	16.980	22.196***	17.674**	21.518***	14.902*	17.843***	10.394
	(7.266)	(10.597)	(6.805)	(8.884)	(6.139)	(8.632)	(6.028)	(8.525)
Conv. Discretionary Trades	0.061	0.982	0.036	1.370	0.087	1.645	0.081	1.278
	(0.463)	(1.631)	(0.385)	(1.304)	(0.368)	(1.303)	(0.363)	(1.276)
Conv. Expected Trades	-6.929**	-10.181***	-2.446	-2.703	-0.823	-1.307	0.133	-0.723
	(2.716)	(3.808)	(2.467)	(3.822)	(2.430)	(3.759)	(2.381)	(3.325)
Constant	-2.520***	-2.543***	-1.732***	-1.780***	-1.257***	-1.319***	-0.901***	-0.956***
	(0.363)	(0.372)	(0.347)	(0.363)	(0.340)	(0.357)	(0.331)	(0.346)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	161,423	161,423	164,214	164,214	167,338	167,338	169,843	169,843
Pseudo R-squared	0.591	0.591	0.669	0.669	0.714	0.714	0.745	0.745
χ^2-statistic	119.99***	112.73***	118.30***	118.23***	113.18***	124.15***	116.34***	124.69***

Notes: Discretionary trades are defined conform Coval and Stafford (2007) and Huang et al. (2023): Sales after inflows are assumed to be 0; buys after outflows are assumed to be equal to 0. The dependent variable, the (cumulative) number of Environmental and Social Incidents, is measured at t+s, where quarter s $\in \{1, 2, 3, 4\}$. Poisson regressions include firm and year-quarter fixed effects. All continuous control variables are winsorized at the 1 and 99 percentiles. Standard errors are clustered at the firm level. * p¡0.10, ** p¡0.05, *** p¡0.01.

Table 33: Cont. Winsorizing Options: Poisson Regressions Results on Future Environmental and Social Incidents

Panel D: Trimming on 1-99%

	Dependent variable: (Cumulative) Future Environmental and Social Incidents in t+s							
	1 quarter (1)		2 quarters (2)		3 quarters (3)		4 quarters (4)	
	(a) All flows	(b) Extreme flows	(a) All flows	(b) Extreme flows	(a) All flows	(b) Extreme flows	(a) All flows	(b) Extreme flows
ESG Discretionary Trades	-2.314	-16.675*	-2.872*	-4.565	-3.072**	-2.989	-2.939**	-4.023
	(1.881)	(8.513)	(1.576)	(6.030)	(1.428)	(5.371)	(1.306)	(4.768)
ESG Expected Trades	21.465**	-4.667	16.002**	-5.065	12.235	-11.222	9.554	-13.264
	(9.998)	(16.493)	(8.113)	(12.203)	(7.627)	(11.498)	(7.415)	(11.063)
Conv. Discretionary Trades	-0.020	1.077	0.099	1.623	0.086	2.284	0.043	1.613
	(0.656)	(2.576)	(0.540)	(1.969)	(0.484)	(1.782)	(0.460)	(1.762)
Conv. Expected Trades	-6.496*	-12.053**	-2.125	-0.212	0.281	3.324	1.452	4.595
	(3.706)	(5.573)	(3.246)	(4.889)	(3.056)	(4.558)	(2.866)	(4.379)
Constant	-2.034***	-2.140***	-1.329***	-1.344***	-0.891***	-0.871***	-0.573**	-0.518*
	(0.295)	(0.298)	(0.285)	(0.289)	(0.281)	(0.286)	(0.279)	(0.279)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	142,607	142,739	147,364	147,713	150,807	151,081	153,211	153,486
Pseudo R-squared	0.583	0.586	0.662	0.666	0.708	0.711	0.740	0.743
χ^2-statistic	144.94***	162.14***	159.86***	155.94***	150.02***	140.14***	138.76***	132.98***
Panel E: Winsorize on 2.5-97.5%								
ESG Discretionary Trades	-4.662**	-24.507***	-4.153**	-10.019	-3.714***	-9.805*	-3.950***	-9.241*
	(2.022)	(8.744)	(1.621)	(6.352)	(1.354)	(5.904)	(1.254)	(5.498)
ESG Expected Trades	35.355***	21.967	30.450***	20.587	27.945***	12.145	22.477**	4.997
	(11.032)	(17.893)	(10.065)	(14.193)	(9.534)	(13.643)	(9.419)	(13.364)
Conv. Discretionary Trades	0.073	2.306	-0.008	2.761	0.018	3.277*	0.004	2.463
	(0.699)	(2.506)	(0.574)	(1.990)	(0.545)	(1.954)	(0.544)	(1.944)
Conv. Expected Trades	-8.688**	-12.723**	-3.228	-1.207	-0.458	1.821	1.102	2.849
	(3.503)	(5.030)	(3.175)	(4.688)	(3.104)	(4.460)	(3.009)	(4.009)
Constant	-2.537***	-2.562***	-1.749***	-1.791***	-1.277***	-1.330***	-0.919***	-0.966***
	(0.372)	(0.379)	(0.356)	(0.369)	(0.348)	(0.362)	(0.338)	(0.352)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	161,423	161,423	164,214	164,214	167,338	167,338	169,843	169,843
Pseudo R-squared	0.591	0.591	0.669	0.669	0.714	0.714	0.745	0.745
χ^2-statistic	115.14***	110.60***	112.29***	108.37***	111.63***	111.92***	116.58***	112.18***

