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Essays on Rational Expectation Equilibrium and Mutual Fund Disclosure

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Abstract

The functioning of financial markets is influenced by information and investor learning. In recent years, the increasing availability of media, big data, and regulatory requirements for enhanced disclosure have provided investors with access to more information than ever before. While this greater supply of information has the potential to improve the quality of financial markets by increasing the price informativeness, it can also create challenges and friction in the learning process for investors. Moreover, the strategic manipulation of information disclosure by agencies due to agency issues presents a further concern. Therefore, it is critical to gain a thorough understanding of the mechanisms by which information affects financial markets. Such comprehension is vital for both investors and policymakers to make informed decisions.

This thesis is to investigate the role of information learning in financial markets, with a specific emphasis on the disclosure practices of mutual funds. Chapter 1 investigates the effects of "correlation neglect" in financial markets, where naive traders neglect the correlation between signal errors. Using a model with both naive and rational traders, the study finds that the impact of naive traders on market quality, as measured by liquidity and mispricing risk, depends on the cost of obtaining information. When information is free and the correlation between signal errors is low, the presence of naive traders can reduce mispricing risk. However, when the correlation is high, mispricing risk becomes U-shaped. When information is costly, market liquidity deteriorates and mispricing risk increases with an increase of naive traders. However, market quality can improve when informed rational traders are driven out of the market by the large mass of naive traders.

In Chapter 2, we argue that highly complex funds' prospectuses limit the ability of investors to effectively use available information and make informed investment decisions. Measuring textual complexity with the Fog Index, our evidence suggests that low-quality funds manipulate their prospectuses, making them more complex, possibly targeting less sophisticated investors. These investors, in turn, use a less sophisticated asset pricing model to evaluate fund performance, react more aggressively to past winners, and are more likely to be attracted by funds with high marketing costs. Our results suggest that funds with low-complexity prospectuses are more trustworthy, and that funds with high-complexity prospectuses are possibly subject to more severe agency issues.

In Chapter 3, I investigate 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.

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1. Financial Markets and Correlation Neglect

1.1 Introduction

Information is valuable to market participants. But excess information availability can lead to availability bias. For example, "stereotyping can develop as a result of repeated news, resulting in representation bias, which encourages overconfidence or too little questioning or analysis of the situation." (Siegel and Yacht (2009)). In fact, many information structures in financial markets generate correlated rather than mutually independent signals. As proposed by Welch (2000), the correlation between signals can be caused by the common fundamental information, or it can result from"direct mutual imitation". The latter suggests that there is a correlation between the biases of signals deviated from the common fundamental.

The motivating idea of this paper is to study how financial markets are influenced when the correlation between signal errors is neglected by some market participants. There is extensive literature documenting the existence of "correlation neglect". For example, Enke and Zimmermann (2019) provide experimental evidence that people neglect the correlation in the updating process; Jiao et al. (2020) find evidence that there is a subset of "naive" traders that exists, who interpret the repeated signals of social networks as genuinely new information like the news media; Tetlock (2011) also find that stock market investors can not completely distinguish between new and old information about firms. In my paper, I model agents who cannot recognise the existence of a positive correlation between signal errors as naive traders.

In financial markets, the correlated signal errors can be captured by some stylized facts: one example is the repetition of media coverage. Some naive investors interpret the repeated signals as genuinely new information (Jiao et al. (2020)). Another example is analyst herding, which is defined as the forecast errors with unusually high consensus in forecasts among analysts (e.g., De Bondt and Forbes (1999); Kim and Pantzalis (2003)). The difference between these two examples is whether information acquisition is costly. In the first example, the cost to learn from media, no matter whether news media or social media, is negligible, and even retail investors can freely acquire this kind of information. In the second case, the analyst service is costly, and this kind of information is always sold to financial institutions, who are relatively sophisticated.

I develop a theoretical model to conceptualise both the examples mentioned above and provide some insights on the economic impact. I build the model on the CARA-normal REE framework (e.g., Grossman and Stiglitz (1980); Admati and Pfleiderer (1986)), and I extend the classical models by introducing two types of traders, rational and naive, under the framework of costly and costless information acquisition. The correlation between signal errors measures the degree of information herding or repetition. Furthermore, another essential assumption emphasizes that, naive traders are unaware of the existence of rational traders due to "correlation neglect", and rational traders are aware of the existence of their naive counterparts. Some literature also assumes disagreement or uncertainty about the composition of market participants (e.g., Gao et al. (2013); Banerjee and Green (2015); Papadimitriou (2020)). Similarly, this paper assumes the market composition perceived by naive and rational traders are different: the naive traders, who neglect the correlation between signal errors, unintentionally neglect the existence of rational traders, because they can not recognize there exists the other type of "smarter" traders who can better understand the information structure than them.

Based on the model, I find that the impact of "correlation neglect" on market quality depends on whether the information is costly or not. If information is free of charge, mispricing risk decreases in the mass of naive traders when the correlation between signal errors is relatively low, but can be U-shaped when the correlation is relatively high. naive traders provide more liquidity than rational traders, but when there are too many naive traders in the market, their existence may amplify signal errors, and make the price too sensitive to public information, increasing the risk of mispricing and worsening market quality.

However, the story is different when information is costly. Under the consideration of information acquisition, the market quality, measured by liquidity and mispricing risk, can be worsened by naive traders even when their mass is small enough.

In this case, the information acquisition decision of naive traders is influenced by their behavioural bias, i.e., "correlation neglect". There may be more or less of them willing to acquire information compared to the case if they were rational traders. However, no matter which case, the aggregate trading intensity of naive traders is always larger than that if they were rational traders, as the naive traders who choose to acquire costly information overestimate the precision of the information acquired and thus trade more aggressively than informed rational traders. In this way, informed naive traders, i.e. those who choose to acquire information, contribute to increasing the price informativeness about fundamentals. At the same time, as the mass of naive traders increases, the rational traders realize the price informativeness is improved and there is less profit margin for information acquisition, so less of them are willing to acquire costly information. It is highlighted that the existence of naive traders does not actually change the overall price informativeness, because rational traders always balance out the excess contribution of naive traders by reducing information acquisition.

The information acquisition model predicts that when there are rational traders who still choose to acquire information in the market, price informativeness is independent of the mass of naive traders. As the mass of naive traders increases, the total mass of informed traders decreases. This causes the aggregate response of agents to price declines, market liquidity deteriorates, and mispricing risk increases accordingly. The impact of naive traders on market quality with costly information acquisition is significantly different from the case without information cost. When the mass of naive traders is not sufficiently high, their existence tends to increase market liquidity and reduce mispricing risk if information is free of charge, but worsens market liquidity and increases mispricing risk if information is costly.

The model gives us implications regarding the empirical properties of financial markets. First, the findings in Jiao et al. (2020) suggest that the intense coverage on social media platforms such as Twitter led to "high volatility of returns and high trading volume" of stocks, because the contents of social media repeat that of news media. My results from the free information model can explain the potential mispricing risk triggered by the repetition of media coverage. Free information is available to retail investors, who are likely to lack the skills to interpret the structure of information and perceive the correlation between signal errors, so the fraction of naive traders among the retail traders may be relatively high, potentially bringing greater mispricing risk to the financial market.

Second, the past few years have seen the decline of active management: "The shift out of active and into passive has long been underway. Between 2014 and 2018, active funds had outflows of 738 billion, while passive funds saw inflows to the tune of 2.5 trillion." (CNBC, 10 Oct, 2019). This paper finds there is a crowding-out effect of "correlation neglect" on information acquisition of rational traders, which can be regarded as one potential explanation for the decline of active management. The excess information availability may amplify the cognitive limitation of some market participants, who trade much more aggressively on the costly information they acquire. Accordingly, financial markets become efficient enough to compress the profit margin of costly information acquisition under the rational perspective, making active management less attractive. Finally, this paper provides some insights into the long lasting debate on whether information efficiency is impaired by the decline of active management. As Qin and Singal (2015) state, "reduced incentives for information acquisition and arbitrage induced by indexing and passive trading" may lead to "degradation in price efficiency". As this paper predicts, the market liquidity worsens and mispricing risk increases with the decline of total informed mass when informed rational traders still exist, but price informativeness can be unacted even when the overall information acquisition declines.

The remainder of this paper is organised as follows. Section 1.2 reviews the relevant literature; Section 1.3 describes the basic framework of model with information cost; Section 1.4 characterises the equilibrium of the model with information acquisition when rational and naive traders coexist; Section 1.5 analyses the properties of market quality as well as the expected utility of traders; Section 1.6 studies the case without information acquisition cost; Section 1.7

concludes.

1.2 Literature Review

This paper is principally related to two strands of theoretical literature: information acquisition, and disagreement.

The first strand of literature, information acquisition, is mainly based on the rational expectation model in Grossman and Stiglitz (1980), where the fundamental issue of how costly information acquisition can be supported by the financial market is solved. The property of strategic substitution of information acquisition is robust in our model, which implies when more traders acquire information, information becomes less valuable (Verrecchia (1982)). In contrast, this paper emphasises an unilateral substitution effect of information acquisition between two types of traders, and only naive traders have a "crowding-out" effect on information acquisition of rational traders, but not vice versa. There are some papers, based on Grossman and Stiglitz (1980), investigating how information acquisition is impacted depending on the degree of "information linkage", e.g., Goulding and Zhang (2018) find that the price is more informative when the degree of scattered information is low; Huang and Yueshen (2021) find that an improving information technology increases the mass of traders who trade faster and thus improves the efficiency of intermediate price. These papers, from different perspectives, demonstrate that more "information linkage" aggravates free riding, and may finally hurt price informativeness by discouraging information acquisition. Analogically, I find the excess contribution to price informativeness by naive traders reduces information acquisition of rational traders, but I find price informativeness can keep the constant under the interaction of the two groups of traders.

The second strand of related literature is about investor disagreement. This series of literature can explain various market anomalies that can be plausibly hard to explain by the rational model (REE), e.g., excess return volatility. Among the underlying mechanisms leading to the disagreement of investors (Hong and Stein (2007)), this paper has both the characteristics of “heterogenous beliefs” and “overconfidence”. On the one hand, “correlation neglect” leads the naive traders to overestimate the precision of aggregate signals, and overconfidence can also leadto the same outcome; on the other hand, “correlation neglect” causes the naive traders unintentionally ignore the role of rational traders in transmitting information to price, which coincides with the outcome due to “heterogenous beliefs”.

In the literature of “heterogenous beliefs”, the investors do not fully update their beliefs based on each other’s trading decisions. For example, in Banerjee and Kremer (2010), investors disagree about the interpretations of public information and thus neglect others’ interpretation; Eyster et al. (2019) considers the traders entirely or partially neglect the relationship between the price and other traders’ information. Similarly, the naive traders in this paper do not update their belief and make the decision in response to the rational traders. But there are two main differences between this paper and the literature of “heterogenous beliefs”: first, the naive traders make decisions without considering rational traders, not because they “agree to disagree” at equilibrium, but because the naive traders neglect the existence of rational traders; second, the naive traders still extract information and learn from price, but in a biased way due to cognitive limitation.

This paper is also strongly related to the literature on overconfidence, where “overconfidence” is modeled as a belief that the precision of signal perceived by a trader is higher than it actually is. In my model, the naive traders overestimate the precision of signals because of “correlation neglect” instead of psychological factors. Odean (1998) finds the influence of overconfidence on price quality depends on who is overconfident, e.g., price takers, the insider, or market maker. Conversely, in a perfectly competitive asset market of my model, how market quality is influenced by naive traders depends on the information cost and the mass of naive traders. Some literature that contains the coexistence of rational and overconfident participants, e.g., Benos (1998), and Kyle and Wang (1997), find that the market depth and price informativeness increase when there are overconfident informed investors participating in the market. My model with free information draws a similar conclusion: the existence of naive traders helps improves market depth when their mass is relatively low. But as the mass of naive traders becomes large enough, more mispricing risk may be introduced.

Some literature that investigates overconfidence considers information acquisition. Odean (1998) introduces a completely competitive model with information acquisition and they find the equilibrium obtained is not influenced by the level of overconfidence. I relax the assumption of Odean (1998) that all traders are overconfident by introducing rational traders, and find the information acquisition at the aggregate level is negatively influenced by the mass of naive traders when it is not large enough. García and Sangiorgi (2011) predicts the full participation of information acquisition by overconfident investors given the existence of informed rational traders, and concludes overconfidence has no effect on market quality. Their results rely on the assumption that overconfident traders agree to disagree with rational traders. My model, however, finds that the overestimation of signal precision does not always make all naive traders acquire information. Ko and Zhijian (2007) develop a variable cost model to study information acquisition of overconfident investors, and find that overconfidence generally improves market quality under some conditions. My model also predicts market quality can be improved by naive traders, not only depending on the overall degree of precision overestimation, but also depending on the cost of information.

1.3 Model with Information Cost

In this section, the model has three events. At time 1, agents decide whether to acquire information. At time 2, agents observe their signals if they pay and trade in a competitive asset market. At time 3, the assets pay off, and all agents consume.

There are two assets in the financial market: one risk-free asset and one risky asset. The payoff of the risky asset is v, which is a mean-zero normal random variable with precision τ.

Information market: At the beginning of period 1, the information market opens. The information seller provides n signals, denoted by s_i, $i \in \{1, ..., n\}$, to the traders who independently decide whether to pay for the information service at a fixed cost of c. Each signal has an error term from the fundamental: $s_i = v + \epsilon_i$, where $\epsilon_i \sim N(0, \frac{1}{\tau_\epsilon})$ and $\epsilon_i \perp v$. The error terms are multivariate normal distributed with correlation $\rho \in (0, 1)$: $\mathrm{Corr}[\epsilon_i, \epsilon_j] = \rho$ for $i \neq j$, where ρ

reflects the degree of information repetition.

Financial market: Once the traders have made their information acquisition decision, period 1 ends and the financial market opens in period 2. The participants in the financial market are:

- Risk-adverse traders: In the economy, there is a unit continuum of traders, each with constant absolute risk aversion (CARA) utility with risk-tolerance parameter $\gamma > 0$. Suppose there is a fraction $\lambda \in [0, 1]$ of the traders to acquire information, and the rest $(1 - \lambda)$ of them keep uninformed.
- Noise traders: The demand of noise traders, x, is a mean-zero normal random variable with precision τ_x ($x \perp v, x \perp \epsilon$).

In the market, there exists both naive traders and rational traders. The naive traders do not know the existence of rational traders, which implies that naive traders assume all traders in the market are homogenous and have the same prior belief as themselves.

Here are some main assumptions:

1. The mass of naive traders is β, and the rest $(1 - \beta)$ of traders are rational.
2. The rational traders correctly anticipate the actual correlation of signal errors, ρ, as well as the mass of naive traders, β.
3. The naive traders neglect the existence of correlation (they take ρ for 0), as well as the existence of rational traders.
4. Both naiveand rational traders independently make their information acquisition decision at time 1.

1.3.1 All-rational Benchmark

In the benchmark, I derive the equilibrium of the trading game when there is no naive traders in the market, namely, $\beta = 0$. As in Grossman and Stiglitz (1980), I consider the rational expectation equilibrium (REE). Suppose that there is a linear price function of the form:

$$p = \eta\left(I\sum_{i=1}^{n} s_i + x\right) = nI\eta\left(v + \frac{I\sum_{i=1}^{n}\epsilon_i + x}{nI}\right) \tag{1.1}$$

where η and I are endogenous coefficients at equilibrium.

The demand of informed and uninformed investors are denoted by D_{inf} and D_{uninf} respectively. The CARA-normal setup implies the informed investor's demand function is

$$D_{inf}\left(\sum_{i=1}^{n} s_i, p\right) = \frac{\gamma\big(E\left[v \mid s_1, s_2, \ldots, s_n, p\right] - p\big)}{\mathrm{Var}[v \mid s_1, s_2, \ldots, s_n, p]} \tag{1.2}$$

Applying Bayes' rule, the conditional moments of the fundamental can be computed from the perspective of the informed trader as follows:

$$Var[v \mid s_1, s_2, \ldots, s_n, p] = \frac{1 + (n-1)\rho}{\tau + (n-1)\rho\tau + n\tau_\epsilon} \tag{1.3}$$

$$E[v \mid s_1, s_2, \ldots, s_n, p] = \frac{\tau_\epsilon \sum_{i=1}^{n} s_i}{\tau + (n-1)\rho\tau + n\tau_\epsilon} \tag{1.4}$$

If there is no correlation between signal errors, $\rho = 0$, the posterior precision of the fundamental for informed traders, $\big(Var[v \mid s_1, s_2, \ldots, s_n]\big)^{-1}$, is $\tau + n\tau_\epsilon$. Otherwise, with positive correlation, the precision of fundamental increased by n signals is:

$$D = \big(Var(v \mid \sum_{i=1}^{n} s_i)\big)^{-1} - \tau = \frac{n\tau_\epsilon}{\Delta} \tag{1.5}$$

where $\Delta^{-1} = \frac{1}{1+(n-1)\rho}$, which can be regarded as the discount factor compared to that without correlation.

The actual precision of aggregate signals does not directly equal to the sum of precision of individual signal, $n\tau_\epsilon$, but equals to the discounted sum of individual precision. The larger ρ, the more precision of aggregate signals is discounted.

The uninformed trader only observes price p, and their demand function is

$$D_{uninf}(p) = \frac{\gamma\big(E[v \mid p] - p\big)}{\mathrm{Var}[v \mid p]} \tag{1.6}$$

Using Bayes' rule, we have

$$\mathrm{Var}[v \mid p] = \left(\tau + \frac{1}{\frac{1}{n^2 I^2 \tau_x} + \frac{1}{D}}\right)^{-1} \tag{1.7}$$

$$\mathrm{E}[v \mid p] = \left(\tau + \frac{1}{\frac{1}{n^2 I^2 \tau_x} + \frac{1}{D}}\right)^{-1} \frac{1}{\frac{1}{n^2 I^2 \tau_x} + \frac{1}{D}} \frac{1}{nI\eta} p \tag{1.8}$$

The market clearing condition is,

$$\lambda D_{inf}\left(\sum_{i=1}^{n} s_i, p\right) + (1-\lambda) D_{uninf}(p) + x = 0 \tag{1.9}$$

To derive the equilibrium price function, I insert the demand functions into the market clearing condition to solve the price in terms of $\sum_{i=1}^{n} s_i$ and x, and then compare with the conjectured price function in equation (1.1) to obtain a system defining the unknown coefficients of I and η.

Proposition 1 (*Financial market equilibrium*) *Given* $(\rho, \lambda, n, \gamma, \tau, \tau_\epsilon, \tau_x)$, *there exists a unique linear REE, in which*

$$p = \eta\left(I \sum_{i=1}^{n} s_i + x\right)$$

where η *and* I *are given in the appendix.* $\frac{1}{\eta}$ *measures the market depth, and* I *measures aggregate trading intensity.*

The aggregate trading intensity of the informed traders increases with the fraction of informed traders $\lambda \in [0, 1]$ uniquely in equilibrium according to the following closed form function

$$I = \lambda\gamma \frac{\tau_\epsilon}{1 + (n-1)\rho} = \frac{\lambda\gamma D}{n} \tag{1.10}$$

Corollary 1 *Given $(\rho, n, \gamma, \tau, \tau_\epsilon, \tau_x)$, price informativeness $\big(Var(v \mid p)\big)^{-1}$ increases with the fraction λ of informed traders.*

To achieve the overall equilibrium, I endogenise the information acquisition process, and consider the situation where traders can decide whether to subscribe to the information service by paying a fixed cost, c. I calculate the ex ante certainty equivalent of the expected utility of trading profit for the informed traders and uniformed traders, denoted by CE_{inf} and CE_{uninf}, respectively.

