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Truth or Dare? ESG Risk Disclosure of Mutual Funds

Liying Wang*

Abstract

This paper investigates ESG risk disclosures by mutual funds when investors learn from their disclosures in addition to past performance. Using a novel natural language processing method to identify ESG-risk disclosure in mutual fund prospectuses, I find that funds with higher ESG risk are more likely to disclose ESG risk than equivalent funds with lower ESG risk. To understand this, I develop a theoretical model which illustrates how ESG risk disclosure reduces investor reliance on past returns, thereby moderating flow performance sensitivity and smoothing fund fee income. I also show that the key predictions of the model hold in practice when I empirically test the model using U.S. mutual fund data. My results suggest that ESG risk disclosure can be used for risk management purposes to mitigate the adverse effects of high ESG risk exposure.

Key words: ESG, Mutual Fund, Natural Language Processing, Risk Disclosure

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"Perhaps one of the most important recent global trends is the growing interest in environmental, social and governance (ESG) matters."

–Investment Company Institute (ICI), 2021 Investment Company Fact Book[1]

1 Introduction

There has been surging interest in environmental, social and governance (ESG) investing in the recent years.[2] For example, more than eight in ten US individual investors (85%) now express interest in sustainable investing.[3] In response to this growing investor interest in ESG investing, many mutual fund families have increased their ESG-related information disclosures. However, these increased disclosures have sparked substantial controversy. Many have expressed concern that these disclosures are largely useless to investors and that these simply reflect fund families jumping on the ESG investment bandwagon.[4] For example, the Sustainability Accounting Standards Board (SASB) states that most sustainability disclosures consist of boilerplate language, which is largely useless to investors.

This paper contributes to the understanding of the value of ESG-related disclosures of mutual funds in their prospectuses.[5] It first constructs a model that illustrates the optimal ESG disclosure policy of mutual funds in an environment where fund investors are concerned about both fund performance and ESG-related outcomes. The model shows that by disclosing ESG risks, funds can reduce the flow-performance sensitivity of fund investors and therefore maintain fund fee income by reducing outflows at times of poor performance. Con-

[1] Investment Company Institute, "2021 Investment Company Fact Book". Available at: https://www.ici.org/doc-server/pdf%3A2021_factbook.pdf.

[2] Santander Asset Management, "Why Do People Invest in ESG Funds?". Available at: https://www.santanderassetmanagement.com/individual-investor.

[3] Institute for Sustainable Investing, Morgan Stanley, https://www.morganstanley.com/content/dam/msdotcom/infographics/sustainable-investing/Sustainable_Signals_Individual_Investor_White_Paper_Final.pdf.

[4] Many investors and industry advisors express concerns about the quality and effectiveness of sustainability reporting, e.g., https://rollcall.com/2022/08/18/esg-fund-disclosures-should-be-streamlined-investor-and-advocacy-groups-tell-sec/ and https://www.pwc.com/gx/en/corporate-reporting/assets/pwc-global-investor-survey-2021.pdf.

[5] Mutual funds use a document called a prospectus, which is required by the Securities Exchange Commission (SEC), to disclose important information.

sequently, funds with higher ESG risks are more motivated to disclose such risks to reduce the adverse impact of ESG shocks. When I confront this model with the data I find that this prediction is borne out in practice, as are a number of other predictions of the model which help to explain the level of ESG-related disclosures that we see in practice. By examining the interplay between investor learning and the optimal risk disclosure decisions of mutual fund managers, I ultimately answer the long-lasting question regarding whether ESG-related disclosures reflect a fund's actual ESG risks or not. This paper demonstrates that ESG risk disclosure is closely related to actual ESG risk, which differs from the literature showing that fund risk disclosure is irrelevant to actual risk.[6]

Existing work has studied ESG disclosure by looking at fund names or considering whether fund companies have signed up to the Principles for Responsible Investment (PRI) (e.g., Curtis, Fisch and Robertson (2021); Gibson, Glossner, Krueger, Matos and Steffen (2021)). This paper is the first to look at ESG disclosure by directly identifying ESG information released in fund prospectuses. Furthermore, this paper is the first to focus on ESG risk disclosure.

This paper addresses the gap in the literature on how ESG-related disclosure and actual ESG risk are related, and sheds further light on whether ESG disclosure is informative or not. My model contributes to the understanding of the underlying mechanism by illustrating the interaction between investor learning and the optimal disclosure strategy of mutual funds. The model, based on the baseline of Berk and Green (2004), assumes that both ESG and managerial skills are factors affecting fund abnormal returns. First, I analyse how fund ESG risk disclosure affects investors' investment decisions through modelling investors' learning process. I find that ESG risk disclosure reduces the sensitivity of fund flows to fund past returns, indicating that investors are less reliant on fund performance when investing. This is due to the fact that ESG risk disclosure reduces investor uncertainty about the fund's prior information. Additionally, as investors update their beliefs, the prior information and the new information (realised performance) become substitutes when investors update their beliefs, meaning that if investors have a greater sense of certainty about the fund, they will be less dependent on fund performance.

Taking the impact of ESG risk disclosures on fund flows into account, I then examine

[6] For example, Sheng, Xu and Zheng (2021) discover that over-disclosure of mutual funds, i.e., funds tend to disclose more risks than they actually have; Krakow and Schäfer (2020) reveal that mutual fund risk disclosure rarely contains fund-specific information.

how mutual fund managers choose their optimal level of ESG risk disclosure. I find that, in the equilibrium, funds with higher actual ESG risk are more likely to disclose ESG risk. The intuition behind this is as follows: a fund with high ESG risk has a portfolio that is more vulnerable to ESG incidents, therefore, if investors are overly sensitive to the past performance of the fund, the fund may suffer significant outflows and high volatility of fund flows. Thus the funds with high ESG risk are more motivated to attenuate the flow-performance sensitivity by disclosing more ESG risk.

Based on the baseline results that the fund ESG risk disclosure is in line with the fund actual ESG risk in the theoretical model, I further investigate the cross-sectional impact of fund characteristics on the positive relationship between ESG risk disclosure and actual ESG risk, where the characteristics include fund fees, fund investment ability, and investor sophistication. I obtain three findings. (i)"*Fee dampening effect*. High fees of funds dampen the positive relationship between ESG risk disclosure and actual ESG risk. (ii)"*Investment ability intensifying effect*". Highinvestment ability of funds intensifies the dependency of optimal disclosure decisions on the fund's actual ESG risk. (iii) "*Investor sophistication intensifying effect*". High investor sophistication intensifies the positive relationship between fund ESG risk disclosure and actual ESG risk.

My findings above are supported by empirical results. I first identify ESG risks from mutual fund prospectuses. It is a challenging task as the descriptions of ESG-related risks are not described in a standardised manner, unlike the other recognised risk types such as market risk, credit risk, and interest rate risk.[7] For example, more than 60% of the funds in my sample directly mention the phrase "market risk" in the principal risk section. However, funds rarely use phrases like "ESG risk" or "environmental risk" directly to describe the ESG-related risks. To solve this problem and accurately detect the ESG-related descriptions, in this paper, I employ the cutting-edge natural language processing (NLP) technique, *Bidirectional Encoder Representations from Transformers* (BERT), to analyse two separate sections in mutual fund prospectuses: the principal strategies section and the principal risks section, and thus identify the ESG-strategy and ESG-risk descriptions, respectively.[8] The

[7]SEC lists some common risk types of mutual funds, e.g., market risk, business or issuer risk, credit risk, interest rate risk, inflation risk, and concentration risk, but there are no standardised descriptions of ESG-related risks.

[8]In a mutual fund prospectus, there are two separate sections: the principal strategies of investing and the principal risks of investing. The former indicates the approach taken by the fund's adviser in deciding which securities to buy or sell, and the latter provides a comprehensive risk profile of the fund's portfolio. I

deep learning-based techniques overcome the shortages of a traditional keyword-based approach and improve the accuracy of identification. My study shows that, from 2011 to 2019, the percentage of funds with ESG strategy descriptions increased from 10.55% to 19.52%, and the percentage of funds with ESG risk descriptions increased from 5.56% to 38.36%, respectively. More funds are inclined to disclose ESG-related information in their prospectuses, especially the ESG risks. I further empirically investigate whether the ESG risk disclosure is a true representation of risk, or simply the result of funds daring to disclose.

I then measure the actual ESG risk levels of mutual funds' holdings using the RepRisk Index (RRI), which is sourced from the RepRisk platform.[9] Calculations of RRI are based on the negative news about a company's ESG activities, which is independent of the company's self-reporting. I use the holding value-weighted average of RRI as a measure of the fund's actual ESG risk. Apart from ESG risk disclosures, I also examine the funds with ESG strategy disclosure, and find ESG strategy disclosures imply a low actual ESG risk in the portfolio. A further interesting point to note is that when ESG strategies are present, funds with ESG risk disclosures tend to have lower risks than those without, and even lower risks than funds with only ESG strategy disclosures. The results demonstrate that the information contents of ESG risk disclosures differ between cases that disclose ESG strategies and those that do not. Without ESG strategy disclosures, ESG risk disclosures reflect high-risk funds' motivation to mitigate the adverse effects of ESG events. However, in the case that a fund discloses the ESG strategies, the ESG risk disclosures signal both the fund's capability to identify ESG risks, as well as its determination to control them at a substantial level. Therefore, ESG risk disclosures always accompany low actual risk when ESG strategy disclosures are present. The results are consistent with the signalling theory (e.g., Spence (1973); Ross (1977); Morris (1987)), i.e., funds that adopt ESG strategies wish to signal their intention to reduce ESG risks by disclosing them.

Finally, I examine whether ESG risk disclosures reflect mutual fund managers' attention to ESG incidents and risk management abilities. I find that, after March 2016, when the introduction of the industry's first Sustainability Rating by Morningstar,[10] funds with ESG

detect the ESG investment strategies and the risks of ESG issues respectively from the strategy section and risk section, respectively.

[9] RepRisk systematically flags and monitors material ESG risks and violations of international standards that can have reputational, compliance, and financial impacts on a company. For details, see section 3.2.

[10] Morningstar is an American financial services firm that provides data and analytics to help professional investment managers craft new products and portfolios. Leveraging Sustainalytics' ESG Risk Ratings, the

risk disclosures tended to sell the stocks after ESG incidents occur. However, before March 2016, the funds with ESG disclosures did not actively sell the stocks with ESG incidents due to relatively low investor attention to ESG issues. The findings are consistent with the stakeholder theory, which explains the influence of stakeholders in companies' decisions and the role of management in order to achieve the exact level of stakeholder demand (e.g., Freeman, Harrison, Wicks, Parmar and Colle (2010)). In this study, the introduction of sustainability ratings encourages investors to consider ESG factors when investing in funds, and thus forces funds with risk disclosure to actively manage ESG risk after March 2016.

1.1 Literature Review

This paper contributes to four strands of the literature including mutual fund investor learning, qualitative risk disclosure, textual analysis, and ESG investing.

First, this paper builds on the investor learning literature. Prior works show that fund flows respond to fund performance (e.g., Ippolito (1992); Chevalier and Ellison (1997); Sirri and Tufano (1998)). On this basis, Lynch and Musto (2003) and Huang, Wei and Yan (2007) further explain the shape of flow–performance based on the premise that investors learn about the managerial ability from a fund's past performance. To interpret the flow-performance relationship, Berk and Green (2004) introduce a competitive capital market model. In their model, the fund's recent performance is regarded as a new noisy signal of skill against prior information, based on which the investors do rational Bayesian learning about unobserved fund manager skills. Under the mechanism of investor learning, the model has predictions consistent with the observed phenomenon of a positive flow-performance relationship. Also, from the perspective of investor learning, Huang, Wei and Yan (2021) explain why more volatile fund past returns lead to a weaker flow-performance sensitivity; furthermore, Abis, Buffa, Javadekar and Lines (2021) demonstrate that the funds with specialised strategies optimally choose to disclose detailed strategy descriptions by endogenizing the optimal disclosure decision of funds. This paper contributes to this stream of literature by showing how ESG risk disclosure will influence fund flows under the mechanism of investor learning.

The second area this paper contributes to is qualitative risk disclosure. There are competing arguments about how risk disclosures affect users' risk perceptions. One is that risk

Morningstar Sustainability Rating for Funds provides a snapshot of how well ESG risk is managed at a fund level relative to its peer group.

disclosure is by and large boilerplate and is not likely to be informative (e.g., Schrand and Elliott (1998)). The alternative is that risk disclosure is informative and affects risk perception. For example, as a convergence argument, if the risk disclosure is about a known risk factor, disclosure decreases the user's risk perception (e.g., Rajgopal (1999); Linsmeier, Thornton, Venkatachalam and Welker (2002)). Following on, as a divergence argument, if the risk disclosure is about an unknown risk factor, disclosure increases the user's risk perception (e.g., Kravet and Muslu (2013)). Bao and Datta (2014) demonstrate that the way risk disclosures affect the risk perceptions of investors depends on the specific risk types disclosed and provides support for all three competing arguments presented above. However, there is a lack of evidence about how fund disclosures of ESG risks affect investors' perceived risks. My paper fills this gap by demonstrating that fund ESG disclosure reduces investors' risk perceptions and attenuates the flow-performance relationship.

Furthermore, my paper adds to the literature of textual analysis on risk disclosure. Li (2006) measures the risk sentiment of annual reports by counting the frequency of words related to risk or uncertainty in the 10-K filings. Sheng et al. (2021) adopt a dictionary-based method to capture fund risk disclosures by extracting the phrases that contain the keywords like "risk" and categorise risks according to their meaning. Hassan, Hollander, van Lent and Tahoun (2019) focus on the specific risk type, i.e., political risk. Rather than a priori deciding on specific words associated with different topics, they distinguish political from non-political topics using a pattern-based sequence classification method developed in computational linguistics. This method is superior to the traditional dictionary-based approach by reducing the reliance on the dictionary. In this paper, I adopt an attention-based method (e.g., Vaswani, Shazeer, Parmar, Uszkoreit, Jones, Gomez, Kaiser and Polosukhin (2017)) instead of relying on a specific word list (e.g., Loughran and Mcdonald (2011); Manela and Moreira (2017); Fisher, Martineau and Sheng (2022)) to identify the ESG-related descriptions in the mutual fund prospectuses, which can effectively avoid semantic confusion.

Finally, this paper contributes to the literature on fund ESG investing. The debate on ESG investing literature focuses on whether funds actually make ESG investments as they promise to do. Candelon, Hasse and Lajaunie (2021) find that a large amount of Socially Responsible Investing (SRI) funds have low SRI scores, and conventional funds still present very high SRI scores, showing that the name and certification of a given fund are not necessarily linked to the investment strategy of the mutual fund managers. Gibson et al.

(2021) do not find better ESG scores in the portfolios of the US mutual funds that sign the internationally-recognised Principles for Responsible Investment (PRI), which shows a substantial disconnection between what institutional investors claim to do and what they really do. Andrikogiannopoulou, Krueger, Mitali and Papakonstantinou (2022) find the evidence of "Greenwashing"[11] in funds and further noted that investors are unable to distinguish between Greenwashing and genuinely green funds. However, Curtis et al. (2021) have a different conclusion where they believe that ESG funds generally offer investors a differentiated and competitive investment product that is consistent with their labelling which is represented by the name. In this paper, I identify ESG funds directly from the contents of their prospectuses, not just limiting to funds with PRI signatories, or having names related to ESG.

The remainder of the paper is organised as follows: Section 2 describes the model and its equilibrium predictions; Section 3 describes the data and methodology to identify ESG-related disclosure; Section 4 lays out the empirical results; and Section 5 concludes.

2 A Model of ESG Risk Disclosure Choice

In this section, I propose an investor learning model to illustrate the mechanisms of how mutual funds optimally choose to disclose their ESG risk in prospectuses.

2.1 Model Setting

In the study of fund active management, Berk and Green (2004) present a model with symmetric information, investor learning, and diminishing returns in relation to fund size. I assume that asymmetric information about the ESG risk between fund managers and fund investors exists, which is different from Berk and Green (2004). Based on this assumption, I study how fund managers optimise their disclosure so that they can maximise the expected utility of the management fees that they charge from investors. This model considers an economy where investors provide competitive capital to mutual funds. Moreover, in such an economy, funds vary in their ESG risks and the abilities to generate returns that exceed

[11] Greenwashing is the process of conveying a false impression or providing misleading information about how a company's products are more environmentally sound.

passive benchmarks. To simplify the model without losing intuition, the source of managers' ability and fund ESG risk are not endogenized in this model.

Funds. I model the excess return (net of fees) of fund i at time t as follows,

$$r_{i,t} = \alpha_i + e_i + \epsilon_{i,t} - C(q_{i,t-1}) - f, \tag{1}$$

where α_i is the fund manager's ability, which is unobservable to fund investors, but known to the mutual fund manager, e_i is the return associated with ESG factor, $\epsilon_{i,t}$ is the fund's idiosyncratic risk that is independently distributed over time with a normal distribution, i.e., $\epsilon_{i,t} \sim N(0, \sigma_\epsilon^2)$, f denotes the management fees per dollar and $C(q)$ captures the decreasing returns to scale as a function of fund size q. Specifically, I assume $C(q) = cq$, where $c > 0$ as the assumption in Berk and Green (2004).