Notes: Discretionary trades are defined conform Coval and Stafford (2007) and Huang et al. (2023): Sales after inflows are assumed to be 0; buys after outflows are assumed to be equal to 0. The dependent variable, the (cumulative) number of Environmental and Social Incidents, is measured at t+s, where quarter s $\in \{1, 2, 3, 4\}$. Poisson regressions include firm and year-quarter fixed effects. All continuous control variables are winsorized at the 1 and 99 percentiles. Standard errors are clustered at the firm level. * p¡0.10, ** p¡0.05, *** p¡0.01.

Table 34: Poisson Regressions Results: Controls added one by one on Future Firm Environmental and Social Incidents.

	Dependent variable: (Cumulative) Future Environmental and Social Incidents in t+s								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ESG DiscretTrades	-0.001	-0.001	-0.001	-0.001	-0.002	-0.002	-0.002	-0.002	-0.002
	(-0.502)	(-0.862)	(-0.748)	(-0.857)	(-0.944)	(-1.087)	(-1.057)	(-1.075)	(-1.101)
ESG ExpectedTrades	0.016***	0.013***	0.012***	0.011***	0.010***	0.010***	0.010***	0.011***	0.011***
	(4.195)	(4.054)	(4.044)	(3.805)	(3.691)	(3.538)	(3.452)	(3.884)	(3.826)
conv. DiscretTrades	0.002	0.001	0.001	0.001	0.000	0.000	0.001	0.000	0.000
	(0.674)	(0.242)	(0.530)	(0.252)	(0.177)	(0.100)	(0.242)	(0.095)	(0.081)
conv. ExpectedTrades	-0.007**	-0.009***	-0.010***	-0.010***	-0.009***	-0.009***	-0.009***	-0.008***	-0.008***
	(-2.325)	(-3.007)	(-3.367)	(-3.387)	(-3.231)	(-3.121)	(-3.143)	(-2.620)	(-2.593)
logsize		0.133***	0.230***	0.244***	0.258***	0.251***	0.244***	0.273***	0.276***
		(5.689)	(8.036)	(8.266)	(8.881)	(8.956)	(8.730)	(9.410)	(9.549)
be_me			0.077***	0.080***	0.084***	0.082***	0.078***	0.067***	0.067***
			(7.321)	(7.448)	(7.966)	(7.974)	(7.840)	(6.990)	(7.002)
niq_be				-0.007**	-0.004	-0.005*	-0.004	-0.002	-0.002
				(-2.451)	(-1.449)	(-1.748)	(-1.431)	(-0.864)	(-0.863)
debt_at					0.048***	0.046***	0.041***	0.041***	0.041***
					(4.672)	(4.502)	(4.051)	(4.138)	(4.216)
capx_at						0.009	0.009	0.000	0.001
						(0.944)	(0.892)	(0.054)	(0.063)
rvol_252d							0.018***	0.025***	0.030***
							(2.626)	(3.606)	(4.150)
ret_12_1								-0.031***	-0.032***
								(-6.814)	(-7.025)
beta_252d									-0.008
									(-1.567)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	223,188	223,185	214,633	191,820	191,026	169,462	163,178	161,423	161,423
Pseudo R-squared	0.577	0.577	0.578	0.581	0.581	0.589	0.591	0.591	0.591
χ^2-statistic	26.09***	52.01***	92.33***	95.66***	108.81***	109.87***	104.02***	113.15***	126.44***