The difference between CE_{inf} and CE_{uninf} measures the benefit of being informed, which is given by

$$\begin{aligned} CE_{inf} - CE_{uninf} &= \frac{\gamma}{2} \log \frac{\mathrm{Var}[v \mid p]}{\mathrm{Var}[v \mid \sum_{i=1}^{n} s_i, p]} \\ &= \frac{\gamma}{2} \log \left(\frac{\tau + D}{\tau + \frac{1}{\frac{1}{n^2 I^2 \tau_x} + \frac{1}{D}}} \right) \end{aligned} \tag{1.11}$$

Lemma 1 *For given $(\rho, n, \gamma, \tau, \tau_\epsilon, \tau_x)$, $CE_{inf} - CE_{uninf}$ is a decreasing function of λ.*

If $CE_{inf} - CE_{uninf} > c$, traders decide to acquire information; otherwise, they do not. Thus, the equilibrium mass λ is determined by

$$CE_{inf} - CE_{uninf} = c \tag{1.12}$$

Proposition 2 (*Overall equilibrium*)*For given $(\rho, c, n, \gamma, \tau, \tau_\epsilon, \tau_x)$, there exists an unique information market equilibrium in which there is $\lambda \in [0, 1]$ fraction of traders acquiring information,* *where*

$$\lambda = \begin{cases} 1 & \text{if } 0 < c \leq \underline{c} \quad \text{(Corner equilibrium)} \\ \hat{\lambda} = \frac{n\hat{I}}{\gamma D} & \text{if } \underline{c} < c < \bar{c} \quad \text{(Interior equilibrium)} \\ 0 & \text{if } c \geq \bar{c} \quad \text{(Corner equilibrium)} \end{cases} \tag{1.13}$$

and the aggregate trading intensity I satisfies

$$nI = \begin{cases} \gamma D & \text{if } 0 < c \leq \underline{c} \\ n\hat{I} = \sqrt{\frac{-A\tau D + D^2}{A\tau_x(\tau + D)}} & \text{if } \underline{c} < c < \bar{c} \\ 0 & \text{if } c \geq \bar{c} \end{cases} \tag{1.14}$$

where

$$A = e^{2c/\gamma} - 1 \tag{1.15}$$

$$\underline{A} = e^{2\underline{c}/\gamma} - 1 = \frac{1}{\gamma^2 \tau_x D + \tau/D + \tau_x \tau \gamma^2} \tag{1.16}$$

$$\bar{A} = e^{2\bar{c}/\gamma} - 1 = \frac{D}{\tau} \tag{1.17}$$

Proposition 3 *For given $(\rho, c, n, \gamma, \tau, \tau_\epsilon, \tau_x)$, the aggregate trading intensity I is monotonically increasing in the precision D of aggregate signals $\sum_{i=1}^n s_i$.*

Corollary 2 *For given $(\rho, c, n, \gamma, \tau, \tau_\epsilon, \tau_x)$, the aggregate trading intensity I is strictly decreasing in the signal correlation ρ for $c < \bar{c}$, and otherwise flat at level $I = 0$.*

From equation (1.7), the price informativeness, denoted by PI, is the inverse of $\mathrm{Var}[v \mid p]$, which is influenced by D through two channels:

$$\begin{aligned} \frac{dPI}{dD} = \frac{d\big(\mathrm{Var}[v \mid p]\big)^{-1}}{dD} &= \frac{d\big(\tau + \frac{1}{\frac{1}{n^2 I^2 \tau_x} + \frac{1}{D}}\big)}{dD} \\ &= \underbrace{\frac{\partial PI}{\partial D}}_{\text{direct effect } (+)} + \underbrace{\frac{\partial PI}{\partial I}\frac{\partial I}{\partial D}}_{\text{indirect effect}(+)} \end{aligned} \tag{1.18}$$

The aggregate signals $\sum_{i=1}^{n} s_i$ not only include the fundamental information, but also bring noise $\sum_{i=1}^{n} \epsilon_i$ into price. The direct channel implies that as D increases, the informative content about fundamental v in $\sum_{i=1}^{n} s_i$ increases relative to the content of error $\sum_{i=1}^{n} \epsilon_i$.

The indirect effect of D on price informativeness is through the trading of informed traders: from Proposition 3, we know the informed traders trade more aggressively at the aggregate level as D increases. Thus the price reflects relatively more information about $\sum_{i=1}^{n} s_i$ comparing to the noise x of liquidity trading.

Proposition 4 *For given $(\rho, c, n, \gamma, \tau, \tau_\epsilon, \tau_x)$, price informativeness is monotonically increasing in D.*

From equation (1.13), we know that when all the traders are rational, their information acquisition decision is influenced by the precision of aggregate signals, regardless of what specifically τ_ϵ, n and ρ represent. It is intuitive because when all traders are rational, they can accurately perceive the value of aggregate signals taking them as a whole.

Proposition 5 *For given $(c, n, \gamma, \tau, \tau_\epsilon, \tau_x)$, when $D \in \Big[A\tau, A\tau\big(1+\sqrt{1+\frac{1}{A}}\big)\Big)$, λ is monotonically increasing in D; when $D \in \Big[A\tau\big(1+\sqrt{1+\frac{1}{A}}\big), +\infty\Big)$, λ is monotonically decreasing in D.*

1.4 Model Equilibrium

In the benchmark, I assume that there are only rational traders in the market, who can accurately perceive the correlation between signal errors, make an information acquisition decision and trade accordingly. In this section, I characterize the equilibrium with naive traders, who neglect the correlation between signal errors and are unaware of the existence of rational traders.

1.4.1 Equilibrium Concept

λ_1 is the informed fraction among the rational traders; and λ_2 is the fraction of informed traders in naive group. The total mass of informed traders in the market is

$$\lambda = (1-\beta)\lambda_1 + \beta\lambda_2 \tag{1.19}$$

Because the naive traders do not know of the existence of rational traders, they think λ_2 is the total mass of informed traders in the market, and they take the precision of aggregate signals for $n\tau_\epsilon$.

D denotes the precision of the aggregate signals perceived by rational traders, which is also the actual precision of aggregate signals: $D = \frac{n\tau_\epsilon}{1+(n-1)\rho}$. F denotes the precision of aggregate signals perceived by naive traders, where $F = n\tau_\epsilon$.

We have $F(n, \tau_\epsilon, \rho) > D(n, \tau_\epsilon, \rho)$, which implies the naive traders overestimate the precision of aggregate signal due to "correlation neglect".

1.4.2 Naive Traders' Perspective

From the assumptions, the naive traders not only overestimate the precision of the aggregate information, but also mistakenly perceive the mass of informed traders as λ_2 instead λ.

Let $\mathrm{Var}_i[\cdot]$ and $\mathrm{E}_i[\cdot]$ represent the variance and the expectation of variable from the perspective of naive traders. D_{inf1}, D_{uninf1}, D_{inf2}, D_{uninf2} denote the demand of informed rational, uninformed rational, informed naive, uninformed naive traders, respectively.

We conjecture a linear price function, and linear demand schedules of uninformed traders. The linear price function is given by

$$p = \eta I \sum_{i=1}^{n} s_i + \eta x \tag{1.20}$$

The demand function of uninformed rational traders is:

$$D_{uninf1}(p) = b_1 p \tag{1.21}$$

and the demand function of uninformed naive traders is:

$$D_{uninf2}(p) = b_2 p \tag{1.22}$$

The informed naive traders maximise their expected utility by trading:

$$\begin{aligned} D_{inf2}\left(\sum_{i=1}^{n} s_i, p\right) &= \frac{\gamma\big(E_i[v \mid s_1, s_2 ... s_n, p] - p\big)}{\mathrm{Var}_i[v \mid s_1, s_2 ... s_n, p]} \\ &= \gamma\tau_\epsilon \sum_{i=1}^{n} s_i - \gamma(\tau + n\tau_\epsilon)p \end{aligned} \tag{1.23}$$

where

$$\mathrm{Var}_i[v \mid s_1, s_2 ... s_n, p] = \frac{1}{\tau + n\tau_\epsilon} \tag{1.24}$$

and

$$\mathrm{E}_i[v \mid s_1, s_2 ... s_n, p] = \frac{\tau_\epsilon \sum_{i=1}^{n} s_i}{\tau + n\tau_\epsilon} \tag{1.25}$$

The naive traders incorrectly take "market clearing condition" as the following form:

$$\lambda_2 D_{inf2}\left(\sum_{i=1}^{n} s_i, p\right) + (1 - \lambda_2) D_{uninf2}(p) + x = 0 \tag{1.26}$$

However, the actual market price does not satisfy equation (1.26), because the "market clearing condition" is conjectured by naive traders, who cannot accurately recognise the composition of market participants. In other words, the uniformed naive traders incorrectly interpret the market price and extract informative content. Let ω_2 denote the informative signal perceived by uninformed naive traders:

$$\omega_2 = (\lambda_2 \gamma \tau_\epsilon) \sum_{i=1}^{n} s_i + x \tag{1.27}$$

which is observationally equivalent to the noisy signal $\omega_2^{'}$:

$$\omega_2^{'} = v + \frac{\lambda_2 \gamma \tau_\epsilon \sum_{i=1}^{n} \epsilon_i + x}{n \lambda_2 \gamma \tau_\epsilon} \tag{1.28}$$

From the perspective of naive traders, they evaluate their ex-ante certainty equivalent, denoted by CE^*_{inf2} and CE^*_{uninf2} for informed and uninformed naive traders, respectively, and make the information acquisition decision. At equilibrium, λ_2 is the fraction of informed trader among them, which reflects their willingness to acquire information.

At equilibrium, the naive traders thinks it is equivalent to be informed or keep uninformed. The equilibrium is determined by

$$CE^*_{inf2} - CE^*_{uninf2} = c \tag{1.29}$$

where c is the cost of information, and

$$CE^*_{inf2} - CE^*_{uninf2} = \frac{\gamma}{2} \log \frac{\mathrm{Var}_i[v \mid p]}{\mathrm{Var}_i[v \mid \sum_{i=1}^{n} s_i, p]} \tag{1.30}$$

At equilibrium, the naive traders think acquiring information is equivalent to being uninformed.

Proposition 6 *For given $(\rho, c, n, \gamma, \tau, \tau_\epsilon, \tau_x)$, there exists a unique fraction $\lambda_2 \in [0,1]$ of informed traders among naive traders:*

$$\lambda_2 = \begin{cases} 1 & \text{if } 0 < c \leq \underline{c}_2 \quad \text{(Corner equilibrium)} \\ \hat{\lambda}_2 = \sqrt{\frac{-A\tau + n\tau_\epsilon}{A\tau_x \gamma^2 (\tau n \tau_\epsilon + n^2 \tau_\epsilon^2)}} & \text{if } \underline{c}_2 < c < \bar{c}_2 \quad \text{(Interior equilibrium)} \\ 0 & \text{if } c \geq \bar{c}_2 \quad \text{(Corner equilibrium)} \end{cases} \tag{1.31}$$

Where $A = e^{2c/\gamma} - 1$.

$$\underline{A}_2 = e^{2\underline{c}_2/\gamma} - 1 = \frac{1}{\gamma^2\tau_x n\tau_\epsilon + \tau/(n\tau_\epsilon) + \tau_x\tau\gamma^2}$$

$$\bar{A}_2 = e^{2\bar{c}_2/\gamma} - 1 = \frac{n\tau_\epsilon}{\tau}$$

1.4.3 Financial Market Equilibrium

The existence of naive traders does not influence the posterior belief of informed rational traders. The demand of informed rational traders is:

$$\begin{aligned} D_{inf1}\left(\sum_{i=1}^{n} s_i, p\right) &= \frac{\gamma\big(\mathrm{E}[v \mid s_1, s_2 ... s_n, p] - p\big)}{\mathrm{Var}[v \mid s_1, s_2 ... s_n, p]} \\ &= \frac{\gamma D}{n}\sum_{i=1}^{n} s_i - \gamma(\tau + D)p \end{aligned} \tag{1.32}$$

Since the rational traders are aware of the existence of naive traders, they correctly conjecture market clearing conditions, which actually pins down the price:

$$\begin{aligned} &(1-\beta)\lambda_1 D_{inf1}\left(\sum_{i=1}^{n} s_i, p\right) + (1-\beta)(1-\lambda_1)D_{uninf1}(p) \\ &+\beta\lambda_2 D_{inf2}\left(\sum_{i=1}^{n} s_i, p\right) + \beta(1-\lambda_2)D_{uninf2}(p) + x = 0 \end{aligned} \tag{1.33}$$

The uninformed rational traders correctly extract information from price:

$$\omega_1 = \left[(1-\beta)\lambda_1\gamma\frac{D}{n} + \beta\lambda_2\gamma\tau_\epsilon\right]\sum_{i=1}^{n} s_i + x \tag{1.34}$$

Let

$$\hat{I} = (1-\beta)\lambda_1\gamma\frac{D}{n} + \beta\lambda_2\gamma\tau_\epsilon, \tag{1.35}$$

which denotes the aggregate trading intensity on $\sum_{i=1}^{n} s_i$ and reflects how aggressively informed traders trade at the aggregate level.

ω_1 is observationally equivalent to the noisy signal $\omega_1^{'}$:

$$\omega_1^{'} = v + \frac{\sum_{i=1}^{n} \epsilon_i}{n} + \frac{x}{n\hat{I}} \tag{1.36}$$

The actual price informativeness, $\text{PI} = \big(\text{Var}(v \mid p)\big)^{-1}$, is interpreted as the posterior precision of the fundamental v given price at equilibrium, which can be correctly perceived by uninformed rational traders.

In the financial market with asymmetric information, informative trading contributes to price informativeness. The informative signal ω_1 extracted by rational traders can be divided into three components:

$$\omega_1 = \underbrace{(1-\beta)\lambda_1\gamma\frac{D}{n}\sum_{i=1}^{n} s_i}_{\text{by informed rational traders}} + \underbrace{\beta\lambda_2\gamma\tau_\epsilon\sum_{i=1}^{n} s_i}_{\text{by informed naive traders}} + \underbrace{x}_{\text{by noisy traders}}$$

The informative content in ω_1 is contributed by (i) the informed rational traders, and (ii) the informed naive traders. We write the price informativeness in the following form:

$$\begin{aligned}\text{PI} =& \big(\text{Var}(v \mid p)\big)^{-1} = \big(\text{Var}(v \mid \omega_1)\big)^{-1} \\ =& \tau + \frac{1}{\frac{1}{D} + \frac{1}{n^2 \hat{\text{I}}^2 \tau_x}}\end{aligned} \tag{1.37}$$

At the interior equilibrium, the difference of the ex-ante certainty equivalent between informed and uninformed rational traders equals to the cost of information:

$$\begin{aligned}CE_{inf1} - CE_{uninf1} =& \frac{\gamma}{2}\log\big(\text{Var}_1[v \mid p]\big) - \frac{\gamma}{2}\log\Big(\text{Var}_1[v \mid \sum_{i=1}^{n} s_i, p]\Big) \\ =& c\end{aligned} \tag{1.38}$$

Substituting equation (1.2) into equation (1.38) and rearrange, we get the expression of price informativeness:

$$PI(\tau, D, c, \gamma) = \left(\mathrm{Var}_1(v \mid p, \beta, \rho)\right)^{-1} = \exp\left\{-\log\left(\mathrm{Var}_1(v \mid p, \sum_{i=1}^{n} s_i)\right) - c\right\} \\ = \frac{\tau + D}{A + 1} \tag{1.39}$$

I interpret the information acquisition decision of rational traders by the following process that: more rational traders are willing to acquire information until price informativeness equals to $\frac{\tau+D}{A+1}$, which is independent of β. The constant can be regarded as the "ceiling of profit" for rational traders: if the actual price informativeness has not reached the "ceiling", there still exists profit margin to earn by information acquisition for rational traders, so λ_1 continuously increases until price informativeness equals to $\frac{\tau+D}{A+1}$.

Given (τ, D, c, γ), the "ceiling of profit" is the same with the price informativeness in benchmark, which implies that the price informativeness at equilibrium does not change in the mass of naive traders as long as there still exists informed rational traders. The general expression of price informativeness is given by:

$$\mathrm{PI} = \begin{cases} \frac{\tau+D}{A+1} & \lambda_1 > 0 \\ \tau + \frac{1}{\frac{1}{D} + \frac{1}{n^2\beta^2\lambda_2^2\gamma^2\tau_\epsilon^2\tau_x}} & \lambda_1 = 0 \end{cases} \tag{1.40}$$

Proposition 7 *There exists an equilibrium such that:*

1. *The fraction of rational traders who acquire information is λ_1; and the fraction of naive traders who acquire information is λ_2;*
2. *The coefficients (η, I, b_1, b_2) in price function and demand schedules are given in Appendix.*

Proposition 8 *Given $(n, \rho, c, \gamma, \tau, \tau_\epsilon, \tau_x)$, price informativeness keeps the constant as β increases until the informed rational traders are entirely crowded out of the market, and then price informativeness increases in the mass of naive traders β.*

The expression of λ_1 when $\lambda_1 \in (0, 1)$ is given by:

$$
\begin{aligned}
\lambda_1 &= \frac{1}{1-\beta}\sqrt{\frac{D-\tau A}{A\tau_x\gamma^2(\tau D+D^2)}} - \frac{\beta\lambda_2 n\tau_\epsilon}{(1-\beta)D} \\
&= \lambda_0 - \frac{\beta}{1-\beta}\underbrace{\left(\lambda_2\Delta - \sqrt{\frac{D-\tau A}{A\tau_x\gamma^2(\tau D+D^2)}}\right)}_{\text{crowed-in (-) or crowed-out (+) effect}}
\end{aligned} \tag{1.41}
$$

where

$$
\Delta = \frac{F}{D} = \frac{n\tau_\epsilon}{D} = 1+(n-1)\rho \quad \Delta \in [1,+\infty) \tag{1.42}
$$

λ_0 denotes the fraction of informed traders when $\beta = 0$ as in the benchmark, when $\lambda_0 \in (0,1)$:

$$
\lambda_0 = \sqrt{\frac{D-\tau A}{A\tau_x\gamma^2(\tau D+D^2)}} \tag{1.43}
$$

The first term of λ_1 in equaiton (1.41) equals to the fraction of informed traders in the absence of naive traders, and the second term is the effect of naive traders on information acquisition of rational traders.

Proposition 9 *Given $(n,\rho,c,\gamma,\tau,\tau_\epsilon,\tau_x)$, when $\rho \neq 0$ and $n \neq 1$,*

1. *If $\lambda_0 \in (0,1)$ when the cost of information is at a moderate level: $A \in \big(\frac{D}{\tau+\tau_x(\tau D+D^2)}, \frac{D}{\tau}\big)$:*
   - *(a) The naive traders always have "crowding-out" effect on information acquisition of rational traders, and the effect increases in ρ.*
   - *(b) As β increasing, the "crowding-out" effect increases. There exists a β^*: all informed rational traders are crowded out of the market when $\beta \geqslant \beta^*$.*
2. *If $\lambda_0 = 0$ when information cost is sufficiently high: $A \in \big(\frac{D}{\tau}, +\infty\big)$, there are no informed rational traders regardless of whether naive traders exist or not.*
3. *If $\lambda_0 = 1$ when price is sufficiently low: $A \in (0, \frac{D}{\tau+\tau_x(\tau D+D^2)})$:*
   - *(a) when $\beta < \frac{\sqrt{\frac{D-\tau A}{A\tau_x(\tau D+D^2)}}-1}{\lambda_2\Delta-1}$, all rational traders are informed;*
   - *(b) when $\beta > \frac{\sqrt{\frac{D-\tau A}{A\tau_x(\tau D+D^2)}}-1}{\lambda_2\Delta-1}$, some rational traders choose not to acquire information.*

The trading intensity helps explain why the naive traders have a crowding-out effect on information acquisition of rational traders. I solve the aggregate trading intensity at equilibrium when $\lambda_1 > 0$:

$$\hat{I} = \sqrt{\frac{D^2 - \tau AD}{n^2 \tau_x \gamma A(\tau + D)A}} \tag{1.44}$$

which is a constant unrelated to the mass of naive traders β. I decompose $\hat{I}$ as:

$$\hat{I} = \underbrace{(1-\beta)\lambda_1 \gamma \frac{\tau_\epsilon}{\Delta}}_{\text{by informed rational traders}} + \underbrace{\beta \lambda_2 \gamma \tau_\epsilon}_{\text{by informed naive traders}} \tag{1.45}$$

β influences the aggregate trading intensity in two ways:

$$\frac{dI(\beta, \lambda_1(\beta))}{d\beta} = \underbrace{\frac{\partial I(\beta, \lambda_1)}{\partial \beta}}_{\text{Direct effect (+)}} + \underbrace{\frac{\partial I(\beta, \lambda_1)}{\partial \lambda_1} \frac{\partial \lambda_1(\beta)}{\partial \beta}}_{\text{Indirect effect(-)}} \tag{1.46}$$

On the one hand, the increase of β has a positive direct effect on the aggregate intensity. As Proposition 3 shows, the larger the precision of signals perceived by traders, the larger the aggregate trading intensity they contribute. Because the naive traders overestimate the precision of aggregate signals, the aggregate trading intensity is larger than that if they were rational, leading a positive direct effect.