Investors. The mutual fund investors do not directly observe the manager's ability α_i and ESG-related return e_i. They only have prior information about α_i and e_i,

$$\alpha_i \sim N(\bar{\alpha}, \sigma_\alpha^2), \quad e_i \sim N(\bar{e}, \sigma_{esg}^2), \tag{2}$$

where the investors' prior on the manager's ability α_i is normal distributed with mean $\bar{\alpha}$ and variance σ_α^2, and the investors' prior information on ESG factor e_i is normally distributed with mean $\bar{e}$ and variance σ_{esg}^2. In particular, σ_{esg}^2 represents investors' uncertainty about ESG, which is affected by the ESG disclosure of mutual funds. For example, if mutual funds disclose the ESG information in the principal risk section, such as providing details about the environmental issues, σ_{esg}^2 is low. Otherwise, if funds do not disclose any ESG information, investors will be more uncertain about the ESG issues, and thus σ_{esg}^2 is high.

Fund Managers. There exists information asymmetry between fund managers and investors. The fund managers of fund i have private information about the investment ability α_i. Moreover, besides the prior belief about the return related to ESG issues e_i that is normally distributed with mean $\bar{e}$ and variance σ_e^2, fund managers also have a private signal s_i about the ESG-related return. The signal s_i is assumed to have an error term from the actual ESG factor: $s_i = e_i + \eta_i$, where $\eta_i \sim N(0, \epsilon_\eta^2)$. The signal shows the portfolio's actual ESG risk. For instance, a lower signal s_i indicates that the fund is likely to encounter ESG events and suffer losses due to ESG issues, indicating a high actual ESG risk. Conversely, a higher s_i implies that the portfolio is relatively safe and has a low probability of being exposed to ESG issues, indicating a low actual ESG risk.

Timeline. In the model, I assume there are three dates, $t = 0, 1, 2$, and 3.

- At $t = 0$, fund i gets the signal s_i, and then makes the disclosure decision that determines the level of σ^2_{esg};
- At $t = 1$, investors allocate their initial dollar holding $q_{i,1}$ to the fund i;
- At $t = 2$, excess return $r_{i,2}$ is realised. After observing $r_{i,2}$, fund investors update their belief about the return in the next period, and reallocate their capital $q_{i,2}$;
- At $t = 3$, fund returns $r_{i,3}$ are realised, and funds are liquidated.

2.2 Equilibrium

In this model, investors' asset reallocation $q_{i,1}$, $q_{i,2}$ and funds' choice of ESG risk disclosure σ^2_{esg} are endogenous. How the optimal disclosure choice is determined in equilibrium is then described. I assume the investors are risk neutral in a competitive market. As in equilibrium, investors who choose to invest in actively managed funds cannot expect to receive positive excess returns on a risk-adjusted basis, thus the size of the fund is determined as follows:

$$\mathbb{E}_t[r_{i,t+1} \mid G_i] = 0, \tag{3}$$

where $r_{i,t+1}$ is defined in equation (1) and G_i is the information set of investors at the time t including $r_{i,t}$ and prior belief. Therefore, the fund size at equilibrium is,

$$q_{i,t} = \frac{\hat{\alpha}_{i,t} + \hat{e}_{i,t} - f}{c}, \tag{4}$$

where $\hat{\alpha}_{i,t} + \hat{e}_{i,t} \equiv \mathbb{E}_t[\alpha_i + e_i \mid G_i]$ is the conditional expectation of investors about the sum of managerial skills and ESG factor. The fund flows can be written as $\text{Flows}_{i,t} = \frac{q_{i,t} - q_{i,t-1}}{q_{i,t-1}}$.

Continuing on, I illustrate how mutual funds choose the optimal disclosure at time 0. Mutual fund managers take into consideration how investors learn from a fund's past performance at time 2. Based on the learning process of investors, fund managers determine σ^2_{esg} given their private information about investment skills and ESG factor. Specifically, the optimal σ^2_{esg} is achieved through ESG disclosure by mutual funds in order to maximise the expected utility of the total management fees charged to investors. Since the initial fund size, $q_{i,1}$, is unrelated to σ^2_{esg}, I only consider the expected utility of management fees charged at time 2 in the optimisation function, which is written as,

$$\sigma^2_{esg} = \underbrace{\arg\max}_{\sigma^2_{esg} \geqslant \sigma^2_s} \mathbb{E}_{i,0}\left[v_i(q_{i,2} f) \mid \alpha_i, s_i\right], \tag{5}$$

where $v_i(\cdot)$ denotes the utility function of mutual funds, which takes the form of mean-variance preference with the coefficient of risk aversion normalised to 1.

Investor Learning. At time 2, the investors form their posterior expectation of the fund manager's ability and the ESG factor through Bayesian updating. That is, after observing the return $r_{i,2}$, the posterior expectation of $\alpha_i + e_i$ is,[12]

$$\mathbb{E}_{i,2}\left[\alpha_i + e_i \mid r_{i,2}\right] = \frac{\sigma_\epsilon^2}{\sigma_\alpha^2 + \sigma_{esg}^2 + \sigma_\epsilon^2}(\bar{\alpha} + \bar{e}) + \frac{\sigma_\alpha^2 + \sigma_{esg}^2}{\sigma_\alpha^2 + \sigma_{esg}^2 + \sigma_\epsilon^2}(r_{i,2} + cq_{i,1} + f). \tag{6}$$

Then I examine how the fund sizes at time 1 and 2 are determined based on the equilibrium condition shown in equation 4. As the initial capital allocation of investors to fund i is only based on their prior belief, the dollar holdings of fund i at time 1 are as follows:

$$q_{i,1} = \frac{\bar{\alpha} + \bar{e} - f}{c}. \tag{7}$$

Substituting equations 6 and 7 into equation (4), I have the dollar holdings of fund i at time 2 as follows,

$$q_{i,2} = \frac{\bar{\alpha} + \bar{e}}{c} + \frac{\sigma_\alpha^2 + \sigma_{esg}^2}{\sigma_\alpha^2 + \sigma_{esg}^2 + \sigma_\epsilon^2}\frac{r_{i,2}}{c} - \frac{f}{c}. \tag{8}$$

The fund flows at time 2 are represented as,

$$\text{Flows}_{i,2} = \frac{\sigma_0^2 + \sigma_{esg}^2}{\sigma_0^2 + \sigma_{esg}^2 + \sigma_\epsilon^2}\frac{r_2}{\alpha_0 + e_0 - f}. \tag{9}$$

Choice of Risk Disclosure. Given the way how investors update their information and reallocate their portfolio at time 2, mutual fund managers choose the optimal risk disclosure σ_{esg}^2 at time 0 to maximise the expected utility. equation (5) can be written as,

$$\sigma_{esg}^2 = \underbrace{\arg\max}_{\sigma_{esg}^2 \geqslant \sigma_s^2} \mathbb{E}_{i,0}\left[\left(\mathbb{E}_{i,2}\left[\alpha_i + e_i \mid r_{i,2}\right] - f\right) \mid \alpha_i, s_i\right] - \frac{f}{2c}\mathbb{V}\text{ar}_{i,0}\left[\left(\mathbb{E}_{i,2}\left[\alpha_i + e_i \mid r_{i,2}\right] - f\right) \mid \alpha_i, s_i\right]. \tag{10}$$

The mutual fund managers form their posterior expectation and variance of the ESG factor through Bayesian updating. The posterior ESG factor is expressed by,[13]

$$\hat{e}_i = e_i \mid s_i \sim N(e_s, \sigma_s^2), \tag{11}$$

[12] The proof is provided in Appendix A.1.

[13] This proof is provided in Appendix A.2.

where

$$e_s = \frac{\sigma_\eta^2 \bar{e} + \sigma_e^2 s_i}{\sigma_\eta^2 + \sigma_e^2}, \quad \sigma_s^2 = \frac{\sigma_\eta^2 \sigma_e^2}{\sigma_\eta^2 + \sigma_e^2}. \tag{12}$$

In the above expressions, e_s and σ_s^2 represent the posterior mean and variance of the ESG factor, respectively. Compared to investors, mutual fund managers always possess superior information about ESG risks associated with their portfolios. A low signal s_i shows that the fund manager anticipates the ESG incidents possibly leading to losses. However, a high signal s_i indicates that the mutual fund's portfolio is relatively safe. Based on my model, I have the following propositions (all the proofs are provided in Appendix A).

In the Proposition 1, I use $\text{Sensitivity}_{i,t}$ to denote the sensitivity of fund flows to fund past performance $r_{i,2}$, i.e., $\text{Sensitivity}_i \equiv \frac{\partial \text{Flows}_{i,2}}{\partial r_{i,2}}$.

Proposition 1 *(flow-performance sensitivity): The flow-performance sensitivity increases with the investor uncertainty about the ESG factor:* $\frac{\partial Sensitivity_i}{\partial \sigma_{esg}^2} > 0$.

According to this proposition, the higher the uncertainty of investors about the ESG factor, the greater the flow-performance sensitivity. This proposition implies the impact of ESG risk disclosure on investor behaviour. ESG disclosure changes the way how investors update their information about the funds at time 2, making investors put more weight on the fund's prior information rather than the new signal, i.e., the fund's realised return from time 1 to time 2. As a result, investors will be less responsive to the fund past performance. Based on this Proposition, funds with a greater level of ESG disclosure are expected to exhibit a weaker relationship between flows and performance in practice.

Proposition 2 *(risk disclosure choice): There exists a lower bound* $\underline{s}$ *and an upper bound* $\bar{s}$ *on the fund's private signal* s_i*. When* $s_i \leqslant \underline{s}$*, the fund optimally chooses to disclose as much ESG risk as possible to reduce* σ_{esg}^2*; when* $s_i \geqslant \bar{s}$*, the fund optimally chooses not to disclose ESG risk to increase* σ_{esg}^2*; when* $s_i \in (\underline{s}, \bar{s})$*, there is a unique optimal* σ_{esg}^2 *to maximise the expected utility, and* $\frac{\partial \sigma_{esg}^2}{\partial s_i}$ *is positive in equilibrium.*

According to this proposition, the optimal level of σ_{esg}^2 increases as the ESG signal s_i increases. For example, if fund i receives a higher signal s_i, indicating that the fund is less likely to experience ESG incidents and suffer sudden incidents, then the fund preferably chooses not to disclose ESG risk or to disclose as little as possible. This makes fund investors less certain about the ESG factor and tend to rely more on the realised returns to update their beliefs, as Proposition 1 shows. Accordingly, investors trade more aggressively on the fund's performance which is less likely to suffer from sudden incidents. In contrast, if the fund's private signal is low which implies the portfolio is expected to be affected by ESG incidents, then the funds choose to disclose ESG information to reduce the sensitivity of the fund flows to returns and to prevent significant outflows as a result of ESG negative events. Proposition 2 illustrates the mechanism that ESG disclosure can change the investors' trading intensity on a fund's past performance and thus help the fund to maximise the total expected utility. Furthermore, I have two further propositions to present the cross-sectional effects of fund characteristics on the positive relationship between optimal σ^2_{esg} and the ESG signal s_i.

Proposition 3 *(fund fee dampening effect): The cross derivative of the optimal* σ^2_{esg} *to* s_i *and* f *is:*

$$\frac{\partial^2 \sigma^2_{esg}}{\partial s_i \partial f} < 0 \tag{13}$$

when $s_i \in (\underline{s}, \bar{s})$.

This proposition suggests that fund fees weaken the positive relationship between the optimal σ^2_{esg} and ESG signal s_i.This is because high fund fees increase the uncertainty in the overall management fees charged by the fund. In other words, the higher the fund fees, the greater the variance of the total revenue in the funds. As mutual funds are risk averse, the increase in the expected total management fees, by changing the investor trading intensity through strategic disclosure, is likely to be offset by the increase in the variance of total revenue. Therefore, when fund fees are high, the marginal utility of adjusting the optimal level of disclosure based on the actual ESG risk is small. This explains why the high-fee funds are less likely to make disclosure decisions depending on their actual ESG exposure. Thus the relationship between ESG disclosure and actual ESG risk is weaker in high-fee funds compared to low-fee funds.

Proposition 4 *(investment ability intensifying effect): The cross derivative of the optimal* σ^2_{esg} *to* s_i *and* α_i *is:*

$$\frac{\partial^2 \sigma^2_{esg}}{\partial s_i \partial \alpha_i} > 0 \tag{14}$$

when $s_i \in (\underline{s}, \bar{s})$.

This proposition shows that fund investment ability intensifies the link between the optimal σ^2_{esg} and the signal s_i. High investment ability and low ESG risk (high signal s_i) are complementary in forming a good posterior expectation of funds about their performance, and in affecting the expected overall management fees charged by them. Therefore, high investment ability increases the marginal utility of funds to adjust flow-performance relationship through implementing strategic disclosure based on their actual ESG risk. Specifically, if a fund has more confidence in its investment ability, the disclosure decision is more likely to be shaped by the actual ESG risks. Conversely, if a fund has low investment ability, its disclosure decision will be less affected by ESG concerns. I hypothesise that the relationship between ESG disclosure and actual ESG risk in the fund is more significant among funds with greater investment ability in practice.

In summary, my model formally shows how mutual funds optimally choose to disclose ESG risk. If a fund expects that it is more likely to suffer from ESG incidents, it will optimally choose to disclose ESG information to a greater extent. Disclosure reduces investors' uncertainty regarding fund priors, thus increasing their reliance on the fund priors rather than recent past returns when updating their beliefs about the fund. In this way, disclosure attenuates the flow-performance sensitivity in order to minimise the impact of shocks on fund size. In addition, the model also illustrates the cross-sectional effects of fund fees and fund investment ability on the relationship between ESG disclosure and the actual ESG risk of a fund respectively. Specifically, high fund fees and low fund investment ability reduce the dependence of ESG disclosure on the actual ESG risk.

3 Data and Methodology

3.1 Mutual Fund Data

I obtain the mutual fund prospectuses from the SEC's "Mutual Fund Prospectus Risk/Return Summary Data Sets" that covers 2011 to 2019. The data are updated quarterly, and are extracted from mutual fund prospectuses tagged in eXtensible Business Reporting Language (XBRL). I extract the "Principal Strategies" and "Principal Risks" sections separately from the original data files. If a fund does not update its prospectus in one quarter, the prior quarter prospectus is treated as the most recent version. The texts are then pre-processed by removing html code and numbers.

The prospectus data and the Centre for Research in Security Prices (CRSP) Survivor Bias-Free Mutual Fund Database are matched. To identify domestic diversified actively managed equity funds, I select funds whose Lipper Classification Code is one of the following: EIEI, LCCE, LCGE, LCVE, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, SCVE.[14] I then eliminate index and ETF funds using the CRSP flags. The fund age is computed as the month-end relative to the fund's first offer date. I obtain fund returns, expenses, total net assets (TNA), asset classification, and other fund characteristics from CRSP. Most funds have multiple share classes, which are assigned the same asset portfolios but differ in fee structures. I combine all the share classes of a fund and aggregate them into one fund. The sum of the TNAs of all the share classes is taken, and the age of the fund is calculated as the age of the oldest share class. For the other characteristics, I use the TNA-weighted average across all the share classes. The fund cashflows are calculated on a quarterly basis. Following the majority of the related literature, e.g., Huang et al. (2007), Keswani and Stolin (2008), the cashflows for fund i in quarter t is the percentage growth of the net increase in total net assets (TNA):

$$Flows_{it} = \frac{TNA_{it} - (1 + R_{it})TNA_{i,t-1}}{TNA_{i,t-1}}, \tag{15}$$

where TNA_{it} is fund i's total TNA at the end of quarter t, R_{it} is fund i's net return in quarter t, and equation (15) assumes fund flows occur at the end of each quarter.

I link the sample of mutual funds to the Thomson Financial Mutual Fund Holdings database using MFLINKS files from the Wharton Research Data Services. I exclude funds with investment objective codes (IOC) of 1, 5, 6 and 7: International, Municipal Bonds, Bond & Preferred, and Balanced.

3.2 Fund Actual ESG Risk Measure

The ESG risk data are from the database RepRisk. Unlike other ESG databases that provide ESG ratings (e.g., the MSCI ESG KLD STATS),[15] RepRisk takes an outside-in approach to access ESG risks by analysing information from public sources and stakeholders, e.g., print

[14] See, https://www.crsp.org/products/documentation/lipper-objective-and-classification-codes.

[15] See details at: https://wrds-www.wharton.upenn.edu/documents/1154/KLD-on-WRDS.pdf.

media, online media, social media including twitter and blogs, government bodies, regulators, think tanks, and newsletters. The data are more reliable than the self-reported sources in providing an objective measure of ESG risk.[16] Reprisk collects news on 28 types of ESG incidents,[17] and calculates RepRisk Index (RRI) based on the news to measure the ESG risk exposure.[18] RRI ranges from 0 (the lowest) to 100 (the highest), which dynamically captures and quantifies a company's exposure to ESG issues. The higher the value, the greater the risk exposure.