Notes: The table reports the relation between ESG and conventional mutual fund trading behavior and future changes in firm-level number of environmental and social RepRisk incidents, measured between quarter t and t+1. Discretionary trades are defined according to Coval and Stafford (2007) and Huang et al. (2023): Sales after inflows are assumed to be 0; buys after outflows are assumed to be equal to 0. Discretionary and expected trades are winsorized at the 0.5 and 99.5%. Controls are added to the model one at a time. All continuous control variables are winsorized at the 1 and 99 percentiles. Poisson regressions include firm and year-quarter fixed effects, and standard errors are clustered at the firm level. Coefficients are standardized and z-statistics are reported in parentheses. * p¡0.10, ** p¡0.05, *** p¡0.01

Table 35: OLS Regression Results: ESG and Conventional Discretionary Trades on Future Stock Returns: omitting MSCI ACWI

	(1) Quarterly Stock Returns in t+1
ESG DiscretTrades	0.002**
	(2.339)
ESG ExpectedTrades	0.002*
	(1.717)
conv. DiscretTrades	-0.002*
	(-1.954)
conv. ExpectedTrades	-0.005***
	(-4.515)
logsize	-0.654***
	(-30.092)
be_me	-0.014**
	(-2.439)
ret_12_1	0.034***
	(15.705)
capx_at	0.001
	(0.234)
beta_252d	-0.022***
	(-4.934)
rvol_252d	0.006
	(1.318)
niq_be	0.015***
	(3.681)
debt_at	-0.003
	(-0.747)
Firm FE	Yes
Year-quarter FE	Yes
Observations	486,327
R-squared	0.173
Within R-squared	0.028
F-statistic	160.69***

Notes: The table reports the relation between ESG and conventional mutual fund trading behavior and future quarterly stock returns. Discretionary trades are defined according to Coval and Stafford (2007) and Huang et al. (2023): Sales after inflows are assumed to be 0; buys after outflows are assumed to be equal to 0. Discretionary and expected trades are winsorized at the 0.5 and 99.5%. All continuous control variables are winsorized at the 1 and 99 percentiles. The dependent variable, future quarterly stock returns, is measured in quarter t+1. OLS regressions include firm and year-quarter fixed effects, and standard errors are clustered at the firm level. Coefficients are standardized and t-statistics are reported in parentheses. * p¡0.10, ** p¡0.05, *** p¡0.01.

Table 36: Predictors of position changes by ESG and conventional mutual funds: one-by-one

Panel A: Sample split for ESG Funds

	Dependent variable: Position Changes						
	(1) Without ESG	(2) MSCI ESG	(3) ΔMSCI ESG	(4) ES incidents	(5) Severe ES incidents	(6) MSCI ESG + ES incidents	(7) MSCI ESG × ES incidents
MSCI ESG		0.0041***				0.0042***	0.0041***
		(7.4449)				(7.4067)	(7.3528)
ΔMSCI ESG			0.0025***				
			(5.2456)				
# ES incidents				-0.0027***		-0.0025***	-0.0032***
				(-2.8221)		(-2.6419)	(-3.2330)
# Severe ES incidents					-0.0029***		
					(-3.9160)		
MSCI ESG × # ES Incidents							0.0046***
							(6.2130)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,152,430	6,144,069	6,105,444	5,661,086	5,661,086	5,655,734	5,655,734
R-squared	0.098	0.098	0.099	0.101	0.101	0.101	0.101
F-statistic	45.86***	43.19***	39.68***	40.79***	41.59***	38.70***	36.05***