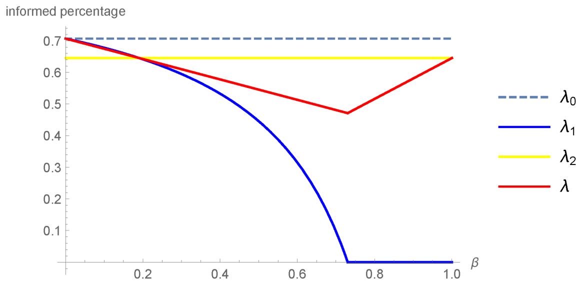
On the other hand, informed naive traders excessively contribute to the aggregate trading intensity and improve price effectiveness. When their contribution is out of proportion to their mass β, more informed rational traders are crowded out and contribute less to price informativeness, leading the negative indirect effect. At equilibrium, the direct effect and indirect effect cancel each other out, and the aggregate trading intensity as well as price informativeness does not change.

Corollary 3 *The aggregate trading intensity is maximised when $\beta = 1$; we have*

$$\frac{\lambda_0 \gamma D}{n} \leqslant \hat{I} \leqslant \lambda_2 \gamma \tau_\epsilon \tag{1.47}$$

Figure 1.1: Mass of Informed Traders

(a) $\lambda_2 < \lambda_0$ $(A = 0.5, \gamma = 1, \tau_\epsilon = 0.5, \tau = 1, \tau_x = 1, n = 6, \rho = 0.1)$



(b) $\lambda_2 > \lambda_0$ $(A = 0.5, \gamma = 1, \tau_\epsilon = 0.5, \tau = 1, \tau_x = 1, n = 6, \rho = 0.9)$

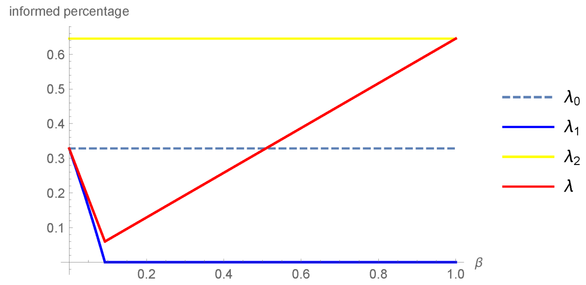
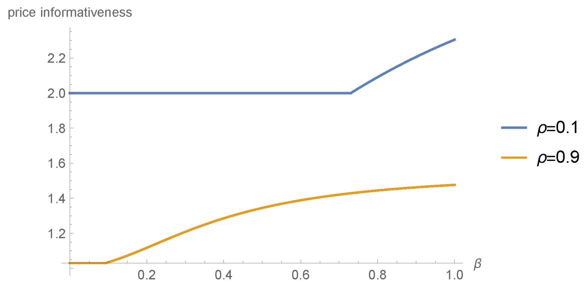


Figure 1.2: Price Informativeness: $(A = 0.5, \gamma = 1, \tau_\epsilon = 0.5, \tau = 1, \tau_x = 1, n = 6)$



The total mass of informed traders λ is given by:

$$\begin{aligned} \lambda &= (1-\beta)\lambda_1 + \beta\lambda_2 \\ &= \max\Big\{ \min\left\{\lambda_0 - \beta(n-1)\rho\lambda_2, (1-\beta) + \beta\lambda_2\right\}, \beta\lambda_2 \Big\} \end{aligned} \tag{1.48}$$

Proposition 10 *Given $(\rho, c, n, \gamma, \tau, \tau_\epsilon, \tau_x)$, when $n > 1$, and $\rho > 0$, the increase of naive traders monotonically reduces λ until informed rational traders are entirely crowded out of the market, and then λ rises gradually to λ_2 as β increases to 1.*

Comparing the total mass of informed traders λ with benchmark λ_0 when there are no naive traders in the market, I find that λ is smaller than λ_0 except that $\beta\lambda_2 > \lambda_0$.

1.5 Model Implications

1.5.1 Market Depth

Formally, the measure of market liquidity is often referred to as Kyle's lambda (Kyle (1985)). The coefficient "Kyle lambda", which is η in equation (1.20), inversely measures market liquidity: a smaller η means that liquidity trading x has a smaller price impact, and thus the market is deeper and more liquid.

Market depth can be regared as the average responsiveness of market participants to price (Vives (2008)). Specially, in my framework, market depth equals to the average responsiveness of the following four types of traders: informed rational, uninformed rational, informed naive, uninformed naive traders:

$$\begin{aligned} \text{Market depth} &= \eta^{-1} \\ &= \lambda_2\beta\gamma(\tau + n\tau_\epsilon) + (1-\beta)\lambda_1\gamma(\tau + D) \\ &\quad - (1-\beta)(1-\lambda_1)b_1 - \beta(1-\lambda_2)b_2 \end{aligned} \tag{1.49}$$

To study how naive traders influences market depth, we discuss in the following three cases: (1) when $\lambda_0 \in (0,1)$; (2) when $\lambda_0 = 1$; (3) when $\lambda_0 = 0$. The first case is the most common when there are only rational traders in the market.

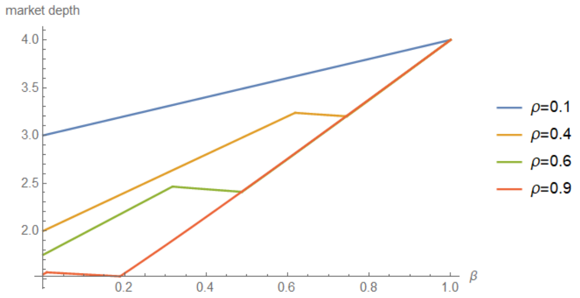
Proposition 11 *At equilibrium when $\lambda_0 \in (0,1)$,*

1. *Market depth (η^{-1}) decreases in the mass of naive traders until all informed rational traders are crowded out of the market.*

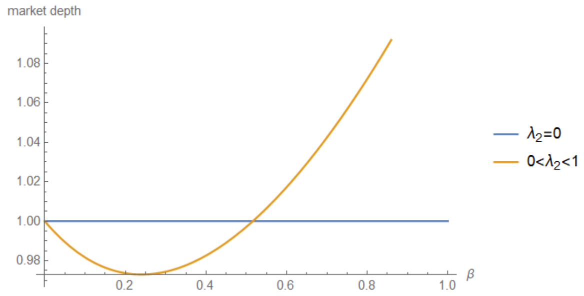
2. *When all informed rational traders are driven out, if ρ is small enough, market depth always increases in β; when β is large enough, if λ_2 is sufficiently high, market depth increases in β; otherwise, there exists ρ^*, if $\rho > \rho^*$, market depth decreases in β.*

Figure 1.3: Market Depth in Corner Cases

(a) $\lambda_0 = 1$ ($A = 0.5, \gamma = 1, \tau_\epsilon = 0.5, \tau = 1, \tau_x = 0.1, n = 6$)



(b) $\lambda_0 = 0$ ($\gamma = 1, \tau_\epsilon = 0.5, \tau = 1, \tau_x = 1, n = 6, \rho = 0.4, A \in \{2.5, 3\}$)



3. *Uninformed rational traders react more sensitively to price than uninformed naive traders,* $|b_2| < |b_1|$.

The effect of naive traders on market depth is ambiguous, depending on whether informed rational traders exist or not. When $\lambda_1 > 0$, the increase of β reduces λ_1, making more rational traders uninformed. Because the informed rational traders who are faced with less inventory risk, have stronger responsiveness to price than the uninformed traders, the decrease of λ_1 reduces the responsiveness of rational traders to price, leading the negative effect on market depth.

After informed rational traders are entirely crowded out of the market, the increase of β improves price informativeness, but aggravates adverse selection for rational traders. If the correlation between signal errors is small enough, the negative effect of adverse selection on market depth is dominated because the price system is efficient enough, so the market depth increases in β. However, if the informed fraction in naive traders is sufficiently small, and the correlation between signal errors is large enough, the negative effect induced by the increase of naive traders dominates when their mass is large enough, leading the decrease of market liquidity. My conclusions echo with Kyle (1985), where the market depth decreases in trading aggressiveness when it is relatively low, and increases when aggressiveness is sufficiently large.

I also study the corner cases when all $\lambda_0 = 1$, and $\lambda_0 = 0$, see Figure 1.3a and Figure 1.3b, respectively.

Proposition 12 *At the corner equilibrium of the benchmark:*

1. *When $\lambda_0 = 1$ and $\lambda_2 = 1$, market depth increases in β when $\lambda_1 = 1$; and decreases when λ_1 decreases until informed rational traders are entirely crowded out.*

2. *When $\lambda_0 = 0$, if $\lambda_2 = 0$, there is no informed traders in the market and market depth keeps the constant; if $\lambda_2 \neq 0$, market depth decreases in β when it is small, and increases in β when it is sufficiently large.*

1.5.2 Mispricing Risk

I use the mean-squared error between the asset's payoff and its price, $\mathrm{E}\left[(p-v)^2\right]$, to measure the mispricing risk that price is deviated from the fundamental (e.g., Odean (1998); Ko and Zhijian (2007); Goldstein and Yang (2017); Vives (2011)).

The expression of $\mathrm{E}\left[(p-v)^2\right]$ is given by:

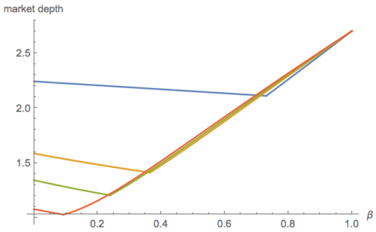
$$\begin{aligned} \mathrm{E}\left[(v-p)^2\right] &= \mathrm{Var}(v-p) \\ &= \frac{(1-\eta n I)^2}{\tau} + \frac{n^2 I^2 \eta^2}{D} + \frac{\eta^2}{\tau_x} \end{aligned} \tag{1.50}$$

When $\lambda_1 > 0$, as β increases, the total mass of uninformed traders increases, and the adverse selection is aggravated in the aggregate level due to the crowding out effect of naive traders. Thus the market liquidity decreases, and the mispricing risk increases in β. This finding is consistent with the behavioural models where more adverse selection increases mispricing (e.g., Daniel et al. (1997); Hong and Stein (1999); Vives (2011)).

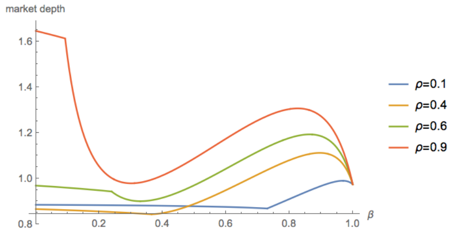
Proposition 13 *At equilibrium when $\lambda_0 \in (0, 1)$, when there are informed rational traders, the mispricing risk increases in β.*

Figure 1.4: Market Depth and Mispricing Risk

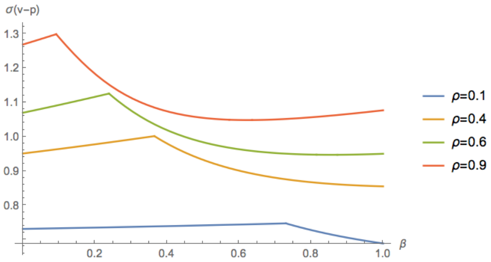
(a) *High* $\lambda_2 = 0.645$ $(\gamma = 1, \tau_\epsilon = 0.5, \tau = 1, \tau_x = 1, n = 6, A = 0.5)$



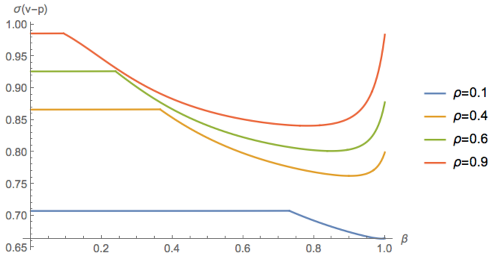
(b) *Low* $\lambda_2 = 0.02$ $(\gamma = 10, \tau_\epsilon = 0.5, \tau = 1, \tau_x = 10, n = 6, A = 0.5)$



(c) *High* $\lambda_2 = 0.645$ $(\gamma = 1, \tau_\epsilon = 0.5, \tau = 1, \tau_x = 1, n = 6, A = 0.5)$



(d) *Low* $\lambda_2 = 0.02$ $(\gamma = 10, \tau_\epsilon = 0.5, \tau = 1, \tau_x = 10, n = 6, A = 0.5)$



1.5.3 Expected Utility

When $\lambda_2 \in (0, 1)$, the naive traders believe there is no difference to acquire information or not. However, the actual expected utility of informed naive traders is not the same with that of the uninformed, which is different from conventional literature about information acquisition (e.g., Grossman and Stiglitz (1980); Goldstein and Yang (2015)).

The expected certainty of uninformed naive traders is:

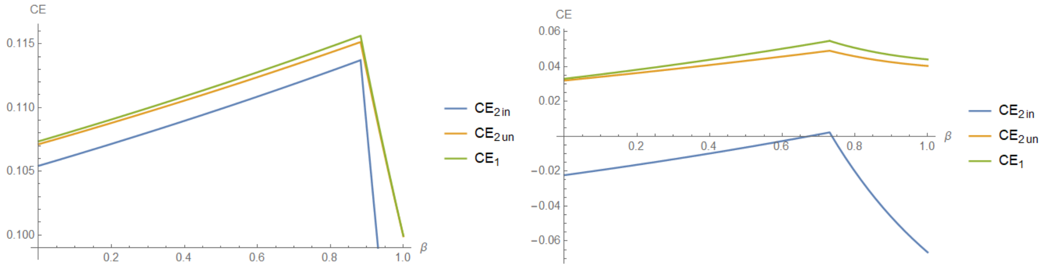
$$\begin{aligned}
\mathrm{E}\left[-\exp\Big\{-\frac{1}{\gamma}(v-p)x\Big\}\right] &= \mathrm{E}\left[-\exp\Big\{-\frac{1}{\gamma}(v-p)D_{uninf2}(p)\Big\}\right] \\
&= -\mathrm{E}\left[\mathrm{E}\left[\exp\Big\{-\frac{1}{\gamma}(v-p)D_{uninf2}(p)\Big\}\Big| p\right]\right] \\
&\neq -E\left[\exp\left\{-\frac{(\mathrm{E}[v-p \mid p])^2}{2\mathrm{Var}[v \mid p]}\right\}\right]
\end{aligned} \tag{1.51}$$

The inequality is induced by $D_{uninf2}(p) \neq \frac{\mathrm{E}[v-p|p]}{\mathrm{Var}[v|p]}$. We calculate the expected utility under the

Figure 1.5: Certainty Equivalent

(a) $A = 0.5, \gamma = 1, \tau_\epsilon = 0.5, \tau = 1, \tau_x = 1, n = 2, \rho = 0.1$

(b) $A = 0.5, \gamma = 1, \tau_\epsilon = 0.5, \tau = 1, \tau_x = 1, n = 6, \rho = 0.1$



rational measure:

$$\begin{aligned} \mathrm{E}\left[-\exp\Big\{-\frac{1}{\gamma}(v-p)x\Big\}\right] &= \mathrm{E}\left[-\exp\Big\{-\frac{1}{\gamma}(v-p)D_{uninf2}(p)\Big\}\right] \\ &= \mathrm{E}\left[-\exp\Big\{-\frac{b_2}{\gamma}(v-p)p\Big\}\right] \end{aligned} \tag{1.52}$$

The term of $(v-p)p$ in equation 1.51 is the product of two correlated normally distributed random variables. After standard normalization, we apply the function of MGF in Craig (1936) to calculate the expected utility of naive traders.

Proposition 14 *1. The expected utility of rational traders is always larger than that of the naive traders.*

2. The expected utility of rational traders can be improved by naive traders.

3. For many sets of the parameters specifying this economy, the expected utility of informed naive traders is lower than that of uninformed naive traders.

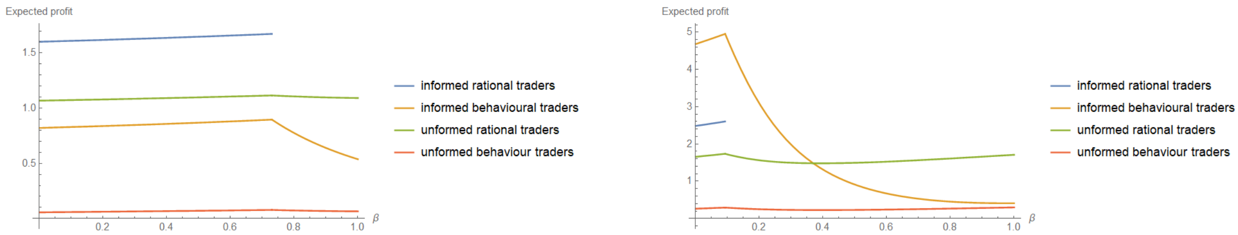
The actual expected utility of naive traders, namely, their welfare as defined in Goldstein and Yang (2015), is impaired by "correlation neglect". Moreover, although the naive traders believe acquiring information has no difference with being uninformed with respect to their expected utility, the welfare is actually weakened more if they choose to acquire information and trade more aggressively than keeping uninformed and trading less sensitively to price.

In Figure 1.5, the certainty equivalent of expected utility of rational traders are always higher than that of naive traders. In Figure 1.5b, the certainty equivalent of informed naive traders

Figure 1.6: Expected Profit

(a) $A = 0.5, \gamma = 1, \tau_\epsilon = 0.5, \tau = 1, \tau_x = 1, n = 6, \rho = 0.1$

(b) $A = 0.5, \gamma = 1, \tau_\epsilon = 0.5, \tau = 1, \tau_x = 1, n = 6, \rho = 0.9$



can even be negative. This does not mean they are expected to lose money in the secondary market. In fact, the traders, regardless they are rational or naive, both exploit benefit from the noise traders. The negative certainty equivalent implies that the risk-adjusted wealth of informed naive traders is expected to be negative, but they may be expected to earn more than the rational traders (see Figure 1.5b). This can help explain why the naive traders can survive in financial markets. They can not recognize the fact that their actual utility is lower than others, but they may achieve higher expected return than their rational counterparts. The issue about the survival of naive traders has been analyzed in some literature, including Benos (1998); Kyle and Wang (1997); Hirshleifer and Luo (2001). My paper echoes with Hirshleifer and Hirshleifer and Luo (2001), which finds that the overconfident naive traders can better exploit noise traders and earn higher returns than their rational counterparts. My paper also further includes information acquisition, and finds that the survival of naive traders is still supported.

1.5.4 An Extension to Costly Information Acquisition Model

In the costly information acquisition model, it is assumed that the informed traders acquire the same bundle of information signals. In this subsection, I study the case that the informed traders acquire heterogenous information. All other model specifications remain the same as in Section 1.4. Under the alternative assumption, I assume that $s_{ji}(i \in (1, 2, ...n))$, which implies that the signal errors are entirely cancelled out when they are aggregated at equilibrium. This assumption can be rationalized by the different sources of information collected by informed traders. At equilibrium, the linear price function is given by

$$p = \eta n I v + \eta x \tag{1.53}$$

The conditional variance about fundamental for informed rational and naive traders are given by:

$$\mathrm{Var}_1\left[v\middle|\sum_{i=1}^{n} s_i, p\right] = \frac{1}{\tau + D + n^2 I^2 \tau_x} \tag{1.54}$$

$$\mathrm{Var}_2\left[v\middle|\sum_{i=1}^{n} s_i, p\right] = \frac{1}{\tau + F + n^2 I^2 \tau_x} \tag{1.55}$$

Based on the information acquisition decision of rational traders, the informed fraction of rational traders is given by:

$$\begin{aligned}\lambda_1 &= \frac{1}{1-\beta}\sqrt{\frac{D-\tau A}{A\tau_x\gamma^2 D^2}} - \frac{\beta\lambda_2 n\tau_\epsilon}{(1-\beta)D} \\ &= \lambda_0 - \frac{\beta}{1-\beta}\underbrace{\left(\lambda_2\Delta - \sqrt{\frac{D-\tau A}{A\tau_x\gamma^2 D^2}}\right)}_{\text{crowed-out (+) effect}}\end{aligned} \tag{1.56}$$

And the price informativeness at equilibrium is given by D/A. The heterogeous private information of traders does not change the prior main conclusions: at equilibrium, price informativeness keeps the constant as β increases until the informed rational traders are entirely crowded out of the market, and then price informativeness increases in the mass of naive traders β. the existence of naive traders still has crowding-out effect on the information acquisition of informed rational traders.