I construct the measure of a fund's actual ESG risk based on the RRI of the stocks in the fund's portfolios. The actual ESG risk exposure is measured in three ways. The first measure is the current RRI representing the short-term risk exposure. The second measure is the peak RRI, which equals to the highest RRI level over the past two years and represents long-term exposure to ESG risks. The third measure is a dummy variable representing the severity of ESG risk, which equals one if the current RRI is greater than 25, and zero otherwise.[19] Using the severity score, I exclude low ESG-risk incidents and only include medium- and high-risk incidents. I calculate the weighted averages of the current RRI, the weighted peak RRI, and the weighted severity score based on the risk measures of stocks in mutual fund portfolios. Mutual funds whose holdings are covered by RepRisk by less than 75% are excluded from my sample.

In the robustness check, I use the data from the most commonly used database, the MSCI ESG KLD STATS, to measure a fund's actual ESG risk. The "strengths and concerns" scores are used by almost 80% of research between 1997 and 2009 (e.g., Hatten, Keeler, James and Kim (2020); Chen and Delmas (2011)). Among them, the "concerns" items refer to threats regarding ESG factors, and the "strengths" items refer to the commitments made that promise to ameliorate such threats. According to previous research, companies with high strengths also have high concerns, as indicated by the positive correlation between KLD strengths and concerns (e.g., Delmas and Blass (2010); Mattingly and Berman (2006)). Hence, simple aggregation methods (subtraction of strengths scores from concerns scores)

[16] The motive of greenwashing makes the company's self-reported information misleading. See Walker and Wan (2012).

[17] For details of the 28 different incidents, see Appendix B.1.

[18] RRI calculation is based on the reach of information sources, frequency, the timing of ESG risk incidents, as well as the risk incident content. The magnitude of the increase depends on the severity, reach, and novelty of the incidents. The RRI decays if there is no new risk exposure. See details at: `https://www.reprisk.com/news-research/resources/methodology`.

[19] As defined by RepRisk, a current RRI below 25 indicates low-risk exposure.

will cause similar results for companies with high scores on both strengths and concerns compared to those with low scores on both strengths and concerns. For the purposes of this paper, I summarise the "concern" scores for each company in the portfolio, and then calculate the weighted average of the concern scores as an alternative measure of fund ESG risk exposure.[20]

3.3 Identify ESG-related Disclosure Using NLP

I utilise deep learning-based NLP techniques to identify the ESG strategy disclosure and the ESG risk disclosure in mutual fund prospectuses. This approach can overcome the limitations of traditional methods such as the dictionary-based approach. The dictionary-based approach is a simple, but an inflexible way of extracting features from texts. For example, Andrikogiannopoulou et al. (2022) create a list of ESG keywords/phrases, and then searched for these words in the text of funds' principal investment strategies. If these keywords are present in the text, the mutual fund is deemed to have adopted the ESG investment strategy. However, the dictionary-based approach has two main limitations. First, it relies heavily on pre-determined word lists to identify the descriptions regarding ESG investing, e.g., ESG, CSR, and responsible investing. However, it is difficult for a pre-defined word list to cover all keywords relating to ESG investing. Especially with the introduction of bigrams, the complexity and variety of vocabularies grow, making it more difficult to compile a complete word list.[21] The second limitation of the dictionary-based approach is that it ignores word sequence, and possibly misunderstands the meaning of words in the document (semantics). However, it is possible for the same word to have different meanings in different permutations. For example, compare these two descriptions drawn from the mutual fund prospectuses in the sample: "the prospects for an industry or company may deteriorate because of a variety of factors, including disappointing earnings or changes in the competitive environment.", "securities of foreign issuers, and consequently ADRs, GDRs, and EDRs may decrease in value due to changes in currency exchange rates,

[20]Similarly, the "strengths" and "concerns" have been examined separately in many papers (e.g., Chatterji, Levine and Toffel (2009); McGuire, Dow and Ibrahim (2012); Walls, Berrone and Phan (2012); Zyglidopoulos, Georgiadis, Carroll and Siegel (2012)).

[21]An N-gram is an N-token sequence of words: a 2-gram (more commonly called a bigram) is a two-word sequence of words like "responsible investing", "social responsibility", or "clean energy"; a 1-gram is just a word like "pollution", or "carbon". It is recognised that a bigram approach is more powerful than a 1-gram for text classification.

the economic climate in the issuers home country or for a variety of other reasons." These descriptions above are not related to ESG risk but they use the keywords "environment" or "climate". When using a dictionary-based approach, it is difficult to distinguish them from the true descriptions of ESG risks, such as "in addition, these companies are at risk for environmental damage claims.", or "the sub adviser evaluates the impact and risk around issues such as climate change, environmental performance, labour standards and corporate governance.".

To overcome the limitations of the dictionary-based approach that is not capable of dealing with complex relationships, I adopt deep learning-based NLP techniques to identify ESG-related disclosures. Deep learning algorithms can automatically extract features from the texts and allow multiple layers to approximate complex relationships (Liang, Sun, Sun and Gao; 2017). In this paper, I use *Bidirectional Encoder Representations from Transformers (BERT)* to build the language model.[22] BERT is a pre-trained, and state-of-the-art language model that excels at learning contextual relations between words in a sentence/text, and generating representations of text context in many natural language tasks. Using BERT to complete NLP tasks typically involves two steps. First, creating a language model using a large amount of unlabelled text, then second, fine-tuning this large model to specific NLP tasks to utilise the large repository of knowledge this model has gained.

By following these two steps, I use a pre-trained BERT model to categorise each sentence in the prospectuses into one of two labels, ESGs and non-ESGs. There are then two NLP tasks. In the first NLP task, I focus on the principal strategy section of the mutual fund prospectuses and identify whether the section contained the descriptions of ESG investment strategies. The steps of identification are as follows. To begin with, I separate the principal strategy descriptions into separate sentences, resulting in 149,589 unique sentences. I then randomly select 5,000 sentences from these sentences and hand-coded each sentence as either ESG or non-ESG. Among the 5,000 sentences, only 106 are ESG-related. The rest of the sentences are irrelevant. To solve the problem of an unbalanced dataset and extend the coverage of ESG-related descriptions in the train sample, I cross-reference the sentences from ESG articles from Wikipedia, Investopedia, Morgan Stanley, and MSCI. After pre-processing, I separate the texts into individual sentences, label each sentence with the ESG reference, and combine them with the extra 5,000 sentences drawn from the prospectuses.

[22]The BERT architecture is composed of several transformer encoders stacked together. Further, each transformer encoder is composed of two sub-layers: a feed-forward layer and a self-attention layer. See details in Vaswani et al. (2017).

The final train dataset contains 7,213 sentences, of which 2,319 are labelled as ESG and 4,894 are labelled as non-ESG. The training sample is then used to train the language model, which is able to recognise patterns in unseen text and identify whether candidate sentences are either ESG-related or non-ESG. After validation, I use the trained model to classify the candidate sentences of mutual fund strategy descriptions.

My second NLP task is to identify the ESG-related risk disclosure in the principal risk section of the chosen prospectuses. First, I separate the principal strategy descriptions in the sample into separate sentences, resulting in 240,576 unique sentences. Since ESG disclosures account for only a small portion of overall risk disclosures, direct classification is not an effective approach. In order to solve this problem, I develop a two-step algorithm to determine whether a sentence describes the ESG risk or not. In the first step, I apply the Retrieve and Rerank methods (Reimers and Gurevych; 2019) to screen the texts and identify the sentences that are most likely to be relevant to ESG, thus narrowing down the training sample. I take the 28 issues and 73 topic tags of ESG risk defined by RepRisk as the queries of the Retrieve and Rerank model. For each search query, I use an orderer based on a cross-encoder that scores the relevance of all candidate sentences for this given search query. The query and each candidate sentence are simultaneously passed to the BERT-based converter network, which then outputs a single score between 0 and 1 indicating how relevant the sentence is to the given query. For each query, I select candidate sentences that match in the top 5% as those that may contain ESG risk disclosure. However, the retrieval system may have retrieved sentences that are not relevant to the search query. To address this issue, in the second step, I randomly select 5,000 samples from these selected sentences with as high a match as possible to the training dataset, and then hand-code each sentence with ESG or non-ESG labels to construct the train dataset. This results in 432 sentences labelled with ESG and the others labelled with non-ESG. Based on the final train dataset, I train a classifier to label sentences related to ESG risk using the BERT language model and apply this model to label the sentences in the overall sample.

[Insert Table 1]

In addition to classifying each sentence in the prospectuses using the deep learning approach, I also classify 500 sentences in the evaluation sample using the dictionary-based approach for comparison.[23] Table 1 compares accuracy, recall, and overall F-value for clas-

[23] I use the word list defined in Baier, Berninger and Kiesel (2020) to implement the dictionary-based

sifying the same evaluation sample under deep learning and dictionary approaches.[24] The deep learning-based method outperforms the dictionary method in all three evaluation scenarios. The dictionary-based approach achieves only an accuracy of 0.3 in ESG risk identification, while the deep learning approach achieves an accuracy of 0.9. This indicates that the dictionary-based approach is more likely to misclassify non-ESG sentences as ESG-related sentences due to its inability to understand the semantics of words in a specific context. In contrast, the deep learning-based approach can learn the subtle relationships that the traditional dictionary-based approach cannot identify, thus improving classification accuracy.

3.4 The Descriptions of ESG Disclosure

Using the NLP method, I examine each sentence of funds' prospectuses, label them, and obtain the pools of sentences that describe ESG investment strategy and ESG risk respectively. On the basis of the labeled sentences, I lemmatize each sentence and fit it into TF-IDF models,[25] where a TF-IDF score represents the importance of a word in a sentence. Following on, I use the aggregate TF-IDF scores of the words in the sentences labelled ESG strategy and ESG risk, and create word clouds,[26] as shown in Figure 1.

[Insert Figure 1]

Compared to non-ESG descriptions in prospectuses, words such as "social", "ESG", "governance", "environmental", and "responsible", have a high frequency in ESG investing descriptions. In contrast, the words, such as "cybersecurity", "breach", "social", "operational", "disaster", and "corruption" are examples of high-frequency words in ESG risk

methodology, see Appendix C.

[24] Accuracy is a measure of how many of the positive predictions made are correct (true positives), where $Precision = \frac{TruePositives}{TruePositives+FalsePositives}$. Recall is a measure of how many positive cases the classifier correctly predicts out of all positive cases in the data, where $Recall = \frac{TruePositives}{TruePositives+FalseNegatives}$. F-score is a measure that combines precision and recall, where $F\text{-}score = 2 * \frac{Precision*Recall}{Precision+Recall}$.

[25] TF-IDF (term frequency-inverse document frequency) is a statistical measure that evaluates how relevant a word is to a document in a collection of documents. TF-IDF for a word in a document is calculated by multiplying the term frequency of a word in a document and the inverse document frequency of the word across a set of documents.

[26] A word cloud is a simple yet powerful visual representation object for text processing, which shows the most frequent word with bigger and bolder letters, and with different colors. The smaller the size of the word, the lesser it's important.

descriptions. Due to the different keywords in ESG strategy descriptions and ESG risk descriptions, it is difficult to apply a uniform word list to identify both the descriptions with ESG strategies and risks. Additionally, these findings suggest that BERT-based deep learning techniques are more effective to NLP tasks of classification than dictionary-based deep learning techniques.

[Insert Figure 2]

My final sample includes 1371 domestic diversified actively managed equity mutual funds with non-missing strategy and risk descriptions. As shown in Figure 2, from 2011 to 2019, the number and percentage of funds with ESG strategies and risk descriptors increased year-on-year from 2011 to 2019. Specifically, the number of funds with ESG investment strategy disclosure increased from 112 in 2011 to 229 in 2019, and the corresponding percentage increased from 10.55% to 19.52%. Furthermore, the number of funds with ESG risk descriptions surged from 59 in 2011 to 450 in 2019, and the corresponding percentage increased from 5.56% to 38.36%. The trend shows that more and more funds are inclined to invest with ESG considerations and to add ESG-related descriptions in their prospectuses for investors' review.

[Insert Table 2]

Table 2 presents summary statistics on fund variables, with cross-sectional statistics for the entire sample of funds in Table 2a, the time-series averages of cross-sectional statistics for the funds with ESG strategy disclosure in Table 2b, and the time-series averages of cross-sectional statistics for the funds with ESG risk disclosure in Table 2c. The average assets under management of funds during this period in the full sample are approximate $1.47 billion, while the average assets under management of funds with ESG strategy disclosure are about $1.27 billion, lower than the average in the entire sample. In contrast, the average assets under management of funds with ESG risk disclosure are about $1.54 billion, higher than the average in the entire sample. Furthermore, in Table 2, it shows that the average quarterly flows of mutual funds with ESG strategy disclosure are approximately 0.5% of assets, which are much higher than those of funds in the entire sample (–0.03%), as well as those funds with ESG risk disclosure (–0.2%).

[Insert Table 3]

Table 3 presents the sector allocation statistics of funds with different disclosure types. I use the Fama–French 12–industry taxonomy to classify the stocks in the funds' holdings,[27] and calculate the proportion of the fund's holdings in the different industries. Based on their prospectuses, I categorise mutual funds into three categories: funds with ESG investment strategies, funds with ESG risk disclosures, and funds without ESG disclosures. Also, Table 3 displays the mean and median industry weights for each fund classification. The funds that disclose ESG investment strategies generally put more weight on specific sectors with relatively low ESG risk (e.g. consumer durables, healthcare, business equipment), and invest less in specific sectors with relatively high ESG risk (e.g. energy, utilities). In contrast, funds that disclose ESG risks tilt their portfolios slightly towards the energy and utilities sectors, which typically face high ESG risks. Although funds with different disclosure types have different allocations to sectors, those differences are small because the funds' portfolios are diverse.

4 Empirical Results

4.1 ESG Risk Disclosure and Fund Flows

Proposition 1 suggests that the ESG risk disclosure attenuates the flow-performance sensitivity of mutual funds. In order to test the proposition, I estimate the following panel regression:

$$\begin{aligned} Flows_{it} =& a + \beta_1 * ESGRisk_{i,t-1} + \beta_2 * ESGRisk_{i,t-1} * Performance_{i,t-1} \\ & + \beta_3 * Performance_{i,t-1} + b * Controls_{i,t-1} + \epsilon_{i,t}, \end{aligned} \tag{16}$$

where $Flows_{it}$ is the cashflows of fund i in quarter t, and a is the regression intercept, the variable $ESGRisk$ indicates the mutual fund's ESG disclosure, $Performance_{i,t-1}$ is the percentile of fund returns among funds in the same Lipper classification in the quarter $t-1$, the control variables, $Controls_{i,t-1}$, include the length of mutual fund prospectuses, standard deviation of fund returns in the past 12 months, fund size, age, expense ratio, turnover ratio

[27] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_12_ind_port.html

as well as fund family size, and $\epsilon_{i,t}$ is the regression error term. I also include style-by-time fixed effects. To address issues of residual cross-sectional dependence within the same time and the residual serial dependence for funds in the same mutual fund family, I double-cluster standard errors by time and fund family.

[Insert Table 4]

Table 4 presents the results of estimating this regression, where $ESGRisk$ presents the ESG risk disclosure of mutual funds. In columns (1) and (2), the measure of funds' ESG-related disclosure, $ESGRisk$, is a dummy variable equal to one if the fund discloses the ESG-related risk in the prospectus, and zero otherwise. In columns (3) and (4), $ESGRisk$ represents the weight of ESG-related contents in the total risk disclosure, which is measured by the percentage of words in sentences categorised as ESG risk out of the total number of words in the principal risk section of the fund. The results are consistent with the investor learning mechanism of the model. The coefficients on the interaction term between performance variable ($Performance$) and ESG risk disclosure variable ($ESGRisk$) are significantly negative, suggesting that flows respond less strongly to the past performance of mutual funds with ESG risk disclosure. As column (2) shows, the sensitivity of fund flows to fund past performance is 0.0623 in the funds without ESG risk disclosure versus 0.048 in the funds with ESG risk disclosure, the difference of which has P-value<0.01.

Consistently, as column (4) shows, as the weight of ESG risk disclosure increases, the fund flows become less sensitive to the fund's past performance. The flow response is reduced by 0.00936 for every 10% increase in ESG risk in the overall risk disclosure. In columns (1) and (3), the coefficients for ESG risk disclosure are insignificant, suggesting that the direct effect of ESG risk disclosure on fund flows is not significant without taking into account the impact of ESG risk disclosure on flow-performance sensitivity.

4.2 ESG Investment Strategy Disclosure and Fund Flows

In this section, I study the influence of fund ESG strategy disclosure on fund flows. I re-estimate the panel regression equation (16) in which the $ESGRisk$ is substituted with $ESGInvest$, i.e., a dummy variable equal to one if the mutual fund discloses the adoption of ESG investment strategy in the prospectus, and zero otherwise. To determine whether a mutual fund discloses the ESG investment strategy, I examine this in two ways. In the first way, I directly check the principal strategy section to examine whether ESG investment strategy descriptions exist. If there is at least one sentence that is classified as ESG-related, $ESGInvest$ equals one, and zero otherwise. In the second way, I identify the adoption of ESG investment strategy from the principal risk section. For example, if a fund states that its adoption of an ESG investment strategy may result in missed investment opportunities and potentially lower returns compared to other funds, it is considered to disclose the adoption of ESG investment strategies, and then the variable $ESGInvest$ equals to one.