Panel B: Sample split for Conventional funds

	Dependent variable: Position Changes						
MSCI ESG		-0.0008***				-0.0009***	-0.0008***
		(-3.6089)				(-3.4860)	(-3.4517)
ΔMSCI ESG			0.0006***				
			(2.9345)				
# ES incidents				-0.0019***		-0.0020***	-0.0020***
				(-3.4110)		(-3.5299)	(-3.5265)
# Severe ES incidents					-0.0016***		
					(-3.8821)		
MSCI ESG × # ES Incidents							0.0004
							(0.9996)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,421,202	20,374,255	20,179,640	17,966,034	17,966,034	17,931,895	17,931,895
R-squared	0.096	0.096	0.097	0.098	0.098	0.098	0.098
F-statistic	54.45***	46.96***	46.07***	47.28***	48.06***	41.67***	37.07***

Notes: OLS regressions on mutual fund (relative) position changes with standard errors are clustered at the fund level. Position Changes is the change in the position of fund i in stock j in quarter t estimated as $\frac{Price_{j,t-1}(NumberShares_{i,j,t}-NumberShares_{i,j,t-1})}{AUM_{i,t-1}}$ (Gantchev et al., 2023; Giannetti and Jotikasthira, 2024). Position Changes is trimmed at the 0.5 and 99.5 percentiles. Industry-weighted MSCI ESG enotes the stock's industry-weighted MSCI ESG score in quarter t. # ES Incidents denotes the number of environmental and social RepRisk incidents in quarter t by firm j. Regressions include fund × year-quarter fixed effects. All lagged continuous control variables are winsorized at the 1 and 99 percentiles. Standard errors are clustered at the fund level. Coefficients are standardized and t-statistics are reported in parentheses. * p¡0.10, ** p¡0.05, *** p¡0.01.

Table 37: Alternative OLS Regression Results on Fund Excess Returns: RPI ESG$_{t-1}$ and RPI ES Incidents$_{t-1}$ separate

	Dependent Variable: Fund Excess Returns in t				
	(1)	(2)	(3)	(4)	(5)
Propensity$_{t-1}$	-0.450	-0.185	-0.588	-0.220	-0.164
	(0.407)	(0.213)	(0.414)	(0.215)	(0.217)
RPI ESG$_{t-1}$	-0.667**	-0.049			-0.062
	(0.327)	(0.140)			(0.142)
RPI ES Incidents$_{t-1}$			0.273	-0.077	-0.085
			(0.265)	(0.114)	(0.114)
logsize$_{t-1}$	-4.710***	-1.476***	-4.728***	-1.457***	-1.464***
	(0.112)	(0.045)	(0.112)	(0.045)	(0.045)
logage$_{t-1}$	-2.136***	0.824***	-2.146***	0.802***	0.812***
	(0.157)	(0.125)	(0.157)	(0.124)	(0.125)
Turnover$_{t-1}$	0.048**	0.015*	0.049**	0.014*	0.014*
	(0.021)	(0.008)	(0.021)	(0.008)	(0.008)
QFlow$_{t-1}$	-0.177	0.118	-0.217	0.090	0.105
	(0.281)	(0.118)	(0.280)	(0.117)	(0.118)
Constant	99.929***	28.582***	100.254***	28.306***	28.394***
	(2.180)	(0.880)	(2.181)	(0.877)	(0.880)
Fund FE	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	No	Yes	No	Yes	Yes
Observations	111,372	111,372	111,668	111,668	110,047
R-squared	0.062	0.855	0.062	0.855	0.855
Within R-squared	0.040	0.020	0.040	0.019	0.020
F-statistic	363.48***	187.23***	367.38***	183.62***	158.24***