1.6 Model without Information Cost

In this section, I turn to the case when the information signals are free of charge, and study how the market is influenced by "correlation neglect" of naive traders.

The information can be regarded as the public information, e.g., media, news, announcements. The model setting is the same as prior sections, except that each trader, either rational or naive, can observe n signals. Traders update their beliefs about the fundamental using the public information and trade accordingly.

The demand of each rational trader is given by:

$$D_1\left(\sum_{i=1}^{n} s_i, p\right) = \frac{\gamma D}{n}\sum_{i=1}^{n} s_i - \gamma(\tau + D)p \tag{1.57}$$

The demand of naivetrader is given by:

$$D_2\left(\sum_{i=1}^{n} s_i, p\right) = \gamma\tau_\epsilon\sum_{i=1}^{n} s_i - \gamma(\tau + n\tau_\epsilon)p \tag{1.58}$$

Based on the market clearing condition:

$$(1-\beta)D_{inf1}\left(\sum_{i=1}^{n} s_i, p\right) + \beta D_{inf2}\left(\sum_{i=1}^{n} s_i, p\right) + x = 0 \tag{1.59}$$

, price can be solved:

$$p = \eta\left(nIv + I\sum_{i=1}^{n}\epsilon_i + x\right) \tag{1.60}$$

where

$$I = (1-\beta)\gamma\frac{D}{n} + \beta\gamma\tau_\epsilon \tag{1.61}$$

and

$$\eta = \frac{1}{\gamma\tau + nI} \tag{1.62}$$

Because price does not reflect any private information in this case, it is meaningless to analyze price informativeness as before. We use the mean-squared error between the asset's payoff and its price, $\mathrm{E}\big[(p-v)^2\big]$, to measure the mispricing risk.

The expression of $\mathrm{E}\big[(p-v)^2\big]$ is given by:

$$\begin{aligned}\mathrm{E}\left[(p-v)^2\right] &= \mathrm{Var}(p-v) \\ &= \eta^2\left(\frac{\gamma^2}{\tau}+\frac{n^2I^2}{D}+\frac{1}{\tau_x}\right)\end{aligned} \tag{1.63}$$

As the mass of naive traders increases, on the one hand, because they underestimate the inventory risk and are willing to provide more liquidity than rational traders, the market depth increases, which reduces $\mathrm{Var}(p-v)$; on the other hand, errors in the public signals are reflected more in the price due to increasing aggressive trading at the aggregate level.

Proposition 15 *1. When $\rho < \frac{1}{\tau_x\gamma^2\tau(n-1)}$, mispricing risk decreases in β.*

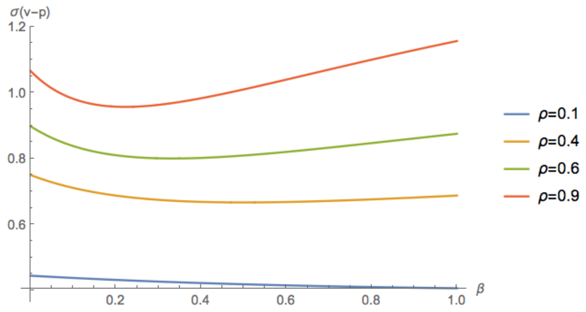
2. When $\rho > \frac{1}{\tau_x\gamma^2\tau(n-1)}$, there exists a β^*, if $\beta \in (0,\beta^*)$, mispricing risk decreases in β; if $\beta > \beta^*$, mispricing risk increases in β.

The positive effect of naive traders on market quality dominates when the correlation between signal errors is sufficiently small, because the market benefits from the liquidity the naive traders provide. However, when the correlation between signals errors is high enough, and the mass of naive traders is sufficiently large, the negative effect on market quality dominates because the price is vulnerable to be deviated by the errors in public signals. The larger the correlation between errors, the more possibility that the market is exposed to mispricing risk.

1.7 Conclusion

In this paper, I develop a model where rational traders interact with naive traders who neglect the correlation between signal errors. I consider two alternative cases with and without

Figure 1.7: Mispricing risk without information acquisition cost: $(\gamma = 1, \tau_\epsilon = 0.5, \tau = 1, \tau_x = 1, n = 6)$



information acquisition cost, and derive the implications about the market quality measured by price informativeness, market liquidity and mispricing risk.

First, I find that the impact of "correlation neglect" on financial markets depends on whether information is costly or not. If the information is free, mispricing risk can improve in the mass of naive traders, but may be impaired by them when their mass and the correlation are both high enough. This is because signal errors cause mispricing risk when the price is excessively sensitive to public signals. However, if information acquisition is costly, the existence of naive traders increases mispricing risk when their mass is not large enough to crowd out all informed rational traders out of the market.

Second, when information acquisition is costly, naive traders have a "crowding out" effect on the information acquisition of rational traders. The total mass of informed traders also declines in the mass of naive traders before informed rational traders are entirely crowded out, meanwhile, price informativeness keeps the same and market liquidity deteriorates. However, when informed rational traders do not exist, market quality, measured by liquidity and mispricing risk, can improve afterwards, depending on the correlation between signals and the mass of naive traders.

Finally, I am able to use the model to derive implications regarding the empirical properties of market quality. In particular, one distinct feature of my model is that the impact of "correlation neglect" on financial markets depends on information acquisition cost and the mass of naive traders. These implications can potentially serve as the explanation of the mispricing risk induced by the repetition of media. Moreover, the information acquisition model helps understand why active asset management has become less attractive in the past few years, and why market quality is potentially impaired.

2. Strategic Disclosure Complexity: Evidence From Mutual Funds

This chapter is based on a paper "Strategic Disclosure Complexity: Evidence From Mutual Funds" with Giovanni Cespa and Aneel Keswani.

2.1 Introduction

Mutual funds are an important vehicle for small investors to access professionally managed portfolios. For example, over 44% of Americans (mostly retail investors), invest in mutual funds.[1] However, mutual fund investors tend to be less sophisticated than institutional investors and are more likely to make mistakes when investing (Barber and Odean (2013)). Abiding by its mission, the Securities and Exchange Commission (SEC), thus advises investors to "never invest in a product that they don't fully understand." Additionally, to ensure that investors make informed decisions, the SEC also asks mutual funds to provide investment information in the form of a prospectus which includes key data such as the fund's investment goals, its investment strategies and principal risks, the fund's fees and expenses, and its past performance. Mutual fund prospectuses are therefore a crucial ingredient of the informational environment in which small investors' decisions are made, which raises a number of important questions.

Are prospectuses drafted in a way to facilitate investors' decisions? Do mutual fund investors correctly select funds based on reliable performance measures? Are prospectuses indicative of

[1] https://www.sec.gov/news/speech/mjw-speech-032114-protecting-retail-investor

a fund's performance? What affects mutual funds' choice of prospectus complexity? While the existing literature has established that mutual fund prospectuses influence investors' decisions,[2] to the best of our knowledge, no study to date examines how the *textual complexity* of funds' prospectuses affects investors' choices and capital allocation. In addition, the literature is silent on the possible determinants of prospectuses' textual complexity or on what potentially leads mutual funds to complicate their prospectuses. In this paper, we tackle both problems by focusing on the textual complexity of the "Principal Strategies" section of mutual funds' prospectuses.[3]

We find that funds whose principal strategies' prospectus section is highly-complex, are more likely to attract less sophisticated investors. Based on this finding, we further show that mutual funds with low investment ability selectively target investors with low sophistication by deliberately choosing prospectuses with a high level of textual complexity. Our findings, therefore, offer an explanation to the puzzling phenomenon that mutual funds with lower complexity prospectuses outperform funds with higher complexity prospectuses (Tucker and Xia (2022)).

Our paper suggests a plausible reason for mutual funds to complicate their prospectuses, arguing that underperforming mutual fund managers choose high textual complexity to target less sophisticated investors. These investors, in turn, reward past winners more and unwisely reward factor-related returns that are thus unrelated to alpha. On this basis, our evidence that prospectus manipulation (i.e., the introduction of unnecessary complexity in fund prospectuses) goes hand in hand with a lack of managerial skills which offers an agency based explanation for why funds with high textual complexity underperform.

We start our analysis by examining how the textual complexity of mutual fund prospectuses affects investment decisions and uncover a negative relationship between textual complexity and investor sophistication. We measure the textual complexity of a fund prospectus using the Gunning-Fog Index calculated on the full text of the "Investment Strategies" section of a fund's prospectus.[4] Investors' sophistication is measured along three dimensions. First, we examine

[2]E.g., Kostovetsky and Warner (2020), DeHaan et al. (2021).

[3]The principal strategies of the fund tell how the fund intends to achieve its investment objective. These strategies indicate the approach the fund's adviser takes in deciding which securities to buy or sell.

[4]The Fog Index is widely used in the accounting and finance literature, e.g., Li (2008) and Callen et al.

the way investors assess fund performance based on the assumption that sophisticated investors use more sophisticated asset pricing models to evaluate fund performance and pay attention to risk factors when adjusting past fund returns (Barber et al. (2016)). Our second measure of investor sophistication is the convexity in the flow performance relationship. Using a cross-section of countries, Ferreira et al. (2012) demonstrate that the flow performance relation is less convex in countries with greater investor sophistication. Furthermore Kim (2019) argues that greater sophistication among US investors over time has diminished flow performance convexity. These papers therefore suggest that more sophisticated investors have less convexity in their flow performance relation.

Our third measure of investor sophistication is the reaction of investors to fund distribution costs. We would expect more sophisticated investors to be more averse to fund distribution costs as these increase tinvestor cost without enhancing investment ability (Evans and Fahlenbrach (2012)). Based on these three criteria we conclude that the investors in funds with low-complexity prospectuses are more sophisticated than those in high-complexity funds. This is because the former do risk-adjustment when evaluating fund performance, show less convexity in their flow performance relation, and are more averse to fund distribution costs compared to the latter.

Given the negative relationship between textual complexity and investor sophistication, we further investigate which funds are more likely to make their prospectuses more complex. One question we need to consider is whether prospectuses are manipulated at the fund-specific level or at the mutual fund family level, as some prospectuses are written jointly by both the asset management companies and the fund managers.[5] To answer this question, we measure the textual complexity of prospectuses in two ways: *fund-overall* textual complexity is measured by the Fog Index based on the full text of the "Investment Strategies" section; and *fund-specific* textual complexity is measured only based on the fund-specific strategy descriptions which

(2013) and reflects the weighted average of the sentence length and the percentage of the "complex" words consisting of three or more syllables. The mathematical formula is: $Fog = 0.4(ASL + PHW)$, where ASL is average sentence length (i.e., number of words divided by the number of sentences), PHW is percentage of complex words. For more details, see Section 2.3.1.

[5]Kostovetsky and Warner (2020) find that the mutual funds in the same mutual fund family have higher textual overlap in prospectuses, indicating that the mutual fund families involve in the writing of the prospectuses.

exclude the content shared with the other funds in the same family.[6] By considering these two kinds of textual complexity, our results show that low-quality funds, such as those with high risk and low past abnormal return, tend to employ complex prospectuses, which is reflected in high *fund-specific* textual complexity. However, there is no significant relationship between fund quality and *fund-overall* textual complexity. These results suggest that the mutual fund managers with low skills tend to complicate the strategy descriptions written specifically for the mutual funds they are in charge of. This is consistent with the fund managers' motivation to hide unfavourable information about their managerial skills and obfuscate their low quality by the use of highly complex prospectuses.

We further examine how low-quality funds manipulate their prospectuses to exploit less sophisticated investors. We find that the mismatch between the price (fund fees) and the performance of high-complexity funds is more severe than that for the funds with low textual complexity.[7] This suggests that low quality funds tend to simultaneously charge high fees that are not commensurate with their skills, and complicate prospectuses to attract unsophisticated investors who are less averse to such higher costs.

The rest of the paper is organised as follows. Section 2.2 reviews the related literature. Section 2.3 describes the data. Section 2.4 studies the relationship between overall textual complexity and investor sophistication. Section 2.5 illustrates the relationship between fund past features and fund textual complexity (both the "fund-overall" and the "fund-specific" complexity), and discusses the motivation of prospectus manipulation. Section 2.6 examines the implications of fund textual complexity on future fund performance, as well as the relationship between the fund expenses and the performance. Section 2.7 draws the conclusions of our analysis.

[6]We discuss the details in Section 2.5.1.

[7]Gil-Bazo and Ruiz-Verdú (2009) demonstrate the fund performance is negatively related to fund fees, and we further find that the mismatch between performance and fees is much more severe for funds with high fund-specific complexity.

2.2 Related Literature

Our paper contributes to the literature on the strategic readability of fund and firm disclosures. As regards the readability of corporate disclosures, Li (2008) finds that the readability of a company's annual report is negatively correlated with the profitability of the company. Furthermore, Li (2008) propose that high levels of textual complexity are caused by firm strategic behaviour, that is, companies with low profitability aim to increase the cost of information processing for investors and thereby delay the discovery of unfavourable information. Lo et al. (2017) complement the findings of strategic obfuscation of company reporting and further clarify that companies most likely to manage their earnings tend to strategically provide more complex annual reports.

For fund disclosures, Hwang and Kim (2017) find that higher textual complexity of closed-end fund shareholder reports is associated with greater discounts to net asset value, and their studies demonstrate that the investors are likely to rely on annual reports to make investment decisions. Joenväärä et al. (2019) evaluate the textual complexity of hedge fund strategy descriptions and find that funds with lexically diverse strategy descriptions outperform the market while funds with a syntactically complex strategy description underperform. They explain this phenomenon by proposing that fraudulent managers are more likely to confuse investors by adopting complex descriptions of their strategies. DeHaan et al. (2021) find that passively managed mutual funds engage in strategic obfuscation by creating unnecessarily complex disclosures and fee structures to steer investors towards the expensive funds. They find a positive correlation between the fees of S&P 500 index funds, which have similar risks and returns, and the complexity of their qualitative disclosures. Compared to index funds, we find that the relationship between fees and textual complexity is different for actively managed mutual funds, as actively managed funds have heterogeneous investment strategies and managerial skills, and the pricing strategy is more complicated. Tucker and Xia (2022) study the readability of the "Principal Strategies" section of mutual fund prospectuses. They conclude that readability provides signaling information about fund performance, i.e. the lower the readability, the lower the fund returns. However, their paper neither examines the abnormal returns that represent fund managerial skills, nor provides a valid explanation for the relationship between readability and fund performance. Our research addresses the issues in their study and, more critically, explains why funds with high textual complexity are more likely to underperform funds with low textual complexity from the perspective of fund investor sophistication and fund strategic behaviour.

2.3 Data and Variables

We obtain the mutual fund prospectuses from the SEC "Mutual Fund Prospectus Risk/Return Summary Data Sets" from 2010 to 2020. The data are updated quarterly, and are extracted from mutual fund prospectuses tagged in eXtensible Business Reporting Language (XBRL). We extract the "Principal Strategies" section from the raw data files. If a fund does not update its prospectus in one quarter, we treat the prior quarter prospectus as the most recent version. We preprocess the text by removing the html code, the abbreviations, and the numbers.

We then match the prospectus data with the Center for Research in Security Prices (CRSP) Survivor Bias-Free Mutual Fund Database. For ease of risk adjustment as is common in most mutual fund studies, we focus on domestic equity funds. To identify domestic diversified actively managed equity funds, we follow the criteria similar to that in Doshi et al. (2015). We first select funds whose Lipper Classification Code is one of the following: EIEI, LCCE, LCGE, LCVE, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, SCVE, and Lipper Object Code is either CA, EI, G, GI, MC, MR, or SG. Then we eliminate index and ETF funds using the CRSP flags and filter out the funds whose name includes the words such as "Index" or "S&P." We also remove funds containing words such as "ETF","MIXED-ASSET TARGET" to ensure all funds not eligible for our criteria are removed. For the remaining funds, we require that the age of the funds is at least two years, and the total net asset size is larger than $5 million. The fund age is computed as the month-end relative to the fund's first offer date. We obtain fund returns, expenses, total net assets (TNA), asset classification, and other fund characteristics from CRSP.

Most funds have multiple share classes, which share the same asset portfolios but differ in the fee structures. We combine all the share classes of a fund and aggregate them into one fund. To deliver this, we calculate the TNA of each fund as the sum of TNAs of all the share classes, and take the age of the fund as the age of the oldest share class. For the other characteristics, we use the TNA-weighted average across all the share classes. We identify the investment style of funds based on Lipper fund classifications, which are assigned to a specific population of equity funds based on the actual holdings. The final sample comprises 1328 active U.S. diversified actively managed equity funds after we merge mutual fund prospectus data with the CRSP mutual fund dataset.

We also require the data of fund holdings in the analysis of mutual fund performance. We link our sample of mutual funds to the Thomson Financial Mutual Fund Holdings using MFLINKS files from the Wharton Research Data Services. We exclude funds with investment objective codes (IOC) of 1, 5, 6 and 7: International, Municipal Bonds, Bond & Preferred, and Balanced.

2.3.1 Measuring the Textual Complexity of Mutual Fund Prospectuses

We measure mutual fund prospectus complexity by measuring the textual complexity of the principal strategies section of mutual fund prospectuses. To measure this textual complexity we use the Fog index which is widely used in the finance and accounting literature to study corporate disclosure and communications with shareholders, e.g., Li (2008), Callen et al. (2013). The Fog Index is calculated as:

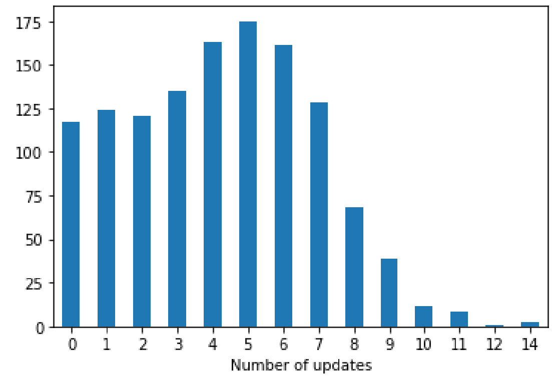
$$Fog = 0.4 * [(words/sentences) + 100 * (complex\_words/words)]. \tag{2.1}$$

The Fog Index is calculated by summing the average sentence length and the percentage of complex words. A sentence's length is calculated by dividing the number of words by the number of sentences. The percentage of complex words is calculated by dividing the number of complex words by the total number of words and multiplying the result by 100. A complex

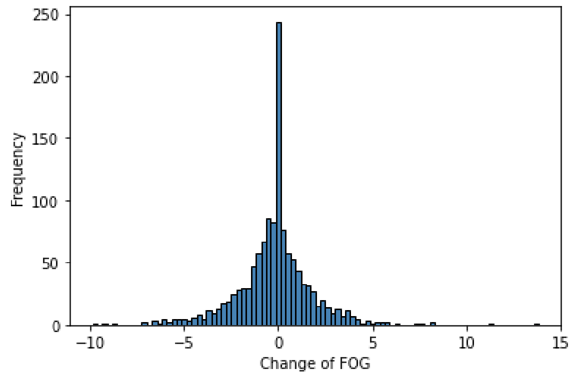
Figure 2.1: Textual Complexity of Mutual Fund Prospectuses from 2010 to 2020

Figure 2.1a shows the distribution of the number of updates to fund prospectuses from 2010 to 2020; Figure 2.1b presents the change in textual complexity of fund prospectuses from 2010 to 2020, based on the difference in the Fog index between the latest version and the first version of each fund prospectus.

(a) The Times of Updates



(b) Change of the Fog Index



word is defined as a word with at least three syllables.[8]

In Figure 2.1, our study describes the updates and trends in changes in our sample of fund prospectuses from 2010 to 2020. As Figure 2.1a shows, from 2010 to 2020, more than 99% of the mutual funds in our sample update their prospectuses less than 10 times, and more than 90% of the funds update their prospectuses less than 7 times.