[Insert Table 5]

Table 5 presents the estimation results. The results show that the ESG investment strategy disclosure increases the fund flows instead of influencing the flow-performance sensitivity, which is different from the way that ESG risk disclosure influences fund flows. In columns (1) and (3), the coefficients on the dummy variables $ESGInvest$ are significantly positive. Both the ESG investment strategy disclosure and ESG investing risk disclosure, which shows the fund adopts ESG strategies, improve the percentage of quarterly cashflows to fund assets by 1.19% and 0.85%, respectively. The results imply that mutual fund investors have a significant preference to funds that disclose the adoption of ESG investment strategy, even though they remind investors that ESG investing would lower returns. Furthermore, I find that the ESG investing disclosure does not change the flow-performance relationship. As shown in column (2) and column (4), the coefficients on the intersection terms between the ESG investing dummy variable and fund past performance are not significant.

4.3 Difference-in-Difference Study on the Impact of ESG Risk Disclosure

The evidence in Section 4.1 shows that the ESG risk disclosure attenuates the flow-performance relationship. To mitigate the concern that this effect is determined by other fund characteristics, my research design incorporates controls for fund-level variables, and style and time-fixed effects. However, the possibility remains that some omitted variables affect both ESG risk disclosure and fund flows, and it is also possible that this evidence is driven by reverse causality. To address these concerns, I focus on the change in the flow-performance relationship before and after the adoption of ESG risk disclosure using both the propensity score matching (PSM) analysis and the difference-in-differences (DiD) analysis.

Funds that have ESG-related disclosures in their prospectuses are used as a treatment group in the sample period. The treatment variable is defined in two ways. In the first way, the treatment variable equals one if a fund has the ESG risk disclosure in the sample period, and zero otherwise. In the second way, I use the weight of ESG risk disclosure as the treatment variable. To compare the changes in flow-performance sensitivity before and after the inclusion of ESG risk disclosure by the mutual funds, I further separate and define the control group. The first control group is made up of all funds that do not disclose ESG risks during the sample period. The second control group is made up of funds that do not disclose ESG risk and are matched to the treatment group using the propensity score matching (PSM) method. PSM analysis begins with estimating propensity scores of the mutual funds using the Probit model, where the dependent variable is a dummy variable of ESG risk disclosure (a value of one with ESG risk disclosure, and zero otherwise), and the explanatory variables are the control variables in the specification of equation (16). Each fund in the treatment group is then matched with the fund with the closest propensity score but without ESG risk disclosure. To test how ESG risk disclosure influences the sensitivity of fund flows to fund performance in a DiD setting, I estimate the following specification:

$$\begin{aligned} Flows_{it} =& a + \beta_1 * Treat * Post * Performance_{i,t-1} \\ &+ \beta_3 * Performance_{i,t-1} + b * Controls_{i,t-1} + \epsilon_{i,t}, \end{aligned} \tag{17}$$

where the *Post* is a dummy variable indicating the time window after a fund discloses the ESG risk.

[Insert Table 6]

Table 6 presents the estimation results of the DiD regressions. In columns (1) and (2), the control group comprises all funds that do not disclose ESG-related risks, and in columns (3) and (4), the control group comprises the funds that are matched to the treatment group under the method of PSM. In addition, in columns (1) and (3), the treatment variable is a dummy variable indicating funds that disclose ESG risk, and in columns (2) and (4), the treatment variable is the weight of ESG risk disclosure in the total risk description. The coefficient on $Treat \times Post \times Performance$ is negative and statistically significant in all the specifications. The results suggest that the introduction of ESG risk disclosure makes investors less sensitive to funds' past performance compared to the period before the inclusion of ESG risk disclosure, which is consistent with Proposition 1 and validates the empirical results in Section 4.1.

4.4 Fund ESG Disclosure and Actual ESG Risk Exposure

In this section, I study how the fund ESG-related disclosure implies the fund's actual ESG risk. In my sample, some mutual funds have no ESG-related disclosure, some mutual funds only disclose ESG risk, some mutual funds only disclose ESG strategy, and some funds disclose both ESG strategy and ESG risk. Taking the mutual fund prospectuses as a whole into account, I consider both the ESG risk disclosure and the ESG strategy disclosure, and study the relationship between ESG disclosure and fund actual ESG risk. Proposition 2 shows that if funds have high ESG risk, they are more likely to disclose the corresponding risk in their prospectuses. Based on that, I hypothesise that the ESG risk disclosure implies the high actual ESG risk in the portfolio of funds. To empirically test this hypothesis, I estimate the following specification:

$$\begin{aligned} ESGActualRisk_{it} =& a + \beta_1 * ESGStr_{i,t-1} + \beta_2 * ESGRisk_{i,t-1} \\ & + \beta_3 * ESGStr_{i,t-1} * ESGRisk_{i,t-1} + b * Controls_{i,t-1} + \epsilon_{i,t}, \end{aligned} \tag{18}$$

where $ESGActualRisk_{i,t}$ represents the actual ESG risk of mutual fund i, $ESGStr_{i,t-1}$ is a dummy variable which equals to one if the mutual fund discloses ESG investment strategy in the principal strategy section, and zero otherwise, $ESGRisk_{i,t-1}$ is the variable that indicates the ESG risk disclosure of funds, and $Controls_{i,t-1}$ is a vector of the control variable, which is the same as in the specification of equation (16).

[Insert Table 7]

Table 7 presents the estimation results of regressions of funds' actual ESG risk exposure against funds' ESG disclosure. In Tables 7a, 7b, and 7c, the dependent variable $ESGActualRisk$ is represented by the current RRI, peak RRI and severity dummy variable, respectively. In columns (1) and (2) of each panel, $ESGRisk$ is a dummy variable that equals to one if the fund has ESG-related risk disclosure, and zero otherwise; in columns (3) and (4), $ESGRisk$ is the weight of ESG risk disclosure in the overall ESG disclosure.

Moreover, the industry-fixed effects are included in the regressions as shown in columns (2) and (4), and are not included in columns (1) and (3).

Table 7 shows that the coefficients of the $ESGStr$ are significantly negative in columns (1) and (3), but are not significant in columns (2) and (4). The results imply that the funds which adopt ESG investment strategy have a lower level of ESG risk as they claim in their prospectuses, but this effect is dominated by the industry allocation of their portfolios. This further demonstrates that the funds which describe the ESG investment strategy in their prospectuses also tend to allocate more weight to the low-ESG risk industry, making their portfolios less exposed to ESG risk. Furthermore, in all the specifications, the coefficients β_2 on $ESGRisk$ are significantly positive, which shows that the funds with ESG risk disclosure have higher ESG risk compared to the funds without ESG risk disclosure. These results are consistent with Proposition 2, which demonstrates that the funds with high ESG risk are more motivated to disclose their ESG risk in prospectuses. However, it is interesting that the positive relationship between ESG risk disclosure and actual ESG risk exposure reverses, in the case that funds adopt ESG investment strategies. It can be shown that in all specifications, the coefficients on the intersection terms of $ESGStr$ and $ESGRisk$ are significantly negative, which results in a negative sum of coefficients on $ESGRisk$.

As the theory demonstrates, if funds have greater ESG risk disclosure, they tend to disclose the corresponding risk to make investors react less aggressively to potential ESG shocks. However, the case is different when mutual funds explicitly disclose their commitment to ESG investment strategies, in which ESG risk descriptions are used to signal the mutual funds' ability to detect and identify ESG risks as well as demonstrate the funds' concern about ESG risks. As a result, in the existence of ESG strategy, risk disclosure implies lower ESG risk in funds' portfolios, even lower than the risk in funds with only ESG strategies.

In the robustness check, I take the value-weighted average of the MSCI concern score based on funds' holdings as an alternative measure of fund actual ESG risk and estimate the regression in equation (18).

[Insert Table 8]

Table 8 presents consistent estimation results with Table 7, that is, ESG strategy disclosure implies low risk, and ESG risk disclosure implies high ESG risk in funds' portfolio respectively, but the coexistence of ESG strategy and ESG risk disclosure signals a lower level of ESG risk compared to funds that only disclose ESG strategy. However, in columns (2) and (4) where the industry fixed effects are included, the coefficient on ESG risk disclosure is not significant. This indicates that the funds which disclose ESG risk put more weight on the industries with high MSCI concern scores. As MSCI concern scores are based on companies' self-disclosures and companies' disclosures have more similarity in the same industry, the industry allocation is more likely to influence the weighted MSCI concern score of a fund. This problem is mitigated when the purely exogenous measures based on the RepRisk index are applied to measure a fund's actual ESG risk.

4.5 The Determinant of Fund ESG Disclosure

4.5.1 The Actual ESG Risk Effect

The results in Section 4.4 show that ESG-related disclosure is informative in predicting funds' actual ESG risks. In this section, I directly test Proposition 2 and investigate how ESG disclosure of mutual funds is determined. Based on the results in Table 7 and Proposition 2, I make a conjecture that a fund's actual ESG exposure is an important determinant of its ESG risk disclosure. More specifically, funds tend to disclose ESG risk when the actual ESG risk is high. I test this hypothesis by estimating the following specification:

$$ESGRisk_{it} = a + \beta_1 * PeakRRI_{i,t-1} + b * Controls_{i,t-1} + \epsilon_{i,t}, \tag{19}$$

where $ESGRisk$ is a dummy variable equal to one if funds disclose ESG-related risk in their prospectuses, and zero otherwise. $PeakRRI$ represents the actual ESG risk exposure in the past two years, $Controls$ is a vector of variables to control a series of fund characteristics, which include the length of mutual fund prospectuses, fund size, fund family size, fund performance in the past 36 months, return volatility in the past 36 months, fund age, expense ratio, and turnover ratio. The industry-fixed effects, and style-time fixed effects are also controlled in the regressions.

[Insert Table 9]

Table 9 presents the estimation results. I divide the sample into sub-samples of funds that disclose ESG strategies and funds that do not. In columns (1) and (2), the sample consists of funds without ESG strategies, and the dependent variable is a dummy variable that equals one if funds have ESG risk disclosure but do not have ESG strategy disclosure, and zero otherwise. The coefficients on long-term risk exposure, $PeakRRI$, are significantly positive, implying that funds with high actual ESG risk are more likely to disclose ESG risk in the prospectuses compared to the funds with low actual ESG risk. This result is consistent with the motivation of mutual fund managers to maximise their expected utility illustrated in Proposition 2.That is, funds with a high ESG risk exposure are motivated to disclose the corresponding risk in their prospectuses in order to reduce the flow-performance sensitivity and smooth their income.

In columns (3) and (4), the sample consists only of funds that disclose ESG investment strategies, and the dependent variable is a dummy variable that equals one if funds disclose both ESG risks and ESG strategies, and zero otherwise. The coefficients on $PeakRRI$ are significantly negative, suggesting that the funds with low ESG risk are more likely to disclose these risks in the principal risk section in the case that they have disclosed the adoption of ESG strategies. By disclosing ESG risk, low-risk funds can demonstrate that they are capable of identifying ESG risks. Following on, the motivations of ESG risk disclosure are different between the cases with and without ESG strategy disclosure. A positive relationship between ESG risk and ESG risk disclosure only exists without industry-fixed effects as shown in columns (5) and (6) where the overall sample has been examined.

The results above indicate that the prospectuses, including both the principal strategy descriptions and the principal risk descriptions, should be considered as a whole when examining the determinants of ESG risk disclosure. In the absence of an ESG strategy, high-risk funds are more likely to disclose their ESG risks. In contrast, with the adoption of ESG investment strategies, funds with low ESG risk are more likely to disclose the ESG risk as the disclosure reflects the ability to understand and control ESG risk.

4.5.2 The Cross-Sectional Effects

In this section, I test Propositions 3 and 4 as well as the implication of the investor-learning assumption. The three hypotheses regarding the impact of fund characteristics on the relationship between fund ESG risk disclosure and the actual ESG risk are as follows.

The first hypothesis based on Proposition 3 is that funds with low expense ratios are more likely to disclose ESG risks if they have more actual ESG risks. This implies that the positive relationship between fund ESG risk and fund disclosure is stronger in funds with low expenses.

The second hypothesis based on Proposition 4 is that compared to funds with low-performance rankings, funds with high-performance rankings are more likely to disclose ESG risk if they have more actual ESG risks. Thus, the positive relationship between fund actual ESG risk and fund ESG risk disclosure is stronger in the funds with high-performance rankings.

The third hypothesis based on the underlying assumption of an investor learning model is that compared to funds with less sophisticated investors, funds with more sophisticated investors are more motivated to disclose ESG risk if they are exposed to higher ESG risk exposure. It follows that funds with more sophisticated investors have a stronger positive relationship between their actual ESG risk and their ESG risk disclosure.

To test the three hypotheses, I estimate the following specifications:

$$\begin{aligned} ESGRisk_{it} =& a + \beta_1 * PeakRRI_{i,t-1} + \beta_2 * CharacterDummy_{i,t-1} * PeakRRI_{i,t-1} \\ &+ b * Controls_{i,t-1} + \epsilon_{i,t}, \end{aligned} \tag{20}$$

where $CharacterDummy$ is a dummy variable that denotes a fund's cross-sectional characteristics. In the regressions, $CharacterDummy$ is represented by the dummy variables that denote high expense ratio ($HighExp$), high-performance ranking ($HighRank$), and high investor sophistication ($HighSophist$) respectively. Other control variables and fixed effects are the same as the specification in equation (19).

[Insert Table 10]

Table 10 represents the estimation results from the cross-sectional effects on fund ESG disclosure choice. To eliminate the influence of ESG strategies, I only study the funds without ESG strategy disclosure. The coefficients on the intersection terms between the dummy variable of fund specific characteristic ($HighExp$, $HighRank$, or $HighSophist$) and $PeakRRI$ are of great interest since they reflect the cross-sectional effect of fund characteristics on the relationship between fund ESG risk disclosure and actual ESG risk. In columns (1) and (2), $CharacterDummy$ equals one if the expense ratios of funds are ranked in the upper half among the funds in the same style, and zero otherwise. The coefficients on the intersection term $HighExp * PeakRRI$ are significantly negative, which shows that high fund fees attenuate the positive relationship between ESG risk disclosure and actual ESG risk. This finding is consistent with Proposition 3, that is, the ESG risk disclosure decisions of funds with high expense ratios are less likely to be influenced by the actual ESG risk compared to the funds with low expense ratios. It is because high fund fees increase the uncertainty in the overall management fees charged by funds and lower the marginal benefit of disclosure decision-making based on a fund's actual ESG risk exposure.

In columns (3) and (4), the dummy variable ($CharacterDummy$) equals one if a fund is ranked in the upper half based on its performance in the past three years among funds with the same investment styles, and zero otherwise. The coefficient on the intersection between $HighRank$ and $PeakRRI$ is significantly positive (with P-value<0.01). Specifically, the coefficient on $PeakRRI$ in the funds with a high-performance ranking is 0.0015 compared to 0.0006 in the funds with a low-performance ranking when the industry fixed effects are controlled. The results are consistent with Proposition 4 that fund high investment ability intensifies the reliance of the ESG risk disclosure on the actual ESG risk. In other words, if funds can achieve good performance, it is advantageous for them to determine the ESG risk disclosure based on their actual ESG exposure. It is because, as the theory demonstrates, the marginal benefit of adjusting the flow-performance relationship through disclosure is higher in cases when funds have high investment ability compared to funds with low investment ability.

The test in columns (5) and (6) compares the relationship between ESG risk disclosure and ESG risk in funds with high investor sophistication and low investor sophistication. According to Huang et al. (2021), the proxy for investor sophistication is whether a fund is a load fund or not. Accordingly, the dummy variable of high-sophistication takes the value of one for no-load funds and zero for load funds, where the load funds are defined to be those with a front-end or a back-end load or with a 12b-1 fee that is higher than 25 basis points a year. The coefficients on the intersection between a high-sophistication dummy variable and Peak RRI are significantly positive with P-value<0.01. The results show that the positive relationship between fund ESG risk disclosure and actual ESG risk exposure is stronger in the funds with high investor sophistication. The finding is consistent with the underlying theoretical assumption that mutual fund managers aim to influence investor learning through ESG disclosure. Thus, when a fund's investors are less sophisticated and have limited learning abilities, the funds themselves are less motivated to strategically disclose ESG risk, resulting in a weaker disclosure-risk relationship. In contrast, if fund investors are sophisticated, the disclosure is more dependent on fund actual ESG risk.