Notes: The table reports the relation between the RPI (Reliance on Public Information) ratio, propensity to invest on future ES risks, and fund excess return. For each fund in each quarter, we calculate the difference between the quarterly fund return and the risk-free rate. Our propensity measure is defined as per Fang et al. (2014) and Chen et al. (2024) on discretionary ownership and is standardized. Standardized propensity scores are trimmed on the 0.5 and 99.5 percentiles. In a similar fashion to Kacperczyk and Seru (2007), we proxy for usage of public ESG information: RPI ESG is defined by the R^2 of a pooled OLS regression of fund holdings changes on changes in the MSCI ESG ratings during 4 lags. RPI ES Incidents is defined by the R^2 of a pooled OLS regression of holdings changes on ES incidents during 4 lags. Values of RPI are bound between 0.01% and 99.9%. Fund portfolio turnover is trimmed at the 0.5 and 99.5 percentiles. All other continuous control variables are winsorized at the 1 and 99 percentiles. Standard errors are clustered at the fund level and are reported in parentheses. * p¡0.10, ** p¡0.05, *** p¡0.01.

Table 38: Alternative OLS Regression Results on Fund Risk-Adjusted Returns: RPI ESG$_{t-1}$ and RPI ES Incidents$_{t-1}$ separate

	Dependent Variable: Risk-Adjusted Fund Returns in t							
	Fama-French 3-Factors α				Carhart 4-Factors α			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Propensity$_{t-1}$	0.004	0.004	0.006	0.007	0.001	0.002	0.002	0.005
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.021)	(0.020)
RPI ESG$_{t-1}$	0.021**	0.004			0.005	-0.013		
	(0.009)	(0.009)			(0.010)	(0.009)		
RPI ES Incidents$_{t-1}$			-0.008	-0.005			-0.008	-0.004
			(0.007)	(0.007)			(0.008)	(0.007)
logsize$_{t-1}$	0.051***	0.057***	0.050***	0.056***	0.065***	0.070***	0.064***	0.068***
	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
logage$_{t-1}$	0.050***	-0.035	0.050***	-0.030	-0.040***	-0.049**	-0.040***	-0.045**
	(0.012)	(0.021)	(0.012)	(0.021)	(0.012)	(0.022)	(0.012)	(0.021)
Turnover$_{t-1}$	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.003***	-0.002***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
QFlow$_{t-1}$	0.161***	0.157***	0.159***	0.155***	0.159***	0.156***	0.156***	0.154***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Constant	-1.253***	-1.141***	-1.226***	-1.130***	-1.281***	-1.343***	-1.262***	-1.336***
	(0.091)	(0.105)	(0.089)	(0.104)	(0.092)	(0.107)	(0.091)	(0.105)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	107,677	107,677	107,931	107,931	107,677	107,677	107,931	107,931
R-squared	0.561	0.583	0.561	0.582	0.533	0.565	0.533	0.564
Within R-squared	0.018	0.018	0.018	0.018	0.020	0.022	0.020	0.021
F-statistic	63.42***	64.17***	61.65***	63.03***	71.21***	73.28***	69.68***	71.28***

Notes: The table reports the relation between the RPI (Reliance on Public Information) ratio, propensity to invest on future ES risks, and fund risk-adjusted return. For each fund in each quarter, Fama-French three-factor returns (columns 1-4) are calculated using fund returns of the past 36 months. Quarterly Carhart's 4-factor returns (columns 5-8) are calculated using fund returns of the past 36 months. We denominate quarterly risk-adjusted returns in basis points per month. Our propensity measure is defined as per Fang et al. (2014) and Chen et al. (2024) on discretionary ownership and is standardized. Standardized propensity scores are trimmed on the 0.5 and 99.5 percentiles. In a similar fashion to Kacperczyk and Seru (2007), we proxy for usage of public ESG information: RPI ESG is defined by the R^2 of a pooled OLS regression of fund holdings changes on changes in the MSCI ESG ratings during 4 lags. RPI ES Incidents is defined by the R^2 of a pooled OLS regression of holdings changes on ES incidents during 4 lags. Values of RPI are bound between 0.01% and 99.9%. Fund portfolio turnover is trimmed at the 0.5 and 99.5 percentiles. All other continuous control variables are winsorized at the 1 and 99 percentiles. Standard errors are clustered at the fund level and are reported in parentheses. * p¡0.10, ** p¡0.05, *** p¡0.01.