To examine the range of variation in the Fog Index for individual funds, we take the difference of the Fog Index between the most recent prospectus and the earliest prospectus over 2010 to 2020. As Figure 2.1b shows, over 90% of mutual funds change their Fog Indexes within $[-3, +3]$ and their average range of change is 0.189. These results show that the prospectuses of mutual funds do not change much, and that the textual complexity remains relatively stable. These results suggest that the mutual funds do not update their prospectuses very frequently and that the complexity of the text remains relatively constant. As Figure 2.1b shows, the distribution of changes in the Fog Index has a thick left tail, suggesting that the textual complexity of a large proportion of mutual fund prospectuses has declined over the past decade.

In each quarter, we rank mutual funds into three groups based on the Fog Index of the most recent prospectus. In the Table 2.1, we report the average fund characteristics of funds in each

[8]To demonstrate how the Fog Index represents the textual complexity of the principal strategy descriptions, I provide two examples with relatively high and relatively low Fog Indexes, see appendix B.1.1 and B.1.2.

Table 2.1: Mean Statistics By Textual Complexity

We report fund characteristics by the textual complexity of their prospectuses. At the end of each quarter, we calculate the textual complexity as the Fog Index based on the most recent prospectus. We then sort funds cross-sectionally into textual complexity terciles(Low, Mid, and High), calculate the mean characteristics within each textual complexity tercile, and finally report the time-series mean of cross-sectional averages. The fund characteristics include the fund total net assets (TNA), fund age, 12b-1 fee(fund marketing and distribution costs), expense ratio, and turnover ratio. Broker denotes the percentage of mutual funds that are in the broker-sold distribution channel in each tercile of funds.

	Fog	TNA ($M)	Fund Age (Years)	12b1 (%)	Exp Ratio (%)	Turn Ratio (%)	TNA_Family ($M)	Broker
Low	20.942	2437.060	18.667	0.1341	1.0676	0.629	106212.701	0.653
Mid	23.231	2304.800	18.176	0.1158	1.046	0.670	140205.288	0.601
High	26.301	1869.503	18.716	0.1100	1.0481	0.638	131306.508	0.583

group classified by their complexity. The funds in the group with the lowest complexity have the average Fog Index of 20.942 versus 26.301 of the funds in the group with the highest complexity. Moreover, the low-complexity funds have the higher total net asset(TNA) on average, and they tend to belong to the mutual fund families with smaller size. We also report the percentage of funds in the broker-sold distribution channel in each textual complexity group.[9] Our results show that the percentage of broker-sold funds in the low-complexity group is higher than that in the high-complexity group, implying mutual funds tend to write more complex prospectuses to serve the investors who buy or sell funds directly.

2.3.2 Mutual Fund Cash Flows

Our dependent variable of interest is the fund flows, which are estimated using data from the CRSP mutual fund database. Following the majority of the related literature, e.g., Huang et al. (2007), Keswani and Stolin (2008), we calculate flows for fund i in quarter t as the percentage growth of the net growth in total net assets (TNA):

$$Flows_{it} = \frac{TNA_{it} - (1 + R_{it})TNA_{i,t-1}}{TNA_{i,t-1}}, \tag{2.2}$$

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. Equation 2.2 assumes fund flows occur at the end of each quarter.

To ensure that extreme values do not drive our results, we winsorise the fund flows at the

[9] A fund is identified as direct-sold if 75% of its assets are held in a share class that charges no front-end load, no back-end load, and no 12b-1 fee, or otherwise, it is broker-sold according to Bergstresser et al. (2009).

bottom and top 1% level, which results in a total of 35153 fund-quarters in our sample finally.

2.3.3 Fund Returns and Performance Measurement

Investors may use different ways to evaluate the past performance of mutual funds. According to the literature,[10] sophisticated investors tend to evaluate funds based on the risk-adjusted return, while unsophisticated investors simply rely on fund returns without risk adjustment.

Barber et al. (2016) and Berk and van Binsbergen (2016) both find that fund flows are better explained by CAPM alphas than by competing models. In addition to CAPM alphas, we examine another three alternative performance measures and compare them to determine which method investors of funds with different textual complexity use to assess the performance of funds. The competing models for evaluating performance are the returns net of fees, the capital asset pricing model (CAPM), the Fama and French (1992) three-factor model (3F), and Carhart (1997) four-factor model that includes the momentum factor.

We use monthly mutual fund returns, i.e. pre-tax but net of management fees, to estimate alphas based on the three asset pricing models. For example, to calculate Carhart four-factor alpha, we first regress the previous 36 months (at least 24 months) of fund excess returns on the four risk factors defined in Carhart (1997), and then store the estimated betas. We then use the estimated betas and the realised risk factors to predict the returns in the next quarter. The quarterly alpha is the difference between the realised fund return and the predicted return, which is

$$\widehat{\alpha}_{it}^{Carhart} = (R_{it} - R_{ft}) - \left[\widehat{\beta}_{it}(R_{mt} - R_{ft}) + \widehat{s}_{it}SMB_t + \widehat{h}_{it}HML_t + \widehat{m}_{it}UMD_t\right], \tag{2.3}$$

where R_{it} is fund i's return net of fees in month t, and R_f is the one-month Treasury bill rates, which proxies for the risk-free rate, $(R_{mt} - R_{ft})$ is the return on the value-weighted market portfolio, SMB, HML, and UMD are the size, value and momentum risk factors defined in

[10] Barber et al. (2016) find that investors' choice of asset pricing model varies according to their level of sophistication, i.e. less sophisticated investors pay less attention to risk factors and thus select simple asset pricing models to evaluate funds.

Carhart (1997).

We calculate the three-factor alpha in the same way we calculate four-factor alpha, except that we only include market, size, and value factors in the regression. Similarly, we apply the same method to calculate three-factor and CAPM alphas in the month t as follows:

$$\widehat{\alpha}_{it}^{FF3} = (R_{it} - R_{ft}) - \left[\widehat{\beta}_{it}(R_{mt} - R_{ft}) + \widehat{s}_{it}SMB_t + \widehat{h}_{it}HML_t\right], \tag{2.4}$$

and

$$\widehat{\alpha}_{it}^{CAPM} = (R_{it} - R_{ft}) - \left[\widehat{\beta}_{it}(R_{mt} - R_{ft})\right]. \tag{2.5}$$

Then the monthly alphas are averaged to produce the quarterly four-factor, three-factor, and CAPM alphas respectively.

In the academic literature, Carhart four-factor alpha is the most common measure of mutual fund performance, e.g., Huang et al. (2007), Keswani and Stolin (2008). In comparison with Carhart's four-factor alpha, CAPM alpha is a less complex performance measure since size, value, and momentum risks are not considered, and thus factor-related returns are not subtracted. Following Song (2020), we decompose CAPM alpha of a fund into two components:

$$\widehat{\alpha}_{it}^{CAPM} = \widehat{\alpha}_{it}^{Carhart} + \Delta_{it}^{risk}, \tag{2.6}$$

where Δ_{it}^{risk} is the factor-related return of fund i in time t compensated by size, value and momentum risk factors. Similarly, we decompose the excess return of a mutual fund into the factor-related return and Carhart four-factor alpha:

$$R_{it} - R_{ft} = \widehat{\alpha}_{it}^{Carhart} + \Delta_{it}^{risk_{all}}, \tag{2.7}$$

where $\Delta_{it}^{risk_{all}}$ represents the factor-related returns of fund i in time t compensated by the market, size, value, and momentum risk factors.

2.4 Investor Sophistication and Prospectus Complexity

In this section, we examine the relationship between prospectus complexity and investor sophistication.

2.4.1 Investors' Choice of Performance Evaluation Model

We first infer the sophistication of investors from the way they evaluate fund performance. With past fund returns, more sophisticated investors tend to take into account more factors that might explain the cross-sectional variation in fund performance and they adjust the raw return of funds accordingly. We conjecture that highly complex and less readable fund prospectuses limit the investors' ability to understand the underlying fund risks which prevents them from wisely choosing the benchmark to evaluate the abnormal return. Specifically, we hypothesise that investors in high-complexity funds are less sophisticated than their counterparts in low-complexity funds.

Barber et al. (2016) find that the more sophisticated investors adopt a more sophisticated asset pricing model to evaluate fund performance. We therefore infer the sophistication of investors by comparing the asset pricing models employed by the investors of funds with different textual complexity levels. We classify the measures of fund performance into two categories. In the less sophisticated category are models such as excess returns and the capital asset pricing model (CAPM), while in the other category are more sophisticated models such as the Fama-French three-factor model (3F) (Fama and French (1992)), and the Carhart four-factor model (Carhart (1997)). For the funds with different textual complexity, we examine which asset pricing model can best explain fund flows.

Using the horse race model developed by Barber et al. (2016), in each quarter, we assign each mutual fund into 10 deciles based on their performance in the past 12 months, using the measures of excess return, CAPM alpha, three-factor alpha, and Carhart four-factor alpha respectively. Decile 1 contains the funds with the poorest performance, and decile 10 contains the best-performing funds. At the same time, we rank each fund into either low, mid or high groups according to the textual complexity of their most recent prospectuses. The low group contains funds with low textual complexity, and the high group contains funds with high textual complexity. We test which performance measure can best explain the fund flows in different textual complexity groups.

We construct four pairs of asset pricing models and compare which of the two models in each pair better reflects investor cash flows. Each pair consists of one less sophisticated benchmark(the excess return or CAPM) and one more sophisticated benchmark(3F, or Carhart 4F). We determine which model in a pair can better explain the investor fund flows by evaluating the relationship between flows and the fund's decile rankings under the two measures. For example, in a comparison of the CAPM and the Carhart four-factor model, we estimate the following regressions:

$$Flows_{i,t,g} = a_g + \Sigma_x \Sigma_y b_{xy,g} D_{ixy,t-1,g} + c_g * Controls_{i,t-1,g} + \mu_{t,g} + \epsilon_{it,g}, \tag{2.8}$$

where g represents the complexity group, $g \in \{low, mid, high\}$, $Flows_{i,t,g}$ is the cashflows of mutual fund i in the complexity group g in quarter t; $D_{ixy,t,g}$ is a dummy variable equal to one if fund i in group g is ranked in the decile x based on the CAPM alpha, and in the decile y based on the Carhart four-factor model in quarter t-1, x =1,...,10, and y =1,...,10; we exclude the dummy variable for $x = 5$ and $y = 5$. The key coefficients of our interest are b_{xy}, which can be interpreted as the percentage of flows of a fund whose past performance is in the decile x based on CAPM alpha and in the decile y based on Carhart four-factor alpha in relative to the mutual fund that ranks in the fifth decile based on both performance measures. The matrix $Controls_{it-1,g}$ represents control variables, and c_g represents a vector of associated coefficient estimates for the funds in complexity group g. The control variables include the lagged flows, the standard deviation of fund monthly returns in the prior 12 months, fund size, age, turnover ratio, expense ratio, and mutual fund family size and other non-performance-related attributes.

If there is no significant preference for CAPM alpha and Carhart four-factor alpha when the investors evaluate fund performance, the coefficients of $D_{ixy,t-1,g}$ and $D_{iyx,t-1,g}$ will be the same, namely $b_{xyt,g} = b_{yxt,g}$. We test this null hypothesis that $\Sigma_x \Sigma_{x>y} b_{xy} = \Sigma_x \Sigma_{x<y} b_{xy}$. Alternatively, $\Sigma_x \Sigma_{x>y} b_{xy} < \Sigma_x \Sigma_{x<y} b_{xy}$ implies investors evaluate funds more based on Carhart four-factor alpha than based on CAPM alpha.

We run the regressions in the three groups(low, medium and high) of mutual funds classified according to the textual complexity. We use x to represent the decile based on the performance of the less sophisticated asset pricing model and y to represent the decile based on the more sophisticated asset pricing model.

Table 2.2 presents the results of model horse race. For the mutual funds in the low-complexity group, as shown in Panel A, B, C and D, $\Sigma_x \Sigma_{x<y} b_{xy} - \Sigma_x \Sigma_{x>y} b_{xy}$ is significantly positive, indicating the null hypothesis is always rejected and the investors of low-complexity funds prefer to evaluate funds using the more sophisticated asset pricing model. However, in all the four panels, the null hypothesis is not rejected in both the medium and high complexity groups, implying that the investors in the two groups have no preference between the two competing models. The results show that the investors in funds with higher textual complexity are less sophisticated than the investors in funds with lower textual complexity, as reflected by the fact that they take fewer risk factors into account when evaluating fund performance. For robustness, we divide each mutual fund into quintiles instead of deciles based on its performance over the past 12 months and do the regression analysis, and the results do not change.

Overall, the finding that investors in low textual complexity funds are more sophisticated than investors in high textual complexity funds implies that the less sophisticated investors are more likely to be misled by the complex descriptions of investment strategies and thus have limited abilities to evaluate fund performance.

2.4.2 Factor-Related Returns and Fund Flows

In section 2.4.1, we find that investors who invest in mutual funds with low textual complexity tend to use more sophisticated asset pricing models to evaluate fund performance. In order to further verify this conclusion, we test whether the sensitivity of fund flows to the factor-related

Table 2.2: Results of Model Horse Race by Textual Complexity

This table presents the results of a pairwise comparison of competing asset pricing models ability to predict the flows of funds in different levels of textual complexity. For example, we estimate the relation between flows and a fund's decile ranking based on the CAPM and Carhart four-factor models by estimating the following regression:

$$Flows_{it,g} = a_g + \Sigma_x \Sigma_y b_{xy,g} D_{ixy,t-1,g} + c_g * Controls_{it-1,g} + \mu_{t,g} + \epsilon_{it,g},$$

where g represents the complexity group, $g \in \{low, mid, high\}$, $Flows_{i,t,g}$ is the cashflows of mutual fund i in the complexity group g in quarter t; $D_{ixy,t-1,g}$ is a dummy variable equal to one if fund i in group g is in the decile x based on the CAPM alpha, and in the decile y based on the Carhart four-factor model in quarter t-1, x =1,...,10, and y =1,...,10; we exclude the dummy variable for $x = 5$ and $y = 5$. The matrix $Controls_{i,t-1,g}$ represents control variables, and c_g represents a vector of associated coefficient estimates for the funds in complexity group g. The control variables include the lagged flows in quarter t-1, the standard deviation of fund monthly returns of the prior 12 months, the logarithm of fund size at the quarter t-1, the fund age at the quarter t-1, the turnover ratio in the prior 12 months, the expense ratio at the quarter t-1, and the logarithm of mutual fund family size at the quarter t-1. We also include time fixed effects $\mu_{t,g}$. We compare the coefficients for which the decile ranks are the same magnitude in each complexity group. Standard errors are double-clustered by fund family and month. *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Panel A: CAPM VS Fama-French 3F

	Low_group	Mid_group	High_group	Overall
$\Sigma_x \Sigma_{x<y} b_{xy} - \Sigma_x \Sigma_{x>y} b_{xy}$	0.4163***	0.1009	0.0914	0.2341**
P-value	0.001	0.5393	0.5172	0.0110
model selection	FF	=	=	FF

Panel B: Panel B: CAPM VS Carhart 4F

	Low_group	Mid_group	High_group	Overall
$\Sigma_x \Sigma_{x<y} b_{xy} - \Sigma_x \Sigma_{x>y} b_{xy}$	0.3082**	-0.1705	0.0716	0.1559
P-value	0.0416	0.5066	0.6032	0.1339
model selection	Carhart	=	=	=

Panel C: Panel C: Excess return VS Fama-French 3F

	Low_group	Mid_group	High_group	Overall
$\Sigma_x \Sigma_{x<y} b_{xy} - \Sigma_x \Sigma_{x>y} b_{xy}$	0.4627***	0.1638	0.2288	0.3086
P-value	0.0009	0.2894	0.1133	0.0002
model selection	FF	=	=	=

Panel D: Panel D: Excess return VS Carhart 4F

	Low_group	Mid_group	High_group	Overall
$\Sigma_x \Sigma_{x<y} b_{xy} - \Sigma_x \Sigma_{x>y} b_{xy}$	0.3177**	-0.0575	0.1554	0.1819*
P-value	0.0146	0.8366	0.2265	0.0695
model selection	Carhart	=	=	Carhart

returns is different between funds with different textual complexity. As the factor-related return is not an effective indicator of the fund managerial skills, investors who are more sophisticated should not treat factor-related returns as alpha should therefore be less reactive to the factor-related returns. Based on this, we test if investors in high-complexity funds respond more aggressively to factor-related returns than investors in the low-complexity funds.

In each quarter, we rank funds according to their Carhart alpha, three factor-related return

(Δ^{risk}), and four factor-related return ($\Delta^{risk_{all}}$) in the past 12 months. The corresponding ranks ranging from zero (low) to one (high) are assigned to them. We create a dummy variable, denoted by $LowC$, to identify the fund group with low textual complexity.

We estimate the following panel regression to examine how investors in each complexity group respond to the factor-related returns:

$$\begin{aligned} Flows_{it} =& a + \beta_1 * \widehat{\alpha}^{Carhart}_{i,t-1} + \beta_2 * \Delta^{risk}_{i,t-1} + b_1 * \widehat{\alpha}^{Carhart}_{i,t-1} \times LowC + b_2 * \Delta^{risk}_{i,t-1} \times LowC \\ &+ dControls_{it-1} + \epsilon_{it}, \end{aligned} \tag{2.9}$$

where a is the regression intercept, ϵ_{it} is the regression error term, the control variables include the lagged cashflows, the standard deviation of fund returns in the past 12 months, fund size, age, expense ratio, turnover ratio, fund family size and the number of equity funds owned by fund family. We 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, we double-cluster standard errors by time and fund family.

The regression results are presented in Table 2.3. Table 2.3 presents the sensitivity of the fund flows to Carhart alpha and the factor-related returns. In column(1), the interaction term between factor-related return (Δ^{risk}) and the low-complexity dummy($LowC$) has a significantly negative coefficient. The sensitivity of flows to factor-related returns for low-complexity funds is 0.0201 compared to 0.0273 for the funds with relatively high textual complexity, indicating that the investors of low-complexity funds react less aggressively to the factor-related returns and are more sophisticated than the investors of high-complexity funds. In column(2), only the time fixed effects are included in regression, and the results are similar to results in column(1). In column(3), we substitute the three factor-related return with the four factor-related returns and rerun the regression. The sensitivity of fund flows to the four factor-related returns for the low-complexity funds is 0.0193, which is significantly smaller than the sensitivity of 0.0292 for the high-complexity funds. The results in column (4) are consistent with the results in column (3), suggesting that investors in funds with higher textual complexity are more reactive to the factor-factor returns, as the returns compensated by the systematic risk factors are unwisely

Table 2.3: Return Decomposition Results: Sensitivity of Fund Flows to Return Components

This table presents regressions coefficient estimates from panel regressions of percentage fund flows (dependent variable) on the components of a fund's return including both the fund's Carhart alpha and the factor-related returns. The ranks ranging from zero to one are assigned to funds according to the factor-related returns and Carhart four-factor alphas in the past 12 months relative to other funds. In columns (1) and (2), the factor returns are related to three factors, i.e., size, value, momentum(SMB, HML, UMD); In columns (3) and (4), the factor returns are related to four factors, i.e., the market, size, value, momentum(MRT, SMB, HML, UMD); Controls include the lagged cashflows at quarter t-1, the standard deviation of fund returns in the prior 12 months, the logarithm of lagged mutual fund size, the lagged fund age, the lagged expense ratio, the turnover ratio in the prior 12 months, the logarithm of lagged fund family size and the number of equity funds owned by fund family. We also include style-by-time fixed effects and the fund fixed effects. Standard errors are double clustered by fund family and time. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)		(2)		(3)		(4)	
	coeff.	P-value	coeff.	P-value	coeff.	P-value	coeff.	P-value
LowC	0.0086***	0.0024	0.0091***	0.0014	0.01***	0.0008	0.0106***	0.0004
$\widehat{\alpha}_{i,t-1}^{Carhart}$	0.0672***	0	0.0595***	0	0.0655***	0	0.0585***	0
LowC*$\widehat{\alpha}_{i,t-1}^{Carhart}$	-0.0069*	0.0776	-0.0065*	0.0988	-0.0064	0.1009	-0.006	0.1236
Δ^{risk}	0.0273***	0	0.0168***	0				
LowC*Δ^{risk}	-0.0072**	0.0492	-0.0085**	0.0195				
$\Delta^{risk_{all}}$					0.0292***	0	0.0193***	0
LowC*$\Delta^{risk_{all}}$					-0.0099***	0.0076	-0.0115***	0.0019
LagRet	0.3356***	0	0.3401***	0	0.3356***	0	0.3397***	0
StdRet	0.0146	0.886	-0.0773	0.3093	-0.1554	0.1203	-0.1683**	0.0224
FundSize	-0.0045***	0	-0.0044***	0	-0.0045***	0	-0.0043***	0
FundAge	-0.0003***	0	-0.0003***	0	-0.0003***	0	-0.0003***	0
ExpRatio	-0.6414***	0.0016	-0.5678***	0.0044	-0.6717***	0.001	-0.6279***	0.0017
TurnRatio	-0.0021*	0.0901	-0.0021*	0.0845	-0.0024*	0.0519	-0.0024*	0.0565
FamilySize	0.0019***	0	0.0019***	0	0.0017***	0	0.0018***	0
No_load	-0.0013	0.4121	-0.0009	0.5549	-0.0011	0.469	-0.0009	0.5568
TimeFE			Y				Y	
Style × TimeFE	Y				Y			
Observation	32363		32363		32363		32363	
R-squared	0.1754		0.1756		0.1748		0.1761	

attributed to the fund managerial skills by the less sophisticated investors.