4.6 Fund Trading on ESG Incidents

In this section, I examine whether ESG risk disclosures reflect a fund's ability to actively manage ESG risk. Ullmann (1985) suggests that risk management is closely related to risk disclosure, i.e., risk disclosure by managers is always followed by risk management disclosure to demonstrate to stakeholders their ability to manage the externalities faced by the firm. Based on that, I conjecture that fund ESG risk disclosure may reflect their risk management ability to control ESG incidents. I examine funds' ability to manage ESG risk by studying how their stocks are traded after ESG incidents have occurred. For example, if a fund sells the stocks of companies that have encountered serious ESG issues (defined as the increase in the current RRI index being larger than 25), it shows that the fund pays enough attention to the ESG risk and monitors the ESG incidents in the portfolio.

Furthermore, I also take into account how investors play a role in ESG risk management of mutual funds. The shareholder theory suggests the influence of stakeholders in the firm decisions and the activities of management play a role in order to achieve the exact level of stakeholder demand (Freeman et al.; 2010). Thus, the relationship between stakeholder demand and management performance is expected to be positive if risk management activities are seen as effective management activities dealing with stakeholders (Ullmann; 1985). In this paper, I take the introduction of funds' sustainability ratings by Morningstar as a milestone in increasing investors' awareness about ESG issues, as well as investors' demand for ESG risk management. On 1 March 2016, Morningstar launched the industry's first sustainability rating for 20,000 funds worldwide, providing investors with a new way to evaluate investments based on ESG considerations. I conjecture that this encourages investors to pay more attention to the ESG performance of mutual funds, which could affect the mutual funds' trading behaviours. Using the above analysis, I hypothesise that funds which disclose ESG risks are more likely to sell stocks suffering from ESG issues after the launch of the Morningstar sustainability rating. In order to test this conjecture, I estimate the following specification:

$$\begin{aligned} Trade_{ij,t} = & a + \beta_1 * ESGDisclosure_{j,t-1} + \beta_2 * ESGDisclosure_{j,t-1} * Post \\ & + b * FundControl_{j,t-1} + c * StockControl_{i,t-1} + \epsilon_{it}, \end{aligned} \tag{21}$$

where $Trade_{ij,t}$ is a dummy variable that equals one if fund i buys stock j, zero if fund i does not trade stock j, and minus one if fund i sells stock j at the quarter t when the ESG incidents occur in the company of stock j, $ESGDisclosure_{i,t-1}$ indicates ESG disclosure of fund i, $Post$ is a dummy variable which equals to one if time t is after March 2016, and zero otherwise, $FundControl_{i,t-1}$ is a vector of fund j characteristics, including fund size, fund family size, turnover ratio, and fund past cashflows, $StockControl_{j,t-1}$ is a vector of stock j characteristics, including the stock price, market capitalisation, shares outstanding, volume, past returns, and return volatility. Furthermore, I include the style-time fixed effects in the regressions.

The overall sample consists of 675,857 ESG incidents. The estimation results of this section of research are presented in Table 11. Columns (1), (2), (3) and (4) show how fund ESG risk disclosure implies ESG risk management abilities. $ESGDisclosure$ is represented by the dummy variable indicating ESG risk disclosure in columns (1) and (2), and by the weight of ESG risk disclosure in columns (3) and (4). The coefficients on $ESGDisclosure$ are not significant in columns (1) and (3) when the difference between periods before and after the introduction of sustainability ratings is not taken into account. According to the results, funds disclosing ESG risks behave no differently from funds not disclosing them when trading stocks that have encountered ESG incidents.

However, when I examine separately the periods before and after the introduction of Morningstar ESG ratings in March 2016, the trading of funds with ESG risk disclosure differs significantly from those without. As shown in columns (2) and (4), the coefficients for the intersection of $ESGDisclosure$ and $Post$ are significantly negative, indicating that funds with ESG risk disclosure are more likely to sell stocks encountering ESG incidents in the period after March 2016, compared to funds without ESG risk disclosure. In accordance with the stakeholder theory, funds that disclose ESG risk implement more active risk management as investors become more concerned about the ESG performance of funds.

On the contrary, Table 11 does not indicate that funds with ESG strategies actively manage ESG risk. In columns (5) and (6), the independent variable $ESGDisclosure$ is represented by the dummy variable of ESG strategy disclosure. The $ESGDisclosure$ coefficient in column (5) is not significant, indicating that funds with ESG strategies do not manage risk more actively than funds without them in the sample period. Even after Morningstar sustainability ratings are introduced, funds that disclose ESG strategies do not appear to actively manage ESG risk, as shown in column (6).

5 Conclusion

In this paper, I focus on ESG risk disclosure in mutual fund prospectuses, and study the interplay between fund ESG disclosure and investor learning. I develop a theoretical model which posits that ESG risk disclosures reduce investors' uncertainty about fund priors, thereby leading to the less reliance on past performance when evaluating funds' future returns, and ultimately attenuates the flow-performance sensitivity. My empirical results support this theory. First, I find that, in light of the impact of fund ESG risk disclosures to attenuate flow performance relationship, funds with high actual ESG risk prefer to disclose their ESG risk in their prospectuses as a means of mitigating potential outflows to smooth their income, thus minimising the adverse effects of ESG incidents.

In addition, this paper demonstrates that ESG risk disclosures signify high ESG risk in the fund portfolio. Conversely, disclosures of a fund's ESG strategy suggest a lower level of ESG risk. Interestingly, funds that disclose both ESG strategy and ESG risk in their prospectuses tend to have lower ESG risk exposure compared to those that only disclose ESG strategy. These results show that, when ESG strategy is adopted, ESG risk disclosure reflects a fund's superior ability to identify ESG risks as well as its propensity to pursue low-risk levels, rather than reflecting the fund's motivation to reduce adverse effects of ESG incidents.

Finally, I illustrate the relationship between fund ESG risk disclosures and ESG risk management activities, and highlight investors' role in driving mutual funds to actively control ESG risk. My findings reveal that the funds that disclose ESG risk tend to sell stocks that have encountered ESG incidents following the introduction of Morningstar' sustainability ratings in March 2016, but this phenomenon was not observable prior to that. These findings support the stakeholder theory that the demand of stakeholders (investors) motivates active risk management activities, and further suggest that the ESG risk disclosure can reflect the risk management abilities of mutual funds.

A Proofs

A.1 Investors' Bayesian Updating

According to equation (2), investors' prior about $\alpha_i + e_i$ is

$$\alpha_i + e_i \sim N(\bar{\alpha} + \bar{e}, \sigma_\alpha^2 + \sigma_{esg}^2). \tag{A.1}$$

At time 2, investors observe the return $r_{i,2} \equiv \alpha_i + e_i + \epsilon_{i,2} - cq_{i,1} - f$, which is equivalent to them receiving a signal about $\alpha_i + e_i + \epsilon_{i,2}$ with the value of $r_{i,2} + cq_{i,1} + f$. Following Anderson (2003) and DeGroot (2005), I have the conditional mean of $\alpha_i + e_i$ given $r_{i,2}$ is,

$$\begin{aligned}
\mathbb{E}_{i,2}[\alpha_i + e_i \mid r_{i,2}] &= \mathbb{E}_{i,2}[\alpha_i + e_i \mid r_{i,2} + cq_{i,1} + f] \\
&= \mathbb{E}_{i,2}[\alpha_i + e_i] + \frac{\mathbb{C}\mathrm{ov}(\alpha_i + e_i, \alpha_i + e_i + \epsilon_{i,2})}{\mathbb{V}\mathrm{ar}(\alpha_i + e_i + \epsilon_{i,2})}\big(r_{i,2} + cq_{i,1} + f - \mathbb{E}_{i,2}[\alpha_i + e_i + \epsilon_{i,2}]\big) \\
&= \frac{\sigma_\epsilon^2}{\sigma_\alpha^2 + \sigma_{esg}^2 + \sigma_\epsilon^2}(\bar{\alpha} + \bar{e}) + \frac{\sigma_\alpha^2 + \sigma_{esg}^2}{\sigma_\alpha^2 + \sigma_{esg}^2 + \sigma_\epsilon^2}(r_{i,2} + cq_{i,1} + f).
\end{aligned} \tag{A.2}$$

A.2 Fund Managers' Bayesian Updating

Mutual fund managers' prior about the ESG factor e_i is normally distributed with mean $\bar{e}$ and variance σ_e^2. The new signal about e_i is $s_i = e_i + \eta_i$, where $\eta_i \sim N(0, \epsilon_\eta^2)$. Following Anderson (2003) and DeGroot (2005), the conditional density of e_i given s_i is normal with conditional mean,

$$\begin{aligned}
\mathbb{E}[e_i \mid s_i] &= \mathbb{E}[e_i] + \frac{\mathbb{C}\mathrm{ov}(e_i, e_i + \eta_i)}{\mathbb{V}\mathrm{ar}(e_i + \eta_i)}\big(s_i - \mathbb{E}[e_i + \eta_i]\big) \\
&= \frac{\sigma_\eta^2 \bar{e} + \sigma_e^2 s_i}{\sigma_\eta^2 + \sigma_e^2},
\end{aligned} \tag{A.3}$$

and the conditional variance,

$$\begin{aligned}
\mathbb{V}\mathrm{ar}[e_i \mid s_i] &= \mathbb{V}\mathrm{ar}(e_i) - \frac{\mathbb{C}\mathrm{ov}^2(e_i, e_i + \eta_i)}{\mathbb{V}\mathrm{ar}(e_i + \eta_i)} \\
&= \frac{\sigma_\eta^2 \sigma_e^2}{\sigma_\eta^2 + \sigma_e^2}.
\end{aligned} \tag{A.4}$$

A.3 Proof of Proposition 1

Let Sensitivity_i denote the sensitivity of fund flows to fund past performance, i.e.,

$$\text{Sensitivity}_i = \frac{\partial \text{Flow}_{i,2}}{\partial r_{i,2}} = \frac{\sigma_\alpha^2 + \sigma_{esg}^2}{(\sigma_\alpha^2 + \sigma_{esg}^2 + \sigma_\epsilon^2)(\bar{\alpha} + \bar{e} - f)}, \tag{A.5}$$

where $\bar{\alpha} + \bar{e} - f > 0$ to ensure that the initial dollar holdings are positive.

I take the derivative of Sensitivity_i with respect to σ_{esg}^2, and get,

$$\frac{\partial \text{Sensitivity}_i}{\partial \sigma_{esg}^2} = \frac{\sigma_\epsilon^2}{(\sigma_\alpha^2 + \sigma_{esg}^2 + \sigma_\epsilon^2)^2(\bar{\alpha} + \bar{e} - f)} > 0. \tag{A.6}$$

The result shows that the sensitivity of fund flows to fund past performance is increasing as investor uncertainty about the ESG factor increases.

A.4 Proof of Proposition 2

Substituting equations (6), (7) and (12) into the objective function in equation (10), and using $\mathcal{L}$ to denote the objective function, I get the following expression:

$$\begin{aligned}
\mathcal{L}(\sigma_{esg}^2) &= \mathbb{E}_{i,0}\Big[\big(\mathbb{E}_{i,2}[\alpha_i + e_i \mid r_1] - f\big) \mid \alpha_i, s_i\Big] - \frac{f}{2c}\mathbb{V}\text{ar}_{i,0}\Big[\big(\mathbb{E}_{i,2}[\alpha_i + e_i \mid r_1] - f\big) \mid \alpha_i, s_i\Big] \\
&= \frac{\epsilon_\epsilon^2}{\sigma_\alpha^2 + \sigma_{esg}^2 + \sigma_\epsilon^2}(\bar{\alpha} + \bar{e}) + \frac{\sigma_\alpha^2 + \sigma_{esg}^2}{\sigma_\alpha^2 + \sigma_{esg}^2 + \sigma_\epsilon^2}\left(\alpha_i + \frac{\sigma_\eta^2 \bar{e} + \sigma_e^2 s_i}{\sigma_\eta^2 + \sigma_e^2}\right) - f \\
&\quad - \frac{f}{2c}\left(\frac{\sigma_\alpha^2 + \sigma_{esg}^2}{\sigma_\alpha^2 + \sigma_{esg}^2 + \sigma_\epsilon^2}\right)^2 \left(\sigma_\epsilon^2 + \frac{\sigma_\eta^2 \sigma_e^2}{\sigma_\eta^2 + \sigma_e^2}\right).
\end{aligned} \tag{A.7}$$

Let $\tau = \frac{\sigma_\alpha^2 + \sigma_{esg}^2}{\sigma_\alpha^2 + \sigma_{esg}^2 + \sigma_\epsilon^2}$, $e_s = \frac{\sigma_\eta^2 \bar{e} + \sigma_e^2 s_i}{\sigma_\eta^2 + \sigma_e^2}$, and $\sigma_s^2 = \frac{\sigma_\eta^2 \sigma_e^2}{\sigma_\eta^2 + \sigma_e^2}$, where e_s and σ_s^2 represent the posterior expectation and variance after updating by the private signal s_i. The objective function $\mathcal{L}$ can be expressed as:

$$\mathcal{L}(\tau) = -\frac{f}{2c}(\sigma_\epsilon^2 + \sigma_s^2)\left(\tau - \frac{c(\alpha_i + e_s - \bar{\alpha} - \bar{e})}{f(\sigma_\epsilon^2 + \sigma_s^2)}\right)^2 + \bar{\alpha} + \bar{e} - f + \frac{c(\alpha_i + e_s - \bar{\alpha} - \bar{e})^2}{2f(\sigma_\epsilon^2 + \sigma_s^2)}, \tag{A.8}$$

where $\tau \in [\frac{\sigma_\alpha^2 + \sigma_s^2}{\sigma_\alpha^2 + \sigma_s^2 + \sigma_\epsilon^2}, 1)$. The lower bound is based on the fact that investors' uncertainty about ESG factors is always greater than mutual funds' posterior uncertainty about ESG factors.

By maximizing the fund expected utility function, I solve the solution of σ_{esg}^2, which determines the optimal ESG risk disclosure. The solution has three cases:

Case I: when the signal $s_i \leqslant \underline{s}$, where $\underline{s} = \frac{(\sigma_\alpha^2+\sigma_s^2)(\sigma_\epsilon^2+\sigma_s^2)(\sigma_\eta^2+\sigma_e^2)f}{c\sigma_e^2(\sigma_\alpha^2+\epsilon_s^2+\sigma_\epsilon^2)} + \frac{(\bar{\alpha}+\bar{e}-\alpha)(\sigma_\eta^2+\sigma_e^2)-\sigma_\eta^2\bar{e}}{\sigma_e^2}$, the objective function $\mathcal{L}$ is decreasing with σ_{esg}^2. The objective function is maximized when $\sigma_{esg}^2 = \sigma_e^2$;

Case II: when the signal $s_i \geqslant \bar{s}$, where $\bar{s} = \frac{f(\sigma_\epsilon^2+\sigma_s^2)(\sigma_\eta^2+\sigma_e^2)}{c\sigma_e^2} + \frac{(\bar{\alpha}+\bar{e}-\alpha)(\sigma_\eta^2+\sigma_e^2)-\sigma_\eta^2\bar{e}}{\sigma_e^2}$, the objective function $\mathcal{L}$ is increasing with σ_{esg}^2, showing the expected utility increases as σ_{esg}^2 increases;

Case III: when the signal $s_i \in (\underline{s}, \bar{s})$, there exists a unique solution of σ_{esg}^2 that maximizes the objective function $\mathcal{L}$, at which,

$$\tau = \frac{\sigma_\alpha^2 + \sigma_{esg}^2}{\sigma_\alpha^2 + \sigma_{esg}^2 + \sigma_\epsilon^2} = \frac{c(\alpha + e_s - \bar{\alpha} - \bar{e})}{f(\sigma_\epsilon^2 + \sigma_s^2)}. \tag{A.9}$$

I take the partial derivative of the optimal σ_{esg}^2, at which equation (A.9) is satisfied, with respect to s. The partial derivative is expressed by:

$$\frac{\partial \sigma_{esg}^2}{\partial s} = \frac{\frac{\partial \tau}{\partial s}}{\frac{\partial \tau}{\partial \sigma_{esg}^2}} = \frac{\frac{\partial \tau}{\partial e_s}\frac{\partial e_s}{\partial s}}{\frac{\partial \tau}{\partial \sigma_{esg}^2}} > 0, \tag{A.10}$$

as $\frac{\partial \tau}{\partial e_s} > 0$, $\frac{\partial e_s}{\partial s} > 0$, and $\frac{\partial \tau}{\partial \sigma_{esg}^2} > 0$. The result shows that as the signal increases, the optimal value of σ_{esg}^2 also increases.

A.5 Proof of Proposition 3 and 4

In Case I and Case II, the value of optimal σ_{esg}^2 is independent with s_i; in Case III, the closed form of the optimal σ_{esg}^2 is expressed by,

$$\sigma_{esg}^2 = \frac{c(\alpha_i + e_s - \bar{\alpha} - \bar{e})(\sigma_\alpha^2 + \sigma_\epsilon^2) - \sigma_\alpha^2 f(\sigma_\alpha^2 + \sigma_\epsilon^2)}{f(\sigma_\epsilon^2 + \sigma_s^2) - c(\alpha_i + e_s - \bar{\alpha} - \bar{e})}. \tag{A.11}$$

I take the derivative of σ_{esg}^2 with respect to the signal s_i, and have

$$\frac{\partial \sigma_{esg}^2}{\partial s_i} = \frac{\partial e_{esg}^2}{\partial e_s}\frac{\partial e_s}{s_i} = \frac{c\sigma_\epsilon^2(\sigma_\epsilon^2 + \sigma_s^2)}{\left(\sqrt{f}(\sigma_\epsilon^2 + \sigma_s^2) - \frac{c(\alpha_i+e_s-\bar{\alpha}-\bar{e})}{\sqrt{f}}\right)^2}\frac{\sigma_e^2}{\sigma_\eta^2 + \sigma_e^2}. \tag{A.12}$$

From equation (A.12), I get $\frac{\partial^2 \sigma^2_{esg}}{\partial s_i \partial f} < 0$ and $\frac{\partial^2 \sigma^2_{esg}}{\partial s_i \partial a_i} > 0$.