The evidence based on this return decomposition suggests that prospectuses with different textual complexity target investors with different abilities. This is consistent with our hypothesis that the investors of the low-complexity funds are more sophisticated, since they pay more attention to the risk factors when evaluating past performance of funds. Overall, the results show that only the investors in the smallest third of funds classified by textual complexity are significantly more sophisticated than the others who invest in the other two thirds of funds. This finding suggests that funds use textual complexity to target investors that are less sophisticated.

2.4.3 Convexity of the Flow-Performance Relation

In this section, we evaluate the investor sophistication by analysing the convexity of the fund flow-performance relation. Investors in mutual funds are more responsive to superior performance than to poor performance, resulting in a more convex flow-performance relation. Sawicki (2001) and Huang et al. (2007) find that the flow-performance relationship is more convex when investors are more sophisticated and the participation costs of funds are lower.[11] If the argument that the textual complexity has an effect on investor sophistication holds, we conjecture that the convexity of flow-performance relation should vary between funds of different complexity.

To investigate the convexity of the flow-performance relation in mutual funds with different levels of complexity, we use linear regression to estimate flow-performance sensitivities at different levels of fund performance. Furthermore we test whether these flow performance sensitivities vary depending on textual complexity. We use a dummy variable *LowC* to indicate whether these funds are in the low textual complexity group, i.e. the lowest third of the textual complexity rankings for the quarter. Each quarter we rank all funds according to their previous 12-month returns in the same style category, or Carhart four-factor alphas. Then we assign the rankings, denoted by *Rank*, ranging from zero (worst) to one (best) corresponding to their performance percentiles. Afterwards we assign the performance ranking variables (Low, Mid and High) to indicate the fund performance at different ranges, namely the lowest quintile, the three middle quintiles, and the highest quintile of performance. The calculation procedure is shown below:

$$\begin{aligned} Low_{i,t-1} &= Min(Rank_{i,t-1}, 0.2) \\ Mid_{i,t-1} &= Min(Rank_{i,t-1} - Low_{i,t-1}, 0.6) \\ High_{i,t-1} &= Rank_{i,t-1} - Low_{i,t-1} - Mid_{i,t-1}. \end{aligned} \tag{2.10}$$

To investigate the impact of fund textual complexity on flow-performance sensitivity at different levels of performance, we take the interaction term between the performance ranking variable and the dummy variable *LowC* for low textual complexity as the explanatory variable in the

[11] Carhart (1997) and Berk and Tonks (2007) demonstrate that the performance of the worst performing mutual funds is more persistent than that of the best performing mutual funds. Sophisticated investors should therefore avoid funds that consistently underperform and avoid overreacting to the superior performance of funds.

Table 2.4: The Effect of Textual Complexity on the Flow-Performance Relationship

This table examines the effect of textual complexity on the sensitivity of fund flows to the past performance. The linear regression is performed by regressing the quarterly flows on funds' fractional performance rankings over the low, medium, and high performance ranges, a dummy variable of the low complexity, and their interaction terms. In column(1), the performance is measured by the raw return in the past four quarters, and in column(2), the performance is measured by the Carhart four-factor alpha. Each quarter, fractional performance ranks ranging from zero to one are assigned to funds according to their performance in the past 12 months relative to other funds. The fractional rank for funds in the bottom performance quintile (Low) is defined as $Min(Rank_{t-1}, 0.2)$. Funds in the three medium performance quintiles (Mid) are grouped together and receive ranks that are defined as $Min(0.6, Rank_{t-1} - Low)$. The rank for the top performance quintile (High) is defined as $Rank_{t-1} - Mid - Low$. The dummy variable $LowC$ equals to one if the funds are ranked in the lowest third according to their textual complexity, and equals to zero if else. Controls include the lagged cashflows at quarter t-1, the standard deviation of fund returns in the prior 12 months, the logarithm of lagged mutual fund size, the lagged fund age, the lagged expense ratio, the turnover ratio in the prior 12 months, the logarithm of lagged fund family size and the number of equity funds owned by fund family. We also include style-by-time fixed effects and the fund fixed effects. Standard errors are double clustered by fund family and time. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Dep Var. Cashflows			
	(1) Raw Return		(2) Carhart Alpha	
Indep Var. Performance	Coeff.	P-value	Coeff.	P-value
Low	0.1015***	0	0.0966***	0
Low*LowC	-0.0573**	0.0258	-0.0148	0.5748
Mid	0.0317***	0	0.039***	0
Mid*LowC	0.0145**	0.0152	0.0054	0.3631
High	0.2067***	0	0.2163***	0
High*LowC	-0.0912***	0.0046	-0.09***	0.0053
LowC	-0.0101**	0.018	0.0044	0.3041
LagFlow	0.3343***	0	0.3339***	0
StdRet	-0.2784	0.0055	-0.1417	0.1552
FundSize	-0.0044***	0	-0.0046***	0
FundAge	0.0003***	0	0.0003***	0
ExpRatio	-0.7436***	0	-0.8273***	0
TurnRatio	-0.0031*	0.0133	-0.0018*	0.1512
FamilySize	0.0016	0	0.002	0
$Style \times TimeFE$	Y	Y	Y	Y
Observations	32363		32363	
R-squared	0.1759		0.1753	

regression.

$$\begin{aligned} Flows_{it} =& a + b_1 \times Low_{i,t-1} + \beta_1 \times Low_{i,t-1} \times LowC_{i,t-1} \\ & + b_2 \times Mid_{i,t-1} + \beta_2 \times Mid_{i,t-1} \times LowC_{i,t-1} \\ & + b_3 \times High_{i,t-1} + \beta_3 \times High_{i,t-1} \times LowC_{i,t-1} \\ & + dControls_{it-1} + \epsilon_{it}. \end{aligned} \tag{2.11}$$

In the regression, we expect a negative coefficient β_3 in the regression, which implies the investors of low-complexity funds are less responsive to the performance in the higher range as they are not the avid chaser of the past winners.

The results of the regression analysis are presented in Table 2.4. The performance variables (Low, Mid, High) are measured based on the returns net of fees in column(1), and based on the Carhart four-factor alphas in column(2). In both column(1) and column(2), the coefficients for the interaction term between the high-performance variable and the low complexity dummy variable are significantly negative, which is consistent to the model prediction(β_3 is negative). As column(1) shows, the sensitivity of low-complexity fund flows to the high-range performance is smaller than that of the higher complexity fund flows (0.1155 vs. 0.2067). In column(2), as the textual complexity increases from low to high, the sensitivity of fund flows to the high-range performance increases by 71.25% (from 0.1263 to 0.2163). The result suggests that the greater readability (less complexity) leads to a significant reduction in the convexity of the flow-performance relation, and shows that the investors in low-complexity funds are more sophisticated than those with higher textual complexity.

2.4.4 Mutual Fund Fees and Fund Flows

In this section, we study investor sophistication by examining the sensitivity of fund flows to different types of fees. Mutual funds can attract investors' attention through marketing, or advertising. Both front-end-load fees and operating expenses are used to pay for marketing (e.g., distribution payments to brokers or advertising). We conjecture that less sophisticated investors have limited ability to choose funds and are more likely to be attracted by the marketing or advertising of mutual funds. However, more sophisticated investors have the ability to select funds and are therefore less likely to be influenced by funds that are heavily marketed but have poor investment ability. In addition, sophisticated investors are aware that marketing costs are passed on to them and are therefore more averse to increased distribution costs. We examine the sensitivity of fund flows to different types of fund fees and examine whether there exists a difference between the high- and low-complexity funds in terms of their sophistication.

The dummy variable *LowC* is adopted to represent the funds with low textual complexity. We divide the mutual fund expenses into the distribution cost and the other operating cost. Following Huang et al. (2007) and Sirri and Tufano (1998), we add one-seventh of the front-end load to the marketing cost(12b1) as the total distribution costs expressed on an annualised basis.[12]

[12]To calculate the total distribution fee, we express loads and the annual marketing expenses on a common annualised basis. To annualise loads, we estimate the period over which the consumer will hold the investment and amortise the load over this period.

Table 2.5: The Effect of Textual Complexity on the Flow-Cost Relationship

This table examines the effect of textual complexity on the sensitivity of fund flows to a variety of mutual fund expenses. The dummy variable *LowC* indicates the funds that are ranked in the lowest tercile according to their textual complexity each quarter. The distribution cost is the sum of one-seventh of the front-end load and the marketing cost(12b1) expressed on an annualised basis. Other costs are the difference between the total expense ratio and marketing costs (12b1). The linear regression is performed by regressing the quarterly flows on funds' expense, a dummy variable of the low complexity, and their interaction terms. The control variables include lagged cash flow at quarter t-1, the standard deviation of fund monthly returns estimated in the past 12 months, the performance of funds at the quarter t-1 measured by the percentile of Carhart four factor alpha, the log of fund size at the quarter t-1, fund age at the quarter t-1, turnover ratio in the past 12 months, expense ratio at the quarter t-1, the log of mutual fund family size at the quarter t-1 and the number of equity funds owned by fund family at the quarter t-1. We also include style-by-time fixed effects and the fund fixed effects. Standard errors are double clustered by fund family and time. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1) All funds		(2) Old Funds(Age>5yrs)		(3) Big Funds(>50% funds)	
	coeff.	P-value	coeff.	P-value	coeff.	P-value
Const	0.005	0.4143	0.0021	0.7282	0.0107	0.2559
LowC	0.0004	0.9095	-0.002	0.6028	-0.0003	0.9668
DistributionCost	0.4677**	0.0186	0.4803**	0.0155	0.4969*	0.0944
LowC*Distribution	-1.0066***	0.0004	-0.9478***	0.0009	-0.3115	0.4822
OtherCost	-1.2665	0.0003	-1.2656	0.0004	-1.0213	0.0321
LowC*OtherCost	0.4499	0.2412	0.6698*	0.082	0.1283	0.8434
LagPerformance	0.0567***	0	0.0562***	0	0.0619***	0
LagFlows	0.3384***	0	0.3428***	0	0.3821***	0
StdRet	-0.2464**	0.0146	-0.2563**	0.0124	-0.5097***	0.001
FundSize	-0.0044***	0	-0.004***	0	-0.0043***	0
FundAge	-0.0003***	0	-0.0002***	0	-0.0004***	0
TurnRatio	-0.0031**	0.0117	-0.0033***	0.0068	-0.0052***	0.0024
FamilySize	0.0012***	0.0004	0.0012***	0.0007	0.0016***	0.0012
$Style \times TimeFE$	Y		Y		Y	
Observations	32363		32363		32363	
R-squared	0.1754		0.1756		0.1748	

Operating costs are the difference between the total expense ratio and marketing costs (12b1). We regress quarterly flows on different types of fund fees along with other control variables, and compare the slope of the flow-cost function between funds with different textual complexity by examining the coefficients of the interaction term between fund fees and complexity dummies.

The results of the multivariate analysis in Table 2.5. In column (1), we study all the funds in our sample. The coefficient on the interaction term between the low-complexity dummy and the distribution cost is significantly negative, indicating that the investors in low-complexity funds are more averse to the distribution cost compared with the investors in high-complexity funds. The point estimates suggest that a 100 basis point increase in the distribution cost reduces the quarterly growth in fund flows by 0.5389% for low-complexity funds, however, it will increase the quarterly growth in the flows of funds with higher textual complexity by 0.4677%. The results show that the investors in low-complexity funds are significantly averse to the increase of the distribution cost, and in contrast, the investors in funds with relatively high textual complexity are more likely to be attracted by the marketing efforts of funds. The results are consistent with our previous conclusion that the investors in low-textual complexity funds are more sophisticated. They know that the distribution costs do not contribute to the investment ability of funds and are also aware that this kind of cost will be passed on to themselves, and thus they are averse to the increase of distribution costs.

2.5 How Do Mutual Funds Choose Prospectus Complexity?

In this section, we examine how mutual funds choose the complexity of their prospectuses. As mutual funds make profits through charging management fees, they are motivated to attract more cashflows and increase the size of their funds to enhance the total fees they can charge. In light of the fact that more complex prospectuses attract less sophisticated investors, we conjecture that funds' investment ability would influence their choice of textual complexity: the funds that lack faith in their own ability to earn alpha will choose more complex prospectuses to target less sophisticated investors, and in contrast, funds with high quality would prefer a low complexity prospectus in order to distinguish themselves from other funds.

2.5.1 Mutual Fund-specific Textual Complexity and Overall Textual Complexity

As discussed in the previous section, we use the Fog Index to measure the textual complexity of a mutual fund, which is calculated from the complete "Principal Strategies" section of the prospectus. To distinguish it from the measure we propose next, we name the Fog Index used in section 2.4 as the overall Fog Index, denoted by $fog_{overall}$. Kostovetsky and Warner (2020) find the mutual funds in the same fund family have higher textual overlap in their prospectuses than the mutual funds belonging to different fund families, implying that mutual fund prospectuses are likely written in collaboration between the fund family and the fund managers, and also contain the information from both of them. We conjecture that, compared to the textual content shared by different funds within the same mutual fund family, the specific text written for the fund itself reveals more specific information about the fund and is more reflective of the motivations of mutual fund managers in deciding on the complexity of its prospectus.

In order to separate the fund-specific text from the full strategy descriptions, we process the prospectuses in the following way: (1) we break down the text of "Principal Strategies" section into individual sentences, (2) for each sentence, we check if there is an identical sentence in the prospectuses of other mutual funds belonging to the same family in the same quarter, (3) if no identical sentence is found, we mark the original sentence as the fund-specific one; otherwise, we mark it as a "common" sentence shared with other funds in the same family, (4) in the final step, we combine the fund-specific sentences of each mutual fund in each quarter into a new text, and then calculate the Fog Index based on the new text. We use fog_{spc} to denote the Fog Index calculated only on the basis of the fund-specific text to measure the fund-specific complexity.[13] There are two reasons why we split fund-specific text from the full text at the sentence level: first, the Fog Index examines the textual complexity at the sentence-level.[14] Keeping the structure of sentences intact, the original information contained in the complex text based on the fund-specific text will not be lost. Second, we find there are numerous identical sentences across the mutual funds in the same family, such as the sentences describing the types of assets they invest in and the governance structure of the fund, suggesting that mutual fund families are likely to involve in writing the prospectuses at the sentence level.

Among our sample of 46726 prospectuses, 89.05% of them contain family-shared content and the remaining 10.95% of them only contain the content written specifically for the funds. We consider two types of fund textual complexity measures, i.e., $fog_{overall}$ and fog_{spc}. The former

[13]We provide an example in Appendix B.1.3, where the sentences in bold are common to multiple funds within the same fund family.

[14]The Fog Index is based on the average number of words per sentence and the percentage of difficult words.

Table 2.6: Descriptive Statistics of Textual Complexity

This table presents the descriptive statistics of two types of mutual fund textual complexity, $fog_{overall}$ and fog_{spc} for all the mutual funds in our sample from 2010 to 2020. The two types of textual complexity are measured by the Fog Index calculated based on the complete content and the contents written specifically for the funds in prospectuses, respectively. The descriptive statistics include the mean, standard deviation, kurtosis, skewness, minimum, 25th percentile, 50th percentile, 75th percentile, and maximum variables.

	mean	*std*	*kurtosis*	*skewness*	*min*	25%	50%	75%	*max*
$fog_{overall}$	23.601	2.405	-0.202	0.446	19.164	21.920	23.309	25.121	29.867
fog_{spc}	25.390	4.145	3.797	1.642	19.438	22.678	24.634	27.060	57.554

reflects the overall textual complexity and is influenced by both the fund family and the fund manager, while the latter only reflects the fund-specific textual complexity and is less influenced by the factors external to the specific fund. The correlation between fund-overall textual complexity and fund-specific textual complexity is 0.4901. Each month, we equally divide the mutual funds into the low, mid, and high groups based on the $fog_{overall}$ and fog_{spc} of their most recent prospectuses. We find that 57.34% of the funds stay in the same group classified by fog_{spc} as the group classified by $fog_{overall}$.

Table 2.6 reports the summary statistics of $fog_{overall}$ and fog_{spc} in our samples. The standard deviation of fog_{spc} is 4.145 and that of $fog_{overall}$ is 2.405. The difference in the standard deviation can be explained by the different investment strategies and the diverse writing styles of the mutual fund managers. Moreover, the fund-specific textual complexity is on average higher than the fund-overall textual complexity, suggesting that mutual fund managers tend to use more complex language to describe their strategies than the common descriptions shared in the fund family. In addition, we find that the distribution of the fund-overall complexity is more symmetric, and is much closer to the normal distribution compared to the distribution of fund-specific complexity. In contrast, the distribution of fund-specific Fog Index is positively skewed and has more outliers. This result suggests that the content written specifically for the fund itself tends to be neutralised by the content common to the fund family and thus the overall prospectuses tend to be less complex. We conjecture that the fund-specific textual complexity is more reflective of the fund manager's motivation in deciding how complex language to use in its strategy description, thereby revealing more information about the fund's actual investment capacity.

2.5.2 The Relationship between Fund Quality and Textual Complexity

In this section, we define fund quality as the ability of a fund to generate high returns with low risks. We hypothesise that the low-quality mutual funds are more likely to provide more complex prospectuses to attract the less sophisticated investors who are more easily exploited, as these investors have a greater tendency to attribute factor-related returns to alpha, reward past winner performance and are less sensitive to fund fees.

We develop a matrix of proxies to measure the quality of funds from different perspectives. First, we use the Carhart four-factor alpha estimated over the 36-month rolling window to measure the fund's ability to deliver abnormal returns. Second, we use the Sharpe ratio to measure the fund risk-adjusted performance, which is calculated by subtracting the risk-free rate of return from the fund return and dividing the result by the standard deviation of the fund returns. In addition, as a part of the fund quality matrix, we consider three different types of fund risks: the first type of risk is the total risk measured by the standard deviation of fund monthly returns. For mutual funds, the standard deviation indicates how far a fund's return deviates from the expected return based on its historical performance and whether the fund's return is volatile. The second type of fund risk we examine is the fund's systematic risk, measured by the loading on the market risk factor, also known as beta, which illustrates how the value of the portfolio deviates from the market. The third type of risk is the fund's downside risk, also known as downside beta, which is constructed using monthly return data conditional on negative market factors.[15] All the risk measures are estimated in the 36-month rolling window. Apart from the two performance measures (Carhart four-factor alpha, Sharpe ratio) and three risk measures (standard deviation of return, beta, downside beta), we also employ the turnover ratio as another measure to evaluate fund quality.[16] In general, a lower turnover ratio indicates higher quality, because the funds with a higher turnover ratio are more

[15]Markowitz (1952) and Roy (1952) proposed a theory based on asymmetric market risk. The relevant risk measure could be the downside beta, a market beta computed only from days on which the stock market declines; Ang et al. (2006) and Ma and Tang (2019) use the downside beta to measure the downside risk.

[16]Mutual fund turnover is calculated as the minimum (of aggregated sales or aggregated purchases of securities), divided by the average 12-month total net assets of the fund.

likely to engage in frequent trading activities and have higher trading costs.[17]

Fund Past Characteristics

In this section, we examine the characteristics of funds at different levels of textual complexity. We classify the mutual funds into three groups (Low, Mid and High) in each month based on $fog_{overall}$ and fog_{spc}, respectively. In order to make the fund characteristics in different levels of textual complexity comparable during the sample period,[18] we calculate the percentile rankings of the Carhart four-factor alphas, the CAPM alphas, the factor-related returns, and the standard deviation of returns for each fund at the end of each month. Next, we calculate the average characteristics of the funds in each textual complexity groups over the whole sample period.

Table 2.7 presents the summary of statistics. The past characteristics of mutual funds in different textual complexity are averaged on an equal-weighted basis in Table Panel A, and on a value-weighted basis in Table Panel B. Table Panel A shows that funds with high specific complexity have significantly higher standard deviation, beta, downside beta and turnover ratio on average than the funds with low specific complexity. In addition, the funds with high specific complexity have lower Carhart four-factor return rankings on average than the funds with low specific complexity, implying that the funds with poorer past performance are more likely to have more complex specific content. The fund-specific textual complexity reflects fund quality with great consistency. Low risk and high performance, the two corresponding characteristics that indicate good fund quality, are always associated with low fund-specific textual complexity.

However, as shown in Table Panel A, where the funds are classified according to their overall Fog Index, the standard deviation of past returns and downside beta are not significantly larger for funds in the high complexity group than the funds in the low complexity group. Only the

[17]Gallagher et al. (2014) show that the lower quality(underperforming) funds have higher portfolio turnover on average.

[18]The mutual funds in our sample exist for different periods from 2010 to 2020. As fund returns and volatility vary widely across rising and falling markets, we rank fund returns and volatility from zero (lowest) to one (highest) for each month to make fund characteristics comparable across different complexity groups over the sample period.

Table 2.7: Past Fund Characteristics in Different Complexity Groups

In the Table 2.7 compares the average fund characteristics across the funds in different textual complexity groups. The mutual funds are ranked in the low, medium, and high terciles according to the fund-overall Fog Index and fund-specific Fog Index based on their most recent prospectus. The past fund characteristics include the standard deviation of fund monthly returns, the loading on the market risk factor(beta), the loading on the negative market risk factor(downside beta), the turnover ratio, the Carhart four-factor alpha, the CAPM four-factor alpha, the three factor-related return(related to SMB, HML, UMD), the four factor-related return(related to MRT, SMB, HML, UMD). The characteristics are estimated over the past 36-month rolling windows. Each month, the ranks ranging from zero to one are assigned to funds according to their return and standard deviation of returns in the past 36 months. Then we take the average over the time-series for all the characteristics of funds in each textual complexity group. Table Panel A reports the equal-weighted averages of fund characteristics, and Table Panel B reports the value-weighted averages of fund characteristics. We also report the difference in the fund characteristics between the high-complexity group and the low-complexity group and the corresponding P-value. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Panel A: Panel A: Equal-weighted

	Overall Fog					Specific Fog				
	L	M	H	H-L	P-value	L	M	H	H-L	P-value
Std_Ret	0.457	0.443	0.460	0.003	0.686	0.442	0.450	0.467	0.025***	0.000
DownBeta	0.993	0.969	0.988	-0.005***	0.000	0.970	0.978	1.002	0.032***	0.010
Beta	0.989	0.994	0.996	0.007***	0.000	0.985	0.994	1.001	0.016***	0.000
TurnRatio	0.629	0.674	0.646	0.018***	0.000	0.643	0.638	0.668	0.024***	0.000
Carhart_Alpha	0.504	0.505	0.493	-0.011***	0.000	0.503	0.499	0.499	-0.004*	0.061
CAPM_Alpha	0.498	0.509	0.495	-0.003	0.136	0.498	0.504	0.499	0.002	0.322
Δ^{risk}	0.490	0.511	0.501	0.010***	0.000	0.494	0.508	0.499	0.005***	0.010
$\Delta^{risk_{all}}$	0.455	0.451	0.454	-0.002**	0.043	0.437	0.454	0.469	0.031***	0.000

Panel B: Panel B: Value-weighted

	Overall Fog					Specific Fog				
	L	M	H	H-L	P-value	L	M	H	H-L	P-value
StdRet	0.357	0.384	0.487	0.130***	0.000	0.330	0.443	0.449	0.120***	0.000
DownBeta	0.985	0.958	1.020	0.034***	0.000	0.960	1.004	1.001	0.041***	0.000
Beta	0.974	0.994	1.019	0.044***	0.000	0.971	0.991	1.017	0.046***	0.000
TurnRatio	0.375	0.496	0.484	0.110***	0.000	0.367	0.446	0.532	0.165***	0.000
CarhartAlpha	0.617	0.616	0.635	0.019***	0.000	0.627	0.612	0.622	-0.005***	0.000
CAPM_Alpha	0.628	0.651	0.652	0.024***	0.000	0.643	0.625	0.652	0.009***	0.000
Δ^{risk}	0.565	0.605	0.586	0.021***	0.000	0.569	0.568	0.606	0.037***	0.000
$\Delta^{risk_{all}}$	0.589	0.608	0.647	0.059***	0.000	0.591	0.599	0.639	0.048***	0.000

systematic risk, as measured by market beta, is higher on average for the funds with high overall textual complexity than for funds with low overall textual complexity. In addition, the fund past performance measured by Carhart four-factor alpha is not significantly lower in the high group than that in the low group. The results suggest that the overall fund textual complexity is not as effective and consistent as the fund-specific textual complexity in reflecting fund quality. The statistics summary in Table Panel B further confirm the conclusion. When the fund past characteristics are value-weighted averaged, the funds with high specific Fog Index have higher risk, higher turnover ratio and lower risk-adjusted returns on average. However, the fund past characteristics do not consistently suggest that lower quality funds tend to have high overall textual complexity.

Overall, the summary statistics of fund past characteristics are consistent with our hypothesis that the textual complexity of fund-specific texts reveals more information about fund quality than the overall textual complexity of fund prospectuses. As fund-specific texts are written specifically for the funds themselves, thus they can directly reflect the motivations of mutual fund managers to complicate prospectuses in order to obfuscate the low investment capacity and exploit the unsophisticated investors, thus enhancing cashflows.

In addition, Table 2.7 shows that funds with higher textual complexity have higher past factor-related returns than funds with lower specific textual complexity. This result suggests that funds with high past factor-related returns are more likely to obfuscate the factor-related returns compensated by the systematic risks with the abnormal returns by adopting high textual complexity in their strategies, as high-complexity prospectuses attract less sophisticated investors who are more likely to attribute factor-related returns to alpha. This result complements our previous findings on the relationship between fund quality and textual complexity by showing that mutual funds with high specific textual complexity are more likely to have more serious agency problems, that is, mutual fund managers with limited ability to generate higher abnormal returns make their prospectuses more complex in order to attract investor who are more responsive to factor-related returns to increase fund flows.

The Determinants of Textual Complexity based on Regression Analysis

In this section, we do the regression analysis to test if there exists a negative relationship between fund quality and their textual complexity controlling for other fund attributes. At the end of each month, we standardise the fund-overall and the fund-specific Fog Index to zero mean and unit standard deviation. The standardised overall Fog Index, fog_nor, equals to $\frac{fog_{overall}-mean(fog_{overall})}{sd(fog_{overall})}$; and the standardised specific Fog Index, fog_spc_nor, equals to $\frac{fog_{spc}-mean(fog_{spc})}{sd(fog_{spc})}$. We separately regress the standardized overall Fog Index and the standardized specific Fog Index on the proxy of fund quality, as the independent variable of our interest, is proxied by six different measures (i.e., Carhart four-factor alpha, beta, downward beta, standard deviation of returns, turnover ratio, and Sharpe ratio). Other fund attributes including

Table 2.8: Fund Quality and Fund Textual Complexity

Table 2.8 shows estimated coefficients from regressions of textual complexity measures on the proxy of fund quality. The dependent variable in Table Panel A is the normalized fund overall Fog Index based on the complete text of the prospectus, denoted by $fog\_nor = \frac{fog-mean(fog)}{sd(fog)}$, and the dependent variable in Table Panel B is the normalized fund-specific Fog Index based on the fund-specific content in their prospectuses, denoted by $fog\_spc\_nor = \frac{fog_{spc}-mean(fog_{spc})}{sd(fog_{spc})}$. Columns 1 through 6 show the regressions with six different proxies of fund quality, i.e., Carhart four-factor alpha, beta, downside beta, the standard deviation of returns, turnover ratio, and Sharpe ratio of funds in the past 36 months. The control variables include the logarithm of lagged mutual fund size, the lagged fund age, the lagged expense ratio, the logarithm of lagged fund family size. We also include style-by-time fixed effects. Standard errors are double clustered by fund family and time. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Panel A: Fund-Overall Textual Complexity

	Dep var. fog_nor					
	(1)	(2)	(3)	(4)	(5)	(6)
Indep var.	Alpha_Carhart	Beta	DownBeta	Std_Ret	Turn_Ratio	Shape_Ratio
Const	0.247***	0.321***	0.377***	0.327***	0.247***	0.345***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
QualityProxy	0.005	-0.074**	-0.032*	0.035*	0.004	0.000
	[0.656]	[0.014]	[0.072]	[0.037]	[0.509]	[0.731]
FundSize	-0.033***	-0.033***	-0.039***	-0.039***	-0.033***	-0.038***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
FundAge	0.001***	0.001***	0.001**	0.001**	0.001***	0.001**
	[0.000]	[0.000]	[0.016]	[0.017]	[0.000]	[0.019]
ExpRatio	-7.601***	-7.584***	-10.974***	-11.251***	-7.823***	-11.071***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
FamilySize	0.000***	0.000***	0.000	0.000	0.000***	0.000
	[0.001]	[0.000]	[0.360]	[0.470]	[0.001]	[0.371]
$Style \times TimeFE$	Y	Y	Y	Y	Y	Y

Panel B: Panel B: Fund-Specific Textual Complexity

	Dep var. Fog_spc_nor					
	(1)	(2)	(3)	(4)	(5)	(6)
Indep var.	Alpha_Carhart	Beta	DownBeta	Std_Ret	Turn_Ratio	Shape_Ratio
Const	0.050	-0.175***	-0.021	0.048**	-0.036	0.118***
	[0.1494]	[0.000]	[0.473]	[0.020]	[0.105]	[0.000]
QualityProxy	-0.108***	0.207***	0.068***	0.067***	0.047***	-0.005***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
FundSize	0.011***	0.006***	0.006**	0.004	0.011***	0.005**
	[0.006]	[0.005]	[0.023]	[0.126]	[0.000]	[0.035]
FundAge	-0.001**	-0.001	-0.002***	-0.001***	-0.001***	-0.001***
	[0.035]	[0.193]	[0.000]	[0.001]	[0.007]	[0.000]
ExpRatio	-9.421***	-11.322***	-9.165***	-12.238***	-9.091***	-12.226***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
FamilySize	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$Style \times TimeFE$	Y	Y	Y	Y	Y	Y

fund size, age, expense ratio, and fund family size are controlled in regressions, and style-by-time fixed effects are included as well. Table 2.8 presents the results of regressions. P-values for the regression coefficients are provided in brackets with standard errors clustered by fund family and time.

In Table Panel A, the dependent variable is the fund standardized overall Fog Index. We find that the lower fund quality does not always imply the high overall textual complexity. In column(2) and column(3), the coefficients on market beta and downside beta are significantly negative, showing that high systematic risk of funds predict lower overall textual complexity when we control a series of fixed effects. However, in column(4), when fund risk is measured by the standard deviation of returns, the relationship between risk and the fund overall textual complexity is reversed. We can see that a higher standard deviation of fund returns is positively correlated to the overall textual complexity. According to the results of Table Panel A, there is no definitive relationship between the fund quality and the overall textual complexity.

It is clearer, however, that fund quality and fund-specific textual complexity are negatively correlated. In Table Panel B, the dependent variable is the fund-specific standarised Fog Index. Columns (2), (3), and (4) show the coefficients on market beta, downside beta, and standard deviation are significantly negative, suggesting funds with higher risks are more likely to have the higher complex contents that are written specifically for the funds themselves. In column (5), the coefficient of turnover rate is significantly positive, which is also consistent with our previous findings that low-quality funds have the higher specific textual complexity. Carhart four-factor alpha and Sharpe ratio are the explanatory variables in columns (1) and (6), and the coefficients on these two explanatory variables are both significantly negative, indicating that fund managers with lower ability to earn abnormal returns are likely to use more complicated language to describe their investment strategies.

The results of regression analysis show that the high textual complexity of fund-specific content likely results from the strategic obfuscation by the low-quality funds, which is consistent with our conjecture that low-quality mutual fund managers tend to manipulate the prospectus to hide the unfavourable information about managerial skills and thus attract less sophisticated investors. In contrast, the negative correlation between fund quality and overall textual complexity is not significant, suggesting that content contributed by fund families is less likely to be manipulated and thus is less reflective of mutual fund quality. To conclude, the results suggest that the mutual fund prospectuses are possibly manipulated at the fund level rather than at the fund family level.

2.6 Prospectus Complexity and Fund Performance

In this section, we examine how textual complexity of mutual fund prospectuses implies fund future performance, and also the implications of textual complexity on the performance-fee relationship. We provide further evidence to support the negative relationship between fund investment skill and prospectus complexity. Our results show that highly complex prospectuses signal that funds are more likely to be involved in agency problems and are less trustworthy.

First, we demonstrate that funds with sufficiently low specific textual complexity tend to generate higher abnormal future returns than funds with relatively high specific textual complexity, which can be explained by the fact that funds with different investment capabilities choose different levels of textual complexity of prospectuses, resulting in divergence in performance. In addition, we examine the association between textual complexity and fund performance-fee relationships, and find that funds with high complexity tend to set prices strategically, leading to the inconsistency between fees and performance.

Our findings build on previous findings that textual complexity affects how effectively investors utilize the information available to make investment decisions, and thus low-quality funds seek to target less sophisticated investors by complex prospectuses, and these funds are more likely to continue to underperform in the future. Moreover, investors in high-complexity funds are less averse to fund fees and lack the ability to effectively evaluate fund performance, and thus funds with poor investment ability have more incentive to complicate their prospectuses and charge high fees that are inconsistent with their managerial skills. Based on the above analysis, we test the following two hypotheses: (1) low-complexity funds perform better than high-complexity funds; and (2) the fees of low-complexity funds are more in line with their performance than those of high-complexity funds. In addition, fund-specific textual complexity is expected to be a better predictor of future fund performance than overall fund textual complexity, since fund-specific textual complexity better reflects a mutual fund manager's motivation to manipulate the prospectus, as shown in section 2.5.

2.6.1 Holding-based Performance Measures

We adopt holding-based performance measures to evaluate the mutual fund performance, as this measure can accurately managerial skills. Return-based performance measures are premised on an accurate measurement of a fund's risk, however, risk is difficult to measure accurately, particularly when the fund is engaged in market timing where risk exposures vary over time (Ferson and Schadt (1996); Patton and Ramadorai (2013)). In the presence of positive characteristics-timing ability, return-based alpha underestimates fund performance as factor-related returns also reflect a portion of the fund's management skills.[19] In other words, if funds with high complexity have positive characteristics-timing ability, their investors' response to factor-related returns is reasonable. Conversely, if they do not exhibit positive characteristics-timing ability, investors respond to factor-correlated returns due to a confusion between alpha and factor-correlated returns. In this study, by applying the holdings-based measures, we investigate whether there exists characteristic-timing ability (Daniel et al. (1997); Grinblatt and Titman (1989)), and we also compare the performance between mutual funds at different levels of complexity. The holding-based performance measures are based on Grinblatt and Titman (1993) and Daniel et al. (1997).

Grinblatt and Titman (1993) use the portfolio weights of the previous year as the benchmark to measure the abnormal returns from the active adjustment of the portfolio. The abnormal return of a fund in month t, denoted by GT, is

$$GT_t = \sum_{j=1}^{N} (\tilde{w}_{j,t-1} - \tilde{w}_{j,t-13}) \tilde{R}_{j,t}, \tag{2.12}$$

where N is the number of stocks in the portfolio, $\tilde{w}_{j,t-1}$ is the portfolio weight on stock j at the end of month $t-1$, $\tilde{w}_{j,t-13}$ is the portfolio weight on stock j at the end of month $t-13$, $\tilde{R}_{j,t}$ is the return of stock j in month t.[20]

[19] In this case, the factor betas are skewed upward, and thus factor-related returns are overestimated.

[20] We choose 12 months as the interval between the two weighted dates. Due to that the portfolios are less likely to take large risk adjustments during the short period, GT serves as a reliable indicator of abnormal returns.

Characteristics selectivity (CS) (Daniel et al. (1997)) compares the returns of the stocks held by a fund to the returns of portfolios of stocks with equivalent characteristics (size, book/market ratio and past momentum). The month t component of the CS measure is defined as

$$CS_t = \sum_{j=1}^{N} \tilde{w}_{j,t-1}(\tilde{R}_{j,t} - \tilde{R}_t^{b_{j,t-1}}), \tag{2.13}$$

where $\tilde{R}_t^{b_{j,t-1}}$ is the month t return of characteristic-based passive portfolio matched to stock j during the month $t-1$.

The characteristics timing (CT) (Daniel et al. (1997)) captures the performance driven by the ability of the mutual fund managers to time the styles. The month t component of this measure is

$$CT_t = \sum_{j=1}^{N} (\tilde{w}_{j,t-1}\tilde{R}_t^{b_{j,t-1}} - \tilde{w}_{j,t-13}\tilde{R}_t^{b_{j,t-13}}). \tag{2.14}$$

We use DGTW to denote the total abnormal returns generated from characteristics-selectivity and characteristics-timing, as measured by the sum of CT and CS. Based on the holding-based performance measures, we study how the textual complexity predicts future abnormal returns of funds.

2.6.2 Textual Complexity and Fund Performance

To compare the performance of funds with different textual complexity, we sort mutual funds into portfolios at the end of each month based on the most recent textual complexity (both specific and overall complexity) of each fund. We divide mutual funds into five groups based on the fund-specific Fog Index in order to differentiate more clearly the performance of funds in different complexity groups and avoid large variations in the Fog index of funds in the same group. Then we compute the equal-weighted and value-weighted average abnormal returns of all the funds measured by GT, CS, and CT, respectively. Then we compute time-series averages of GT, CS, and CT of each quintile.