A.6 Alternative Model

In this alternative model, I assume that the ESG factor is unknown to investors. Disclosures make investors aware of the existence of risk factor. Based on this setup, I examine and compare the sensitivity of cash flows to fund performance without and with disclosure.

Case without disclosure. From the perspective of investors, the excess return (net of fees) of fund i at time t as follows,

$$r_{i,t} = \alpha_i + \epsilon_{i,t} - C(q_{i,t-1}) - f. \tag{A.13}$$

Investors take this form of fund excess return to update their expectation about the funds and thus the size of mutual funds is determined. In this case, the fund flows at time 2 are represented as,

$$\text{Flows}_{i,2} = \frac{\sigma^2_\alpha}{\sigma^2_\alpha + \sigma^2_\epsilon} \frac{r_2}{cq_{i,1}}, \tag{A.14}$$

and the sensitivity of fund flows to fund past performance is represented as,

$$\text{Sensitivity}_i = \frac{\partial \text{Flows}_{i,2}}{\partial r_{i,2}} = \frac{\sigma^2_\alpha}{\sigma^2_\alpha + \sigma^2_\epsilon} \frac{1}{cq_{i,1}}. \tag{A.15}$$

Case with disclosure. From the perspective of investors, the excess return (net of fees) of fund i at time t as follows,

$$r_{i,t} = \alpha_i + e_i + \epsilon_{i,t} - C(q_{i,t-1}) - f. \tag{A.16}$$

The fund flows at time 2 are represented as,

$$\text{Flows}_{i,2} = \frac{\sigma^2_\alpha + \sigma^2_{esg}}{\sigma^2_\alpha + \sigma^2_{esg} + \sigma^2_\epsilon} \frac{r_2}{cq_{i,1}}, \tag{A.17}$$

and the sensitivity of fund flows to fund past performance is represented as,

$$\text{Sensitivity}_i = \frac{\partial \text{Flows}_{i,2}}{\partial r_{i,2}} = \frac{\sigma^2_\alpha + \sigma^2_{esg}}{\sigma^2_\alpha + +\sigma^2_{esg} + \sigma^2_\epsilon} \frac{1}{cq_{i,1}}. \tag{A.18}$$

The sensitivity of fund flows to fund past performance in the case with disclosure is larger than the sensitivity in the case without disclosure, showing that if ESG factor is unknown to investors, disclosure will increase the sensitivity of fund flows to fund past performance.

B RepRisk Risk Tag

B.1 28 ESG Issues

RepRisk covers 28 issues, including 6 environmental, 10 social issues, 7 governance issues, and 5 cross-cutting issues, which are listed below.

Environmental Issues

- Animal mistreatment, which refers to the torture, mistreatment or abuse of animals, through experiments, husbandry, trophy hunting, etc.
- Climate change, GHG emissions, and global pollution. This issue covers impacts of company activities on ecosystems or landscapes such as forests, rivers, seas, etc., contamination of groundwater and water systems, deforestation, impacts on wildlife, etc.
- Impacts on landscaptes, ecosystems, and biodiversity. This issue includes pollution, mainly atmospheric, that has negative impacts beyond the surroundings in which the emissions occur. This includes, for example, criticism related to climate change, carbon, and other greenhouse gas emissions, coal-fired power plants, gas flaring, carbon credits, etc.
- Local pollution. This issue covers pollution into air, water, and soil that has a primarily local effect, including oil spills, etc.
- Waste issues. This issue relates to inappropriate disposal or handling of waste from the company's production processes or projects, as well as waste trafficking.
- Overuse and wasting of resources. This issue refers to a company's overuse, inefficient use of waste of renewable and nonrenewable resources, such as energy, water, commodities, etc.

Social Issues

- Child labor. This issue refers to the use of child labor by an employer, according to the ILO Conventions. This includes, for example, child prostitution, child pornography, child trafficking, etc. for those under 18 years old.

- Discrimination in employment. This issue refers to treating people differently or less favorably because of characteristics that are not related to their merit or the inherent requirements of the job, such as gender, religion, nationality, age, etc. Discrimination can arise either when gaining access to employment or once employees are in work.

- Forced labor. This issue refers to the use of forced or compulsory labor by an employer. This includes, for example, bonded labor, prison labor, exploitative practices, full or partial restrictions on freedom of movement, withholding of wages, threats of deportation for illegal workers, etc.

- Freedom of association and collective bargaining. This issue refers to violations of workers" rights to organize and collectively bargain. This includes, for example, interfering with union formation and participation, retaliation against striking workers, refusal to comply with union agreements, etc.

- Human rights abuses, corporate complicity. This issue is linked when a company is accused of committing or being complicit in human rights abuses. This includes, for example, violence against individuals, threat of violence, child and forced labor, human trafficking, organ trafficking, privatization of water sources, privacy violations, supporting oppressive regimes or terrorist organizations, trading in "blood diamonds" or "bush gold," etc.

- Local participation issues. This issue relates to activities of a company that leads to problems or worries for a community, such as a village or town or a group of people with common interests, values, preferences, social background, etc. This includes, for example, land- and water-grabbing, negative impacts on a community's livelihood/employment opportunities, relocation of communities, safety impacts, access to lifesaving drugs, etc.

- Local participation issues. This issue covers instances in which local communities or individuals are not appropriately consulted about the activities of a company, do not benefit appropriately from their activities, or when companies use unethical tactics, such as imprisonment or harassment, to silence their critics.

- Occupational health and safety issues. This issue refers to health and safety matters in the context of employee relations within a company. This includes, for example, lack of safety for employees at work, occupational accidents related to poor health and safety measures, sickness among workers related to production processes, negligence resulting in work-related accidents, etc.

- Poor employment conditions. This issue refers to poor employment conditions. This includes, for example, “slave-like” working conditions, “sweatshop” labor, harrasment and mistreatment of employees (including sexual), issues related to labor contracts and/or pay, illegal employment, unfair dismissals, spying on employees, etc.

- Social discrimination. This issue refers to treating people differently or less favorably because of certain characteristics, such as gender, racial, ethnic, or religious, outside of an employment setting (such as customers). See “Discrimination in employments” for discriminatory treatment of employees.

Governance Issues

- Anti-competitive practices. This issue refers to business or government practices that prevent, reduce or manipulate competition in a market. This includes, for example, bid-rigging, dumping, exclusive dealing, price fixing, dividing territories, government-granted monopolies, limit pricing, tying, resale price maintenance, collusion, etc.

- Corruption, bribery, extortion, money laundering. This issue refers to corruption, bribery, extortion and money laundering. The understanding of corruption is based on the 10th Principle of the UN Global Compact. This includes, for example, use of slush funds, aggressive lobbying, overcharging, nepotism, cronyism, connections to organized crime, etc.

- Executive compensation issues. This issue refers to the compensation (salary, bonus and other remuneration) of top management, regardless of their performance. This includes, for example, excessive bonuses, salaries, pensions, termination settlements, benefits, etc.

- Fraud. This issue refers to intentional deception made for personal gain or damage to another individual (lying with financial or legal impacts). This includes, for example, counterfeiting, forgery, embezzlement, insider trading, fraud related to bankruptcy, investments or securities, breach of fiduciary duty, false advertising/billing/claims/documentation, misleading investors, stock price manipulation, etc.

- Misleading communication. This issue refers to when a company manipulates the truth in an effort to present itself in a positive light, and in the meantime contradicts this self-created image through its actions. Also refers to when a company misleads consumers about its products and services. This includes, for example, "greenwashing," false advertising, off-label marketing, "astroturfing," etc.

- Tax evasion. This issue refers to general efforts to not pay taxes by illegal means. This includes, for example, tax fraud, use of tax havens, etc.

- Tax optimisation. This issue refers to the practice of minimising tax liability through tax planning. While not illegal, it may be associated with abuse of the law.Often criticised for robbing a state of potential tax revenues, particularly in developing countries.This includes, for example, tax inversion, the relocation of a company"s headquarters to a low-tax country while retaining operations in a high-tax country, and tax avoidance, taking advantage of beneficial tax "loopholes."

Cross-Cutting Issues

- Controversial products and services. This issue refers to the sale of products or services that provoke strong disagreement or disapproval. This includes, for example, alcohol, weapons, drones, biofuels, drugs used for state executions, gambling, genetically-modified organisms, nuclear power/fuel, palm oil, ozone-depleting substances, seed and/or animal patents, PCBs, pornography, socially-controversial financial services, tobacco, tropical wood products, etc.

- Products (health and environmental issues). This issue refers to providing a product or service which poses an unnecessary risk to the consumer's health or the environment.This includes, for example, recalls of toxic or dangerous products (including drugs), contaminated food, medical treatments leading to unintended health consequences, transportation services providing safety risks to customers, etc.

- Supply chain issues. This issue refers to companies who are held accountable for the actions of their suppliers. Both vendors and subcontractors are considered part of the supply chain.

- Violation of international standards. This issue refers to breaches of international standards set by: International governmental organisations with a global nature that are open for all states to join, including all UN-related bodies. International treaties with a global nature that are currently in force and that are, in principle, open for all states to sign. International customary law.

- Violation of national legislation. This issue refers to the violation of national and state legislation in relation to an environmental, social, or governance issue. This includes, for example, breaches of national or regional laws, breaches of bilateral or regional treaties, court actions by government agencies or other companies for questionable business practices, breaches of domestic laws for crimes committed abroad, business with nationally-sanctioned countries, etc.

B.2 73 Risk Topic Tags

The 73 Topic Tags covered by RepRisk are as follows: Abusive/Illegal fishing, Access to products and services, Agricultural commodity speculation, Airborne pollutants, Alcohol, Animal transportation, Arctic drilling, Asbestos, Automatic and semi-automatic weapons, Biological weapons, Chemical weapons, Cluster munitions, Coal-fired power plants, Conflict minerals, Coral reefs, Cyberattack, Deep sea drilling, Depleted uranium munitions, Diamonds, Drones, Economic impact, Endangered species, Energy management, Epidemics/Pandemics, Forest burning, Fracking, Fur and exotic animal skins, Gambling, Gender inequality, Genetically modified organisms (GMOs), Genocide/Ethnic cleansing, Greenhouse gas (GHG) emissions, Health impact, High conservation value forests, Human trafficking, Hydropower (dams), Illegal logging, Indigenous people, Involuntary resettlement, Land ecosystems, Land grabbing, Land mines, Lobbying, Marijuana/Cannabis, Marine/Coastal ecosystems, Migrant labour, Monocultures, Mountaintop removal mining, Negligence, Nuclear power, Nuclear weapons, Offshore drilling, Oil sands, Opioids, Palm oil, Plastics, Pornography, Predatory lending, Privacy violations, Protected areas, Racism/Racial inequality, Rare earths, Salaries and benefits, Sand mining and dredging, Seabed mining, Security services, Ship breaking and scrapping, Soy, Tax havens, Tobacco, wastewater management, Water management, Water scarcity.

C Word List

The word list about ESG constructed by Baier et al. (2020) is as follows: ESG, Environmental, Ethic, Carbon, SRI, Responsible Investing, Human Rights, Green, Climate Change, Renewable Energy, Social Responsibility, Pollution, Sustainable Business Practice, Sustainable development goals, Biological, Clean energy, SDG, Toxic, Public health, Labour standards, Access to medicine, Community relations, Diversity, HIV and AIDS, Privacy and free expression, Health and safety, Nutrition, Security, ILO core conventions, Product safety, Weak governance zones, Supply chain labour standards, Society, Charity, Education, Employment, Corporate governance Business ethics, Sustainability management and reporting, Audit and control, Bribery and corruption, Disclosure and reporting, Board structure, Political influence, Stakeholder engagement, Remuneration Responsible marketing, UNGC compliance, Shareholder rights, Whistle-blowing system, Governance of sustainability issues, Transparency, Talent, Environmental, Ecosystem service, Climate change, Environmental management, Access to land, Biofuels, Environmental standards, Biodiversity management, Climate change strategy, Pollution control, Water, Emissions management reporting, Product opportunities, Reporting, Waste and recycling, Supply chain environmental standards.

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Figure 1: The Word Cloud of Mutual Fund ESG Disclosure

Figures 1a and 1b display the word clouds based on the descriptions of ESG investment strategy and ESG risk in mutual fund prospectuses respectively. Word clouds use TF-IDF (term frequency-inverse document frequency) representation, which evaluates how relevant a word is to a document in a collection of documents. In this example, the TF-IDF value for a word can be determined by multiplying the term frequency of the word across the ESG strategy (risk) descriptions and inverse document frequency across all texts in the sample.

(a) ESG Investment Strategy Disclosure

(b) ESG Risk Disclosure

Figure 2: The Trend of Funds with ESG-related Disclosure

In Figure 2, the histograms display the number of funds with ESG strategy disclosure (green) and ESG risk disclosure (blue) from 2011 to 2019. The line charts plot the percentage of funds with ESG strategy disclosure (green) and ESG risk disclosure (blue) among all the funds in the sample from 2011 to 2019.

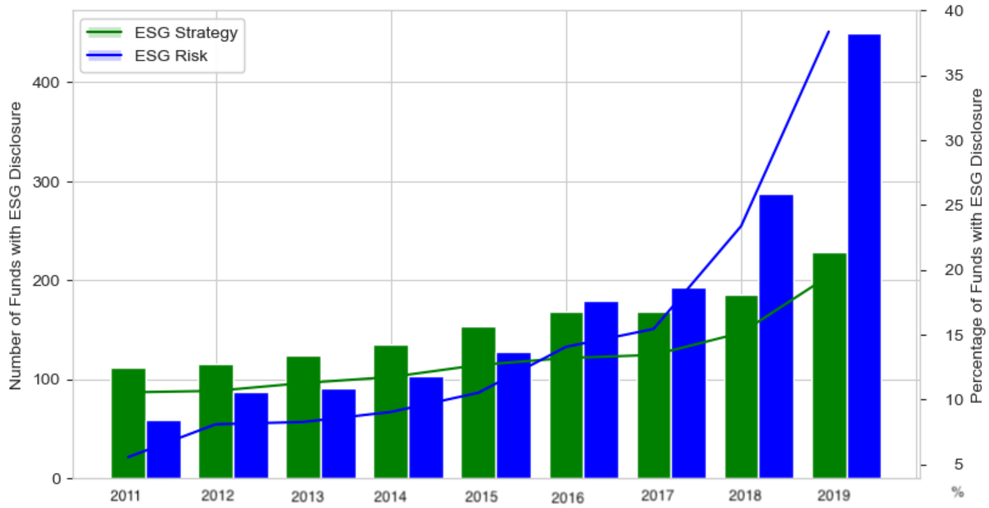

Table 1: Text Classification Results Using Different Methods

Table 1 presents a comparison of different methods for classifying ESG strategy and ESG risk sentences. There are two methods being compared: deep learning and traditional classification based on word lists. Three metrics are used to evaluate the classification results: Precision, Recall, and F-score. Precision is a measure of how many of the positive predictions made are correct (true positive), where $Precision = \frac{TruePositives}{TruePositives+FalsePositives}$. Recall is a measure of how many of the positive cases the classifier correctly predicted, over all the positive cases in the data, where $Recall = \frac{TruePositives}{TruePositives+FalseNegatives}$. F-score is a measure combining both precision and recall, where $F\text{-}score = 2 * \frac{Precision * Recall}{Precision+Recall}$.

(a) Classification of ESG Strategy Descriptions

	Deep Learning			Word List		
	Precision	Recall	F-score	Precision	Recall	F-score
Non-ESG	0.99	0.98	0.99	0.76	0.56	0.65
ESG	0.88	0.93	0.91	0.43	0.64	0.52
Average	0.93	0.96	0.95	0.59	0.6	0.58
Weighted Average	0.98	0.97	0.98	0.65	0.59	0.60

(b) Classification of ESG Risk Descriptions

	Deep Learning			Word List		
	Precision	Recall	F-score	Precision	Recall	F-score
Non-ESG	0.97	0.95	0.96	0.95	0.56	0.65
ESG	0.90	0.94	0.92	0.30	0.64	0.52
Average	0.93	0.94	0.94	0.63	0.74	0.62
Weighted Average	0.95	0.94	0.94	0.86	0.71	0.76

Table 2: Mean Statistics by ESG Disclosure

Table 2 reports fund characteristics based on ESG disclosure. Panels 2a, 2b, and 2c present the mean statistics of the characteristics of funds in the full sample, funds with ESG strategy disclosure, and funds with ESG risk disclosure, respectively. The fund characteristics include fund total net assets (TNA), fund age, expense ratio, turnover ratio, fund family size, length of prospectuses, quarterly cashflows, and monthly returns.

(a) Mutual Funds in Full Sample

	TNA ($M)	Age (Years)	Exp Ratio	Turn Ratio	Family Size ($M)	Length (Word Count)	Cashflows	Returns
Count	39647	39647	38846	38657	39647	39642	39647	39647
Mean	1474.88	14.73	0.0109	0.65	56030.11	372	-0.0003	0.0093
Std	3307.037	9.07	0.0038	0.66	174139.6	274	0.1334	0.0242
10%	22.5	4.49	0.0071	0.15	101.7	245	-0.0856	-0.0182
50%	333.7	13.67	0.0107	0.50	9455.4	322	-0.0169	0.0116
90%	3542.22	24.36	0.0147	1.25	86973.8	452	0.0817	0.0363

(b) Mutual Funds with ESG Strategy Disclosure

	TNA ($M)	Age (Years)	Exp Ratio	Turn Ratio	Family Size ($M)	Length (Word Count)	Cashflows	Returns
Mean	1270.69	14.24	0.0109	0.68	26789.35	412	0.0050	0.0095
Std	2907.595	8.98	0.0033	0.70	55612.8	306	0.1289	0.0240
10%	20.18	4.02	0.0071	0.17	67.06	297	-0.0781	-0.0184
50%	251.9	12.89	0.0107	0.49	8930	324	-0.0139	0.0118
90%	2769.52	24.29	0.0150	1.37	78839.4	669	0.0913	0.0356

(c) Mutual Funds with ESG Risk Disclosure

	TNA ($M)	Age (Years)	Exp Ratio	Turn Ratio	Family Size ($M)	Length (Word Count)	Cashflows	Returns
Mean	1539.143	14.30	0.0106	0.55	37067.78	596	-0.0020	0.0100
Std	3470.683	8.69	0.0040	0.47	84014.18	544	0.1301	0.0242
10%	22	3.50	0.0070	0.14	90.9	301	-0.0827	-0.0154
50%	286	13.61	0.0102	0.43	11809.3	325	-0.0166	0.0121
90%	3910.92	25.01	0.0142	1.11	91024.7	1269	0.0716	0.0363

Table 3: Industry Allocation of Fund Portfolios

Table 3 presents the mean and median of the sector weights in the fund portfolios. The funds are classified into three categories based on their prospectuses: those that disclose ESG investment strategy, those that disclose ESG risks, and those without any ESG disclosures. The sector weights are examined on each type of fund.

	Mean			Median		
	ESG Strategy	ESG Risk	Non-ESG	ESG Strategy	ESG Risk	Non-ESG
Consumer Nondurables	5.25%	4.85%	5.02%	4.53%	4.17%	4.52%
Consumer Durables	1.95%	1.50%	1.76%	1.32%	0.79%	1.16%
Manufacturing	8.01%	6.74%	7.70%	7.55%	6.23%	7.17%
Energy	4.76%	5.53%	5.33%	4.13%	4.62%	4.54%
Chemicals	3.16%	2.84%	2.93%	2.82%	2.46%	2.56%
Business Equipment	20.76%	19.54%	19.78%	20.02%	18.30%	18.44%
Telecommunication	2.87%	3.41%	3.05%	2.03%	2.39%	2.07%
Utilities	2.08%	2.92%	2.53%	0.17%	0.89%	0.88%
Wholesale and Retail	9.80%	8.81%	9.74%	9.54%	8.55%	9.41%
Healthcare	9.39%	8.57%	9.04%	9.31%	8.69%	9.12%
Finance	17.63%	19.28%	18.24%	17.26%	19.28%	17.78%
Others	9.78%	9.67%	9.89%	8.94%	8.81%	9.10%

Table 4: Regressions of Fund Flows on ESG Risk Disclosure Variable, Past Performance, and Interaction Terms

Table 4 presents estimated coefficients from pooled OLS regressions of quarterly fund flows on an ESG risk disclosure variable, past performance, and interaction terms. Past performance is measured using the percentile of prior 12-month net returns relative to other funds in the same style category. Columns (2) and (4) include the interaction between ESG risk disclosure variable and past performance, whereas columns (1) and (3) do not. In columns (1) and (2), the ESG risk disclosure variable equals to one if the principal risk section includes the ESG risk descriptions, and zero otherwise. In columns (3) and (4), the ESG risk disclosure variable equals to the weight of ESG descriptions in the overall risk descriptions. All specifications include style-time fixed effects, and control for other fund characteristics. T-statistics are provided in brackets with standard errors clustered by fund family and time. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Fund Flows			
ESG Risk Disclosure Measure	$\text{ESGRisk}_{\text{Dummy}}$		$\text{ESGRisk}_{\text{Weight}}$	
	(1)	(2)	(3)	(4)
Const	0.0684*** (5.4005)	0.0666*** (5.2583)	0.0692*** (5.5204)	0.068*** (5.4285)
ESGrisk	0.0000 (0.032)	0.0094*** (2.6718)	0.0130 (0.9766)	0.0609** (2.2688)
ESGrisk*Performance		-0.0185*** (-2.9596)		-0.0936* (-1.8905)
Performance	0.0598*** (26.055)	0.0623*** (25.075)	0.0598*** (26.052)	0.0613*** (25.26)
Length	0.0016 (0.8252)	0.0017 (0.8958)	0.0014 (0.7431)	0.0015 (0.7875)
Size	0.0041*** (8.3517)	0.0041*** (8.3013)	0.0042*** (8.3699)	0.0041*** (8.3326)
LogfamilySize	-0.0019*** (-5.1841)	-0.0019*** (-5.1395)	-0.0019*** (-5.2022)	-0.0019*** (-5.1623)
Volatility	-0.275*** (-2.8519)	-0.2805*** (-2.9127)	-0.2738*** (-2.8397)	-0.2766*** (-2.8704)
Age	-0.0424*** (-31.218)	-0.0425*** (-31.232)	-0.0424*** (-31.232)	-0.0424*** (-31.239)
ExpRatio	-0.0231 (-0.1145)	-0.0162 (0.0805)	-0.0254 (-0.1263)	-0.0169 (-0.0837)
TurnRatio	-0.0013 (0.7904)	-0.0013 (0.8)	-0.0012 (-0.7592)	-0.0012 (-0.7651)
Actual12b1	0.2954 (0.9668)	0.2973 (0.9728)	0.2909 (0.9524)	0.2872 (0.9394)
Style × Time FE	Y	Y	Y	Y
Observations	37248	37248	37248	37248
R^2	0.0737	0.0739	0.0738	0.0738

Table 5: Regressions of Fund Flows on ESG Investing Disclosure Variable, Past Performance, and Interaction Terms

Table 5 presents estimated coefficients from pooled OLS regressions of quarterly fund flows on an ESG investing disclosure variable, past performance, and interaction terms. Past performance is measured using the percentile of prior 12-month net returns relative to other funds in the same style category. Columns (2) and (4) include the interaction between ESG investing disclosure variable and past performance, whereas columns (1) and (3) do not.In columns (1) and (2), the ESG investing variable equals to one if the principal strategy section includes the ESG investment strategy descriptions, and zero otherwise. In columns (3) and (4), the ESG investing disclosure variable equals to one if the principal risk section includes the ESG investing descriptions, and zero otherwise. All specifications include style-time fixed effects, and control for other fund characteristics. T-statistics are provided in brackets with standard errors clustered by fund family and time. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Fund Flows			
ESG Investing Disclosure	ESG Strategy Dummy		ESG Investing Dummy	
Measure	(1)	(2)	(3)	(4)
Const	0.0684*** (5.4687)	0.0688*** (5.4896)	0.0652*** (5.248)	0.065*** (5.2257)
ESGInvest	0.0119*** (3.4774)	-0.0025 (0.2004)	0.0085** (2.329)	0.0199** (2.6143)
ESGInvest*Performance		0.0191 (1.1345)		-0.0215 (-1.4494)
Performance	0.0582*** (24.846)	0.0576*** (23.874)	0.0596*** (25.952)	0.0599*** (25.856)
Loglength	0.0014 (0.777)	0.0015 (0.8003)	0.0019 (1.038)	0.0019 (1.0398)
Logtna	0.0041*** (8.3012)	0.0041*** (8.2776)	0.0042*** (8.4473)	0.0042*** (8.449)
LogfamilySize	-0.0018*** (-5.1051)	-0.0018 (-5.1013)	-0.002*** (-5.434)	-0.002*** (-5.4443)
Volatility	-0.2723*** (-2.8142)	-0.2749*** (-2.8377)	-0.2694*** (-2.7835)	-0.2688*** (-2.7751)
Logage	-0.0422*** (-31.248)	-0.0422*** (-31.25)	-0.0421*** (-31.25)	-0.0421*** (-31.247)
ExpRatio	-0.0295 (-0.1463)	-0.0385 (0.1912)	-0.0171 (0.0846)	-0.0162 (-0.0801)
TurnRatio	-0.0014 (-0.8864)	-0.0014 (0.8782)	-0.0013 (0.8409)	-0.0013 (-0.8381)
Actual12b1	0.3009 (0.9845)	0.3163 (1.0356)	0.3971 (1.2996)	0.4028 (1.3182)
Style × Time FE	Y	Y	Y	Y
Observations	37418	37418	37490	37490
R^2	0.0738	0.0738	0.0733	0.0733

Table 6: Difference-in-Difference Regressions of Fund Flows on Interaction Terms between ESG Risk Disclosure Variable and Past Performance

Table 6 presents the results of difference-in-difference regressions. In columns (1) and (3), *Treat* is a dummy variable that equals to one if funds include ESG risk descriptions in their principal risk section, and zero otherwise. In columns (2) and (3), *Treat* represents how much weight ESG risk disclosure has in the overall risk disclosure. In columns (1) and (2), the control group includes funds that do not disclose ESG risks during the sample period, and in columns (3) and (4), the control group includes funds that do not disclose ESG risks under Propensity Score Matching (PSM). The dummy variable *Post* represents the period after ESG risk disclosure has been incorporated into prospectuses. All specifications include style-time fixed effects, and control for other fund characteristics. T-statistics are provided in brackets with standard errors clustered by fund family and time. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

	Fund Flows			
Control Group	Funds without Risk Disclosure		PSM Group	
Treatment Variable	$\text{ESGRisk}_{\text{Dummy}}$	$\text{ESGRisk}_{\text{Weight}}$	$\text{ESGRisk}_{\text{Dummy}}$	$\text{ESGRisk}_{\text{Weight}}$
	(1)	(2)	(3)	(4)
Const	0.0508***	0.0547***	0.0408***	0.046***
	(4.11)	(4.45)	(2.41)	(2.73)
Treat*Post*Performance	-0.01***	-0.0542**	-0.0112***	-0.0565**
	(-2.87)	(-2.02)	(-3.1)	(-2.06)
Performance	0.0607***	0.0603***	0.0616***	0.0609***
	(25.4)	(25.38)	(21.3)	(21.25)
Loglength	0.0023	0.0016	0.006**	0.0051**
	(1.22)	(0.86)	(2.32)	(1.98)
Logtna	0.0031***	0.0031***	0.0027***	0.0027***
	(7.63)	(7.64)	(5.54)	(5.61)
Volatility	-0.292***	-0.2906***	-0.3682***	-0.366***
	(-2.95)	(-2.93)	(-3.09)	(-3.07)
Logage	-0.0422***	-0.0422***	-0.0438***	-0.0439***
	(-29.79)	(-29.8)	(-26.41)	(-26.43)
ExpRatio	0.4342**	0.4397**	0.0299	0.0388
	(2.19)	(2.22)	(0.12)	(0.15)
TurnRatio	-0.0016	-0.0016	0.0004	0.0005
	(-1.03)	(-1.01)	(0.22)	(0.23)
Actual12b1	-0.1798	-0.1837	0.2069	0.1959
	(-0.6)	(-0.61)	(0.55)	(0.52)
Style × Time FE	Y	Y	Y	Y
Observations	35649	35649	24923	24923
R^2	0.071	0.0709	0.0787	0.0785

Table 7: Regressions of Fund Actual ESG Risk Exposure on ESG Disclosure Variable

Table 7 presents the estimated coefficients from pooled OLS regressions of fund actual ESG risk exposure on fund ESG disclosure variable. The dependent variables are the current RRI, peak RRI, and severity score at quarterly t in 7a, 7b, and 7c, respectively. The predictive variables include the ESG risk disclosure variable *ESGRisk*, ESG strategy disclosure variable *ESGStr*, and the intersection between them at quarter $t-1$. *ESGrisk* is represented by the ESG risk disclosure dummy variable in columns (1) and (2), and the weight of ESG risk disclosure in the overall risk disclosure in columns (3) and (4). *ESGStr* is represented by the ESG strategy disclosure dummy variable in columns (1), (2), (3) and (4). The regressions in columns (2) and (4) include the industry-fixed effects. All specifications include style-time fixed effects, and control for other fund characteristics. T-statistics are provided in brackets with standard errors clustered by fund family and time. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

(a) Actual ESG Risk Measure: Current RRI

	Current RRI			
ESGRisk Measure	$\text{ESGRisk}_{\text{Dummy}}$		$\text{ESGRisk}_{\text{Weight}}$	
	(1)	(2)	(3)	(4)
Const	26.579***	24.68***	26.182***	24.645***
	(34.66)	(33.93)	(34.72)	(34.3)
ESGStr	-0.41***	-0.1102	-0.4434***	-0.1661
	(3.46)	(-0.98)	(-3.92)	(-1.55)
ESGRisk	0.9126***	0.4016***	6.2861***	3.0235***
	(7.25)	(3.63)	(7.15)	(3.86)
ESGRisk*ESGStr	-2.2152***	-1.7432***	-18.089***	-13.299***
	(8.78)	(7.49)	(-9.84)	(-8.14)
Loglength	0.0148	-0.0061	0.0925	0.0031
	(-0.14)	(-0.006)	(0.88)	(0.03)
Logtna	-0.1268***	-0.1009***	-0.125***	-0.0996***
	(-4.65)	(-4.07)	(-4.58)	(-4.01)
LogfamilySize	0.2821***	0.1842***	0.2795***	0.1825***
	(14.06)	(10.06)	(13.94)	(9.98)
Performance	-0.1463	0.0557	-0.1488	0.0561
	(-1.11)	(0.46)	(-1.13)	(0.46)
Volatility	-187.7***	-147.6***	-188.45***	-148.1***
	(-26.87)	(-21.19)	(-26.99)	(-21.28)
Logage	0.9362***	0.6616***	0.9416***	0.6694***
	(14.9)	(11.64)	(15)	(11.78)
ExpRatio	-214.29***	-135.19***	-214.16***	-135.3***
	(-13.06)	(-9.02)	(-13.01)	(-9.01)
TurnRatio	-0.2699***	-0.1774***	-0.2759***	-0.1783***
	(-4.16)	(-2.86)	(-4.25)	(-2.87)
Industry FE	N	Y	N	Y
Style× Time FE	Y	Y	Y	Y
Observations	30769	30722	30769	30722
R^2	0.09	0.258	0.0903	0.258

(b) Actual ESG Risk Measure: Peak RRI

	Peak RRI			
ESGRisk Measure	$\text{ESGRisk}_{\text{Dummy}}$		$\text{ESGRisk}_{\text{Weight}}$	
	(1)	(2)	(3)	(4)
Const	38.644***	36.048***	38.243***	36.069***
	(46.087)	(45.43)	(46.43)	(46.07)
ESGStr	-0.289***	0.0416	-0.313**	-0.0052
	(-2.1783)	(0.33)	(-2.29)	(-0.04)
ESGRisk	0.9268***	0.334***	6.75***	2.9918***
	(6.8582)	(2.82)	(7.34)	(3.66)
ESGRisk*ESGStr	-2.2044***	-1.6709***	-18.499***	-13.232***
	(-8.084)	(-6.61)	(-9.7)	(7.67)
Loglength	0.1137	0.087	0.191	0.0848
	(0.981)	(0.83)	(1.7)	(0.83)
Logtna	-0.1197***	-0.093***	-0.1178***	-0.0918***
	(-3.9509)	(-3.38)	(-3.89)	(-3.33)
LogfamilySize	0.3043***	0.199***	0.3014***	0.1971***
	(13.675)	(9.82)	(13.55)	(9.73)
Performance	-0.1963	0.0454	-0.1992	0.0454
	(-1.3263)	(0.33)	(-1.35)	(0.33)
Volatility	-219.96***	-165.02***	-220.66***	-165.47***
	(-27.072)	(-20.37)	(-27.17)	(-20.44)
Logage	1.0445***	0.7663***	1.0502***	0.7748***
	(14.759)	(12.02)	(14.86)	(-12.15)
ExpRatio	-229.76***	-145.44***	-229.67***	-145.62***
	(-12.393)	(8.6)	(-12.36)	(-8.6)
TurnRatio	-0.3323***	-0.2363***	-0.3377***	-0.2358***
	(-4.3822)	(-3.34)	(-4.46)	(-3.33)
Industry FE	N	Y	N	Y
Style×Time FE	Y	Y	Y	Y
Observations	30763	30722	30763	30722
R^2	0.0913	0.2603	0.0918	0.2605

(c) Actual ESG Risk Measure: Severity Score

ESGRisk Measure	Severity Score			
	$\text{ESGRisk}_{\text{Dummy}}$		$\text{ESGRisk}_{\text{Weight}}$	
	(1)	(2)	(3)	(4)
Const	0.5845***	0.5367***	0.5758***	0.5366***
	(31.76)	(31.03)	(31.76)	(31.37)
ESGStr	-0.007***	-0.0011	-0.0078***	-0.0024
	(-2.45)	(-0.41)	(-2.84)	(-0.92)
ESGRisk	0.0199***	0.0077***	0.1313***	0.0539***
	(6.59)	(2.87)	(6.19)	(2.85)
ESGRisk*ESGStr	-0.0503***	-0.0379***	-0.4095***	-0.286***
	(-8.1)	(-6.62)	(-9.08)	(-7.15)
Loglength	0.0017	0.0011	0.0034	0.0012
	(0.63)	(0.46)	(1.33)	(0.51)
Logtna	-0.0016**	-0.0015**	-0.0016**	-0.0014**
	(-2.45)	(-2.43)	(-2.39)	(-2.38)
LogfamilySize	0.0052***	0.0031***	0.0052***	0.0031***
	(10.78)	(7.12)	(10.66)	(7.04)
Performance	-0.0054	0.0000	-0.0054	0.0000
	(-1.67)	(0.03)	(-1.69)	(0.03)
Volatility	-4.975***	-3.7931***	-4.9929***	-3.8045***
	(-28.79)	(-21.94)	(-28.9)	(-22.01)
Logage	0.0218***	0.0153***	0.022***	0.0155***
	(14.32)	(11.06)	(14.41)	(11.19)
ExpRatio	-4.7111***	-3.1107***	-4.7064***	-3.1114***
	(-11.76)	(-8.54)	(-11.72)	(-8.53)
TurnRatio	-0.0084***	-0.0059***	-0.0086***	-0.0059***
	(-5.43)	(-3.98)	(-5.53)	(-4.00)
Industry FE	N	Y	N	Y
Style × Time FE	Y	Y	Y	Y
Observations	30763	30722	30763	30722
R^2	0.0918	0.2574	0.0911	0.2575

Table 8: Regressions of Fund MSCI Concern Score on ESG Disclosure Vairable

Table 8 presents the estimated coefficients from pooled OLS regressions of fund MSCI concern score on fund ESG disclosure. The dependent variables are the weighted average of MSCI concern scores based on the fund portfolios. The predictive variables include the ESG risk disclosure variable, ESG strategy disclosure dummy variable, and the intersection between them at quarter $t-1$. *ESGRisk* is represented by the ESG risk disclosure dummy variable in columns (1) and (2), and the weight of ESG risk disclosure in the overall risk disclosure in columns (3) and (4). *ESGStr* is represented by the ESG strategy disclosure dummy variable in columns (1), (2), (3) and (4). The regressions in columns (2) and (4) include the industry-fixed effects. All specifications include style-time fixed effects, and control for other fund characteristics. T-statistics are provided in brackets with standard errors clustered by fund family and time. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	MSCI Concern Score			
ESGRisk Measure	$\text{ESGRisk}_{\text{Dummy}}$		$\text{ESGRisk}_{\text{Weight}}$	
	(1)	(2)	(3)	(4)
Const	1.1662***	1.1259***	1.1679***	1.1395***
	(24.26)	(23.76)	(24.66)	(24.34)
ESGStr	-0.0223***	-0.0166**	-0.0269***	-0.0211***
	(-3.15)	(-2.42)	(3.92)	(-3.14)
ESGRisk	0.0199**	-0.008	0.1094**	-0.0637
	(2.52)	(-1.1)	(2.17)	(-1.35)
ESGRisk*ESGStr	-0.1071***	-0.0762***	-0.6737***	-0.4459***
	(-6.27)	(-4.49)	(6.31)	(-3.98)
Loglength	-0.0098	-0.0101	-0.01	-0.0126*
	(-1.38)	(-1.47)	(-1.45)	(-1.88)
Logtna	-0.0132***	-0.011***	-0.0132***	-0.0109***
	(-7.72)	(-6.67)	(-7.72)	(-6.66)
LogfamilySize	0.0064***	0.0034***	0.0064***	0.0034***
	(5.12)	(2.81)	(5.09)	(2.79)
Performance	-0.0196**	-0.0068	-0.0197**	-0.0068
	(-2.35)	(-0.84)	(-2.36)	(0.84)
Volatility	-7.4897***	-6.543***	-7.4965***	-6.5436***
	(-17.67)	(15.29)	(-17.68)	(-15.29)
Logage	0.0106***	0.006	0.011***	0.0064
	(2.81)	(1.66)	(2.92)	(1.78)
ExpRatio	-4.639***	-2.3815**	-4.6649***	-2.3904**
	(-4.8)	(-2.47)	(-4.83)	(-2.48)
TurnRatio	-0.0015	-0.0051	-0.0015	-0.0049
	(-0.38)	(-1.39)	(-0.38)	(-1.34)
Industry FE	N	Y	N	Y
Style × Time FE	Y	Y	Y	Y
Observations	33051	32987	33051	32987
R^2	0.02	0.0925	0.02	0.0924

Table 9: The Choice of Fund ESG Disclosure

Table 9 presents how the choice of ESG disclosure depends on the past long-term ESG risk of funds. The sample in columns (1) and (2) only contains funds that do not disclose ESG strategies, and the dependent variables are the dummy variables equal to one if $ESGRisk_{Dummy} = 1$ and $ESGStr = 0$, and zero otherwise. The sample in columns (3) and (4) only contains funds that disclose ESG strategies, and the dependent variables are the dummy variables equal one if $ESGRisk_{Dummy} = 1$ and $ESGStr = 1$, and zero otherwise. The regressions in columns (5) and (6) are based on the overall sample, and the dependent variables are equal to one if $ESGRisk_{Dummy} = 1$. The independent variable of interest is the peak RRI index ($PeakRRI$), which represents the long-term ESG risk exposure in the past two years. The industry fixed effects are included in columns (2), (4), and (6). All specifications include style-time fixed effects, and control for other fund characteristics. T-statistics are provided in brackets with standard errors clustered by fund family and time. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

	$\text{ESGRisk}_{\text{Dummy}}$					
Sample	Funds without ESG Strategy Disclosure		Funds with ESG Strategy Disclosure		Overall Sample	
	(1)	(2)	(3)	(4)	(5)	(6)
Const	-1.0867***	-1.0178***	-1.8737***	-1.3328***	-1.18***	-1.1202***
	(-22.25)	(-10.48)	(-13.52)	(-4.93)	(-25.12)	(-12.27)
PeakRRI	0.0022***	0.0011***	-0.0056***	-0.0068***	0.001***	-0.0002
	(8.32)	(3.73)	(6.06)	(-7)	(3.86)	(-0.72)
Loglength	0.2043***	0.2022***	0.4115***	0.4035***	0.2321***	0.2308***
	(27.93)	(27.59)	(22.26)	(20.97)	(33.17)	(32.9)
Logtna	-0.0019	-0.0006	0.014***	0.017***	0.0002	0.0014
	(-1.26)	(-0.37)	(3.02)	(3.58)	(0.17)	(1)
LogfamilySize	0.0035***	0.0031***	-0.0053	-0.0074**	0.0017*	0.0014
	(3.5)	(3.12)	(-1.53)	(-2.11)	(1.7)	(1.44)
36M-Performance	0.006	0.0151**	-0.0676**	-0.0417*	-0.0003	0.0105
	(0.89)	(2.23)	(-2.98)	(-1.85)	(-0.05)	(1.58)
36M-Volatility	-0.7008**	-0.5589*	-4.021***	-2.7049**	-1.0813***	-0.8928***
	(-2.23)	(-1.78)	(-2.17)	(-2.09)	(-3.55)	(-2.9)
Logage	-0.0143***	-0.0126***	-0.0179	-0.0237*	-0.016***	-0.0158***
	(-3.79)	(-3.34)	(-1.49)	(-1.91)	(-4.4)	(-4.33)
ExpRatio	0.9842	1.3763**	9.7805***	12.801***	1.9256***	2.561***
	(1.57)	(2.19)	(4.06)	(5.29)	(3.11)	(4.08)
TurnRatio	-0.0221***	-0.0215***	-0.0634***	-0.0614***	-0.0253***	-0.0245***
	(-8.3)	(-7.99)	(-5.59)	(-5.5)	(-9.49)	(9.07)
Industry FE	N	Y	N	Y	N	Y
Style × Time FE	Y	Y	Y	Y	Y	Y
Observations	26709	26709	4136	4136	30845	30845
R^2	0.0485	0.0558	0.1229	0.145	0.0547	0.0611

Table 10: Cross-sectional Effects of Fund Characteristics on ESG Disclosure Choices

Table 10 examines the effect of fund characteristics on the relationship between fund ESG risk disclosure and actual ESG risk exposure. The sample only contains funds without ESG strategy disclosure, and the dependent variable is a dummy variable equal to one if funds disclose ESG risk, and zero otherwise. The predictive variables include the Peak RRI index ($PeakRRI$), and the intersection terms between $PeakRRI$ and the dummy variable that represents a fund's characteristic. The three characteristics of a fund being examined are, in order, expense ratio, performance ranking, and investor sophistication. In columns (1) and (2), the dummy variable of fund characteristic is represented by a high-expense dummy variable $HighExp$, which equals to one if the expense ratios of funds are ranked in the upper half among the funds in the same investment styles, and zero otherwise. In columns (3) and (4), the dummy variable of fund characteristic is represented by a high-performance rank dummy variable $HighRank$, which equals one if a fund is ranked in the upper half based on its performance in the past three years among funds with same investment styles, and zero otherwise. In columns (5) and (6), the dummy variable of fund characteristic is represented by a high investor sophistication dummy variable $HighSophist$, which equals one if a fund is no-load funds and zero otherwise, where the load funds are defined to be those with a front-end or a back-end load or with a 12b-1 fee that is higher than 25 basis points a year. The specifications in columns (2), (4), and (6) include industry-fixed effects. All specifications include style-time fixed effects, and control for other fund characteristics. T-statistics are provided in brackets with standard errors clustered by fund family and time. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Fund Characteristics	ESGRisk$_{\text{Dummy}}$					
	Expense Ratio		Fund Performance		Investor Sophistication	
	(1)	(2)	(3)	(4)	(5)	(6)
Const	-1.0905*** (-22.31)	-1.0221*** (-10.51)	-1.0652*** (-21.75)	-0.9937*** (-10.23)	-1.1044 (-22.36)	-1.0355*** (-10.68)
PeakRRI	0.0022*** (8.45)	0.0012*** (3.95)	0.0017*** (6.17)	0.0006* (1.94)	0.002*** (7.43)	0.0008*** (2.82)
HighExp*PeakRRI	-0.0003* (1.75)	-0.0003* (-1.68)				
HighRank*PeakRRI			0.0009*** (4.75)	0.0009*** (4.76)		
HighSophist*PeakRRI					0.0003*** (2.79)	0.0004*** (3.2)
Loglength	0.2039*** (27.87)	0.2019*** (27.54)	0.2045*** (27.89)	0.2024*** (27.56)	0.2048*** (27.93)	0.2028*** (27.6)
Logtna	-0.0022 (-1.45)	-0.0008 (-0.55)	-0.002 (1.34)	-0.0007 (0.44)	-0.0014 (-0.91)	6.46E-05 (0.04)
LogfamilySize	0.0036*** (3.59)	0.0032*** (3.21)	0.0035*** (3.5)	0.0031*** (3.11)	0.0041*** (4.08)	0.0038*** (3.77)
36M-Performance	0.0054 (0.8)	0.0144** (2.13)	-0.0381*** (-3.51)	-0.0291*** (-2.68)	0.0063 (0.94)	0.0153** (2.26)
36M-Volatility	-0.7136** (2.27)	-0.564* (-1.8)	-0.7004*** (-2.24)	-0.5446* (-1.74)	-0.6791** (-2.17)	-0.5388* (-1.72)
Logage	-0.0141*** (-3.73)	-0.0124*** (-3.29)	-0.014*** (3.69)	-0.0123** (-3.24)	-0.0144*** (-3.81)	-0.0126*** (-3.34)
ExpRatio	1.6955** (2.21)	2.0657*** (2.69)	0.9778 (1.56)	1.3733** (2.19)	1.4285** (2.2)	1.8994*** (2.91)
TurnRatio	-0.022*** (-8.25)	-0.0214*** (-7.94)	-0.0226*** (-8.5)	-0.022*** (-8.17)	-0.0216*** (-8.15)	-0.021*** (-7.81)
Industry FE	N	Y	N	Y	N	Y
Style × Time FE	Y	Y	Y	Y	Y	Y
Observations	26709	26709	26709	26709	26709	26709
R^2	0.0487	0.0559	0.0494	0.0566	0.0488	0.0562

Table 11: The Trading of Funds on ESG incidents

Table 11 examines how funds with different characteristics of ESG disclosure trade stocks in relation to the ESG incidents. The dependent variable equals one if fund i buys stock j in the quarter t in which stock j encounters an ESG incident, minus one if fund i sells, and zero otherwise. The independent variables include the ESG disclosure variable $ESGDisclosure$, and the intersection term between the disclosure variable $ESGDisclosure$ and the dummy variable $Post$, where $Post$ denotes the time period after March 2016. The ESG disclosure variable $ESGDisclosure$ is represented by the ESG risk disclosure dummy variable $ESGRisk_{Dummy}$ in columns (1) and (2), the weight of ESG risk disclosure $ESGRisk_{weight}$ in columns (3) and (4), and the ESG strategy disclosure dummy $ESGStr$ in columns (5) and (6). The specifications in columns (2), (4), and (6) include industry-fixed effects. All specifications also include style by time fixed effects and control for other stock and fund characteristics. T-statistics are provided in brackets with standard errors clustered by fund family and time. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Trade					
ESG Disclosure Measure	$\text{ESGRisk}_{\text{Dummy}}$		$\text{ESGrisk}_{\text{weight}}$		ESGStr	
	(1)	(2)	(3)	(4)	(5)	(6)
Const	1.8117***	1.8068***	1.8119***	1.8074***	1.8117***	1.8094***
	(14.86)	(14.85)	(14.83)	(14.81)	(14.86)	(14.85)
ESGDisclosure	0.0202	0.0971***	-0.0246	0.5832***	0.0128	0.0363*
	(1.17)	(4.19)	(-0.2)	(2.96)	(0.79)	(1.68)
Post*ESGDisclosure		-0.1121***		-0.8227***		-0.0434
		(-3.45)		(-3.34)		(-1.37)
PRC	-0.0971***	-0.0962***	-0.097***	-0.0964***	-0.0972***	-0.0969***
	(-5.77)	(-5.73)	(-5.76)	(-5.73)	(-5.79)	(-5.77)
Stocksize	0.0311*	0.0301*	0.031*	0.0304*	0.031*	0.0308*
	(1.92)	(1.86)	(1.92)	(1.88)	(1.92)	(1.91)
Shrout	-0.0542***	-0.0534***	-0.0539***	-0.0533***	-0.054***	-0.0537***
	(-3.06)	(-3.02)	(-3.05)	(-3.02)	(-3.06)	(-3.04)
Vol	-0.0267***	0.0058	-0.0268***	-0.0268***	-0.0269***	-0.0269***
	(-4.68)	(1.52)	(-4.7)	(-4.71)	(-4.7)	(-4.72)
Performance	-0.1055***	-0.0267***	-0.1059***	-0.1058***	-0.1057***	-0.1056***
	(-11.97)	(-4.69)	(-12.01)	(12)	(-12)	(-11.99)
Volatility	0.4482***	-0.1056***	0.4496***	0.45***	0.4488***	0.4466***
	(4.26)	(-11.98)	(4.28)	(4.28)	(4.27)	(4.25)
Logtna	0.0056	0.4481***	0.0057	0.0054	0.0058	0.0057
	(1.48)	(4.26)	(1.49)	(1.41)	(1.52)	(1.48)
LogfamilySize	-0.0304***	-0.0303***	-0.0302***	-0.03***	-0.0302***	-0.0301***
	(-10.6)	(-10.6)	(-10.54)	(-10.48)	(-10.48)	(10.45)
TurnRatio	-0.2004***	-0.1994***	-0.2006***	-0.2002***	-0.2011	-0.2008***
	(-12.12)	(12.09)	(-12.15)	(12.14)	(-12.2)	(-12.17)
Cashflows	1.8778***	1.8793***	1.8789***	1.8772***	1.8788***	1.8786***
	(18.59)	(18.67)	(18.62)	(18.63)	(18.63)	(18.63)
Style × Time FE	Y	Y	Y	Y	Y	Y
Observations	675857	675857	675857	675857	675857	675857
R^2	0.0751	0.0754	0.075	0.0753	0.075	0.0751