Table 2.9: Fund Textual Complexity and Performance

This table reports future fund performance for quintile portfolios obtained from single sorting of funds on the fund-specific textual complexity in Table Panel A. The measures of fund performance include the GT abnormal returns, characteristic-selectivity (CS) alphas, characteristic-timing (CT) alphas. At the end of each month, we sort funds by the textual complexity into quintiles to obtain five portfolios. After obtaining 5 portfolios, we calculate both the equal-weighted and value-weighted abnormal returns over the next months, and then rebalance the portfolios. Finally, we obtain average monthly post-ranking portfolio alpha by taking average over the entire time-series. The 5-1 quintile spread is the spread on zero-investment long-short portfolio that is long on quintile five and short on quintile one, the 3-1 quintile spread is the spread on zero-investment long-short portfolio that is long on quintile three and short on quintile one, the 5-3 quintile spread is the spread on zero-investment long-short portfolio that is long on quintile five and short on quintile three. All returns are expressed in % per month. Newey-West corrected p-values are reported in parentheses. Table Panel B presents estimated coefficients of fund returns on the low fund-specific textual complexity dummy, as well as controls for other fund characteristics. The dependent variable is the average monthly fund returns from t+1 to t+3, i.e., the GT abnormal returns in column(1), the DGTW abnormal returns in column(2), Carhart four-factor alphas in column(3) and the factor-related returns in column(4). The fund-specific textual complexity is measured by the Fog Index based on the fund specific content from the most recent fund prospectus. We then sort funds into quintiles according to their fund-specific textual complexity. *LowC* takes the value one, if a fund is in the lowest complexity quintile, else it takes the value zero. The additional control variables are the performance measured by the average Carhart four-factor alpha over the past 12 months, the realized volatility measured by the standard deviation of fund monthly returns in the past 12 months, the lagged fund age, the logarithm of lagged fund size, the logarithm of lagged fund family size, the lagged expense ratio of the fund, the lagged turnover ratio, and the fund flows in the past one year. We include style-by-time fixed effects. Standard errors are double clustered by fund family and time. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Portfolio Sorting according to Fund-Specific Textual Complexity

	GT		CS		CT	
	(1)	(2)	(3)	(4)	(5)	(6)
Portfolios	EW	VW	EW	VW	EW	VW
1	0.0522*	0.0258	0.0600**	0.0912***	0.0108	-0.013
	[0.087]	[0.305]	[0.018]	[0.005]	[0.341]	[0.436]
2	0.0287	0.0167	0.0504*	0.0773**	-0.0082	0.0148
	[0.343]	[0.578]	[0.057]	[0.017]	[0.52]	[0.417]
3	0.0254	0.0203	0.0582**	0.0081**	0.0081	0.0148
	[0.423]	[0.503]	[0.028]	[0.525]	[0.525]	[0.417]
4	0.0228	0.0038	0.0484*	0.0812**	0.0031	0.0155
	[0.461]	[0.912]	[0.07]	[0.047]	[0.787]	[0.368]
5	0.0306	0.0193	0.0493*	0.0329	0.0014	0.0006
	[0.335]	[0.517]	[0.098]	[0.311]	[0.909]	[0.966]
All	-0.0216*	-0.0065	-0.0107	-0.0583***	-0.0094	0.0136
	[0.068]	[0.731]	[0.505]	[0.009]	[0.109]	[0.294]
(3)-(1)	-0.0268**	-0.0055	-0.0018	-0.0112	-0.0028	0.0278*
	[0.028]	[0.730]	[0.898]	[0.659]	[0.69]	[0.068]
(5)-(3)	0.0052	-0.001	-0.0089	-0.0471	-0.0066	-0.0142
	[0.669]	[0.963]	[0.563]	[0.101]	[0.251]	[0.348]

Panel B: Multi-Variate Performance Regression

	(1) GT		(2) DGTW		(3) Alpha_Carhart		(4) Δ^{risk}	
	coeff.	P-value	coeff.	P-value	coeff.	P-value	coeff.	P-value
Const	-0.088***	0.006	-0.197***	0.000	-0.058**	0.031	0.210***	0.000
LowC	0.023***	0.000	0.032***	0.000	0.010*	0.087	-0.020***	0.001
LagPerformance	0.217	0.834	1.633	0.250	5.962***	0.000	19.643***	0.000
Flow	0.013	0.917	0.156	0.308	0.543***	0.000	-0.458***	0.000
TurnRatio	0.014**	0.029	-0.026***	0.000	-0.057***	0.000	0.040***	0.000
FundSize	-0.005***	0.001	-0.002	0.316	0.001	0.761	0.011***	0.000
Volatility	3.001***	0.000	7.735***	0.000	-3.395***	0.000	-15.357***	0.000
FundAge	-0.005	0.313	-0.018***	0.005	0.004	0.408	0.032***	0.000
ExpRatio	1.871**	0.018	-1.509	0.129	-0.514	0.512	0.936	0.192
FamilySize	0.000	0.813	0.000	0.385	0.000**	0.022	0.000	0.727
Observations	68701		68701		107179		107179	
Style × Time FEs	Y		Y		Y		Y	

Table Panel A shows the performance of portfolios sorted by the fund-specific Fog Index (fog_{spc}). Measured by GT, the equal-weighted portfolio of the lowest textual complexity beat the highest portfolio by 2.16 basis points a month. The difference in performance between portfolio (1) and portfolio (5) is mainly attributable to the difference between the lowest quintile (1) and the middle quintile (3). However, the difference in performance between portfolio (3) and portfolio (5) is not significant, which suggests that there is no significantly difference between the performance of funds with relatively high specific complexity. Under the CS measure, the value-weighted portfolio with the lowest specific textual complexity outperforms the portfolio with the lowest specific textual complexity by 5.83 basis points a month. However, the CT abnormal returns of these five portfolios are not significantly different from zero, indicating that no significant abnormal returns are generated from fund characteristics-timing ability. The sorting results based on fund specific textual complexity show that only sufficiently low textual complexity indicates relatively high managerial skills and predicts better future fund performance. However, when fund-specific strategy textual complexity is high enough, the difference of performance is not significant. The results are consistent with our previous findings that low-quality mutual fund managers try to obfuscate unfavourable information through complex prospectuses, but the high-quality funds, which target the sophisticated investors, tend to differentiate themselves by low textual complexity as a way to signal their high-quality.

In order to exclude the impact of other factors on fund performance, we use the multivariate regression analysis to investigate the relation between fund-specific textual complexity and subsequent fund performance. This methodology allows us to control for additional fund characteristics. To verify the result in the Table Panel A that the funds with sufficiently low complexity outperform the other funds, we include the dummy variable, denoted by *LowComplexity*, as the explanatory variable in the regression to indicate whether a fund is in the lowest quintile based on the fund-specific Fog Index. The dependent variable in the regression is the fund performance, measured by the average of monthly GT, DGTW (sum of CS and CT), Carhart four-factor alpha from month t+1 to t+3. GT and DGTW are holding-based performance measures before subtracting fees, accommodating both the abnormal returns generated from characteristics selectivity and characteristics timing of mutual funds, and Carhart four-factor alpha is the return-based performance measure after subtracting fees. Apart from above measures of fund performance, we further take the factor-related return as the dependent variable in the regression analysis to examine whether the textual complexity can predict future fund factor-related returns. The factor-related returns do not reflect the managerial skills but reflect the level of fund risk exposure. Song (2020) finds that investors chase past returns associated with positive fund factors, as investors conflate factor-related returns with alpha, leading to the mismatch between the managerial skills and size of mutual funds. According to the findings, we conjecture that mutual funds with high textual complexity are more motivated to enhance their factor-related return, as their investors tend to reward the factor-related returns more than the investors in the low-complexity funds. We include the additional control variables in the regressions including the performance in the prior 12 months measured by Carhart four-factor alpha, the fund flows over the prior year, the turnover ratio, the logarithm of the assets under management, the realized volatility, the age of the fund, the expense ratio of the fund, the logarithm of the assets under management in the whole fund family. We also add style-by-time fixed effects, to absorb variation in performance due to Lipper style classification.

Table Panel B reports the results of the multivariate regression. The coefficient on the effect of low complexity dummy variables on future fund performance is significantly positive under the GT, DGTW and Carahrt four-factor measures, suggesting that specific textual complexity has predictive power for fund managerial skill and that sufficiently low specific complexity is a good signal of higher abnormal returns of mutual funds in the future. In addition, we find that funds with low specific textual complexity have 2 basis points per month lower risk-related returns than other funds (P-value 0.001). This result suggests that the level of risk exposure and factor-related returns of funds are associated with the fund-specific textual complexity. That is, funds with high textual complexity tend to increase their factor-related returns in order to take advantage of less sophisticated investors who have a limited ability to distinguish factor-related returns from abnormal returns and are more responsive to factor-related returns. As a result, mutual funds can thereby attract more cash flows and also obfuscate their lack of management capability.

2.6.3 Textual Complexity and Performance-Fee Relationship

In this section, we examine the implications of fund textual complexity on the relationship between mutual fund fees and performance. The seminar model of active portfolio management, Berk and Green (2004), demonstrates that the fund's fees are in line with the expected before-fee risk-adjusted returns in the rational market.[21] However, the negative correlation between fund expense ratios and fund performance has been widely documented in the empirical studies (Fama and French (2010); Gil-Bazo and Ruiz-Verdú (2009)). Gil-Bazo and Ruiz-Verdú (2009) explain this conundrum as a consequence of the strategic fee-setting adopted by underperforming mutual funds. Specifically, underperforming funds target less sophisticated investors who are less sensitive to mutual fund fees and therefore charge higher fees to make more money, as low after-fee performance does not likely translate into significant outflows.

In the above explanation, investor sophistication plays an important role in determining a mutual fund's pricing strategy. Specifically, it is because underperforming funds have less sophisticated investors who are less sensitive to fees, that funds have more incentive to strategically set high fees. Therefore, we conjecture that funds with weak investment capabilities may simultaneously manipulate prospectuses and strategically set high fees. Complex prospectuses attract less sophisticated investors who are less averse to fees and have limited ability to utilize the fund's past performance to evaluate funds, and thus funds can charge high fees without

[21] In Berk and Green (2004), the expected after-fee risk-adjusted return of any fund equals zero at equilibrium, which implies a positive relation between fees and before-fee performance of the actively managed mutual funds.

sacrificing fund flows. Conversely, if the prospectus is more readable and investors tend to be more sophisticated and fee-sensitive, it is difficult for mutual funds to benefit from a high pricing strategy. Based on the above analysis, we make the hypothesis that mutual funds with low textual complexity are more likely to have fees commensurate with their actual performance.

According to our hypothesis, mismatch between performance and fees is exacerbated in the funds with high textual complexity. We apply a dual classification approach to analyse the performance-fee relationship for funds with different levels of complexity. We first classify mutual funds into two groups for each period based on whether the fund's fees are above or below the median. In a second step, we divide the two groups of funds into five portfolios according to their most recent fund-specific textual complexity. Then we report the subsequent performance for the ten mutual fund portfolios for each characteristic. We adopt the holding-based GT measure when calculate the future fund abnormal returns, as this measure accommodates both the market timing and the stock selectivity abilities of mutual funds, and captures the manager's ability to adjust the portfolio profitably through active management.

Table Panel A reports future portfolio performance when portfolios are double-sorted by fund expense ratios and fund-specific textual complexity. On the one hand, when the expense ratios of funds are high, the lowest specific complexity portfolio significantly outperforms the highest specific complexity portfolio by 4.17 basis points per month. However, the difference between the low complexity portfolio and the high complexity portfolio is not significant when their expense ratios of funds are low. On the other hand, when the fund specific textual complexity is low, the high-expense portfolio significantly outperforms the low-expense portfolio by 6.17 basis points per month. However, the difference between the high-expense portfolio and the high-expense portfolio is not significant when textual complexity is high. The results of the portfolio ranking validate the hypothesis that funds with low complexity have fees that are more consistent with their before-fee performance.

To further test the implications of textual complexity on the performance-fee relationship, we constructed a dummy variable, denoted by $LowComplexity$, to denote the fund ranked in the first or second-lowest quintile sorted by the latest fund-specific Fog Index. The dependent

Table 2.10: Fee-Performance Relationship with Different Textual Complexity

Table Panel A reports the future GT abnormal returns of portfolios of mutual funds sorted according to the fund-specific textual complexity and fund expense ratio. Mutual funds are first sorted into two equal-sized groups according to whether the expense ratio is above or below its median value. In the second step, funds are further divided into five groups according to their fund-specific textual complexity. The table reports the average GT abnormal returns of the five portfolios and the differences in the future GT abnormal returns between selected portfolios. Table Panel B examines the effect of fund-specific textual complexity on the relationship between fund abnormal returns and expense ratio. The dependent variable is the average monthly fund returns from t+1 to t+3, i.e., the GT abnormal returns in column(1), the DGTW abnormal returns in column(2), Carhart four-factor alphas in column(3). The fund-specific textual complexity is measured by the Fog Index based on the fund specific content of the most recent fund prospectus. We then sort funds into complexity quintiles each month according to their most recent prospectuses. *LowC* takes the value one, if a fund is in the lowest or the second-lowest complexity quintiles, else it takes the value zero. The additional control variables are the performance measured by the average Carhart four-factor alpha over the past 12 months, the realized volatility measured by the standard deviation of fund monthly returns in the past 12 months, the lagged fund age, the logarithm of lagged fund size, the logarithm of lagged fund family size, the lagged expense ratio of the fund, the lagged turnover ratio, and the fund flows in the past one year. We include style-by-time fixed effects. Standard errors are double clustered by fund family and time. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Portfolio Sorting based on Expense Ratio and Textual Complexity

Fog_spc portfolios	Low exp. mean	P-value	High exp. mean	P-value	H-L mean	P-value
1	0.0188	0.477	0.0839	0.018	0.0651***	0.001
2	0.0045	0.876	0.0467	0.178	0.0422**	0.018
3	0.0259	0.416	0.0324	0.352	0.0065	0.729
4	0.0172	0.579	0.025	0.449	0.0078	0.663
5	0.0207	0.519	0.0422	0.209	0.0215	0.214
All	0.0019	0.912	-0.0417**	0.021	-0.0435*	0.087
(3)-(1)	0.0071	0.647	-0.0515**	0.013	-0.0585**	0.026
(5)-(3)	-0.0052	0.706	0.0098	0.63	0.015	0.544

Panel B: Multi-Variate Performance-Fee Regression

	(1) *GT*		(2) *DGTW*		(3) *Alpha_Carhart*	
	coeff.	P-value	coeff.	P-value	coeff.	P-value
Const	-0.087***	0.006	-0.196***	0.000	0.184***	0.000
ExpRatio	1.407*	0.086	-2.014*	0.054	-3.181***	0.000
LowC*Exp	1.212***	0.007	1.386***	0.010	1.202**	0.012
LagPerformance	0.276	0.790	1.704	0.229	7.026***	0.000
LagFlows	0.017	0.890	0.165	0.281	0.438***	0.000
TurnRatio	0.014**	0.029	-0.026***	0.000	-0.054***	0.000
FundSize	-0.005***	0.001	-0.002	0.312	-0.001	0.755
Volatility	3.031***	0.000	7.776***	0.000	-7.643***	0.000
LogAge	-0.005	0.373	-0.017***	0.007	-0.008*	0.073
FamilySize	0.000	0.761	0.000	0.320	0.000***	0.008
Observations	68685		68685		107179	
Style × Time FEs	Y		Y		Y	

variable in our regression is the average monthly performance of fund i from month t+1 to month t+3, measured by GT, DGTW (sum of CT and CS) and 4-factor alpha, respectively. We control for the other attributes in the same way as Section 2.6.2. As mutual fund fees are closely related to fund investment style, we include style-time fixed effects to exclude variation in expense ratios across fund classifications.

The results are presented in Table Panel B. In columns (1) and (2), the dependent variables GT and DGTW are holding-based performance measures before fees are subtracted. In column (3), the dependent variable is the Carhart four-factor alpha, which measures the fund's abnormal returns net of fees. We are interested in the coefficient on the interaction term between the low specific complexity dummy variable and the expense ratio. The positive coefficient suggests that the expense ratios of the low-complexity funds are more consistent with their performance than those of high-complexity funds. As shown in column (1), the coefficient of the expense ratio on GT for low-complexity funds is 2.619, which is 86% higher than the coefficient for high-complexity funds, indicating that the expense ratio of low-complexity funds is more commensurate with the fund managerial skills than that of high-complexity funds. In column (2), where fund performance is measured by DGTW, although the coefficient of expense ratio on fund performance is negative, the mismatch between fund performance and fund expenses is much lower for low-complexity funds than for high-complexity funds (the coefficient of fund performance to fund expenses is -0.628 for low-complexity funds and -2.014 for high-complexity funds). Similarly, in column (3) where fund performance is measured by the Carhart four-factor alpha, the overall relation between expense ratio and fund performance, as measured by the sum of the coefficients of $ExpRatio$ and $LowComplexity * Exp$, is negative, but the mismatch between expense ratios and performance is substantially lower for low-complexity funds than for high-complexity funds. Based on the results, we conclude that strategic pricing is more commonly abused by the low-performing funds with high specific complexity than by the funds with low specific complexity.

We interpret the underperformance of high-complexity funds as the agency problem in which high-complexity funds target less sophisticated investors by strategic obfuscation. From the result that high-complexity funds only significantly underperform when their expense ratios are high, we can conclude that high fees and high specific complexity are adopted complementarily by the suspect funds with low skills that are motivated to exploit the less sophisticated investors. More specifically, funds with low investment skills have an incentive to charge higher fees while employing more complex prospectuses to attract the investors who are not sensitive to high fees. Furthermore, high fund-specific textual complexity is more likely to result from the strategic manipulation when the funds charge high fees at the same time; conversely, the agency problem is not severe when the funds charge lower fees.

The results corroborate our hypothesis that some high-complexity funds exploit investors by charging fees that are not commensurate with their investment abilities. That is, mutual funds are likely to strategically charge high fees while complicating their prospectuses to attract less sophisticated investors who have limited ability to make investment decisions. Conversely, the agency problem is not severe when the funds charge lower fees and have low-complexity prospectuses. As a result, the fees of low-complexity funds are more in line with their management capabilities than those of high-complexity funds.

2.7 Conclusion

We examine both the reasons and the impact on investment decisions of mutual funds' prospectus manipulation. Our paper presents new evidence of agency conflicts between mutual funds and their investors that stem from qualitative funds disclosure. Mutual fund prospectuses are designed to provide investors with clear, concise and relevant information to help them make informed decisions. However, complex prospectuses fail to achieve this goal and we show that these are instead used by underperforming funds to try and exploit less sophisticated investors.

Our paper makes several contributions. First, we find a negative relation between textual complexity and fund investor sophistication, suggesting that highly complex prospectuses limit the ability of investors to assess available information and make informed investment decisions. Second, we find that investors in low-complexity funds are more sophisticated, as they tend to use more advanced asset pricing models to evaluate fund performance, are less reactive to past winner returns (demonstrate less flow performance convexity) and are more averse to fund distribution costs. Conversely, less sophisticated investors are more responsive to factor-related returns and more likely to chase past winners than to withdraw money from past losers (demonstrate more flow performance convexity), and tend to be attracted by funds that are more aggressively marketed.

In addition, we find that low fund manager investment ability is associated with a high level of prospectus' textual complexity in relation to the content written *specifically* for the fund. This also suggests that managers do this in order to target unsophisticated investors. We further find that prospectuses are mostly manipulated at the specific fund level, rather than at the mutual fund family level, which corroborates the motivation for prospectus manipulation to obfuscate low managerial skills. Our results further show that low fund-specific textual complexity, is a positive indicator of managerial skill, predicts better future fund performance, and that the fees of funds with low specific textual complexity are more in line with performance compared to those of funds with high specific textual complexity.

3. Truth or Dare? Mutual Funds ESG Risk Disclosure

3.1 Introduction

There has been surging interest in environmental, social and governance (ESG) investing in the recent years.[1] For example, more than eight in ten US individual investors (85%) now express interest in sustainable investing.[2] 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.[3] 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.[4] It first constructs a model that illustrates the optimal ESG

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

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

[3] 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`.

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

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. Consequently, 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.[5]

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 et al. (2021); Gibson et al. (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

[5]For example, Sheng et al. (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.

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 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.[6] For example, more than 60% of the funds in my sample

[6]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

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.[7] The 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.[8] 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

risks.

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

[8]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 3.3.2.

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,[9] funds with ESG 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 et al. (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.

3.1.1 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 et al. (2007) further explain

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

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 et al. (2021) explain why more volatile fund past returns lead to a weaker flow-performance sensitivity; furthermore, Abis et al. (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 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 et al. (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 et al. (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 et al. (2017)) instead of relying on a specific word list (e.g., Loughran and Mcdonald (2011); Manela and Moreira (2017); Fisher et al. (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 et al. (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 et al. (2022) find the evidence of "Greenwashing"[10] 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 3.2 describes the model and its

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

equilibrium predictions; Section 3.3 describes the data and methodology to identify ESG-related disclosure; Section 3.4 lays out the empirical results; and Section 3.5 concludes.

3.2 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.

3.2.1 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 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,

$$r_{i,t} = \alpha_i + e_i + \epsilon_{i,t} - C(q_{i,t-1}) - f, \tag{3.1}$$

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,

$$\alpha_i \sim N(\bar{\alpha}, \sigma_\alpha^2), \quad e_i \sim N(\bar{e}, \sigma_{esg}^2), \tag{3.2}$$

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_{esg}^2;
- 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.

3.2.2 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:

$$\mathbb{E}_t[r_{i,t+1} \mid G_i] = 0, \tag{3.3}$$

where $r_{i,t+1}$ is defined in equation (3.1) 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,

$$q_{i,t} = \frac{\hat{\alpha}_{i,t} + \hat{e}_{i,t} - f}{c}, \tag{3.4}$$

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,

$$\sigma_{esg}^2 = \underbrace{\arg\max}_{\sigma_{esg}^2 \geqslant \sigma_s^2} \mathbb{E}_{i,0}\left[v_i(q_{i,2}f) \mid \alpha_i, s_i\right], \tag{3.5}$$

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,[11]

$$\mathbb{E}_{i,2}\left[\alpha_i + e_i \mid r_{i,2}\right] = \frac{\sigma_\epsilon^2}{\sigma_\alpha^2 + \sigma_{esg}^2 + \sigma_\epsilon^2}(\bar{\alpha} + \bar{e}) + \frac{\sigma_\alpha^2 + \sigma_{esg}^2}{\sigma_\alpha^2 + \sigma_{esg}^2 + \sigma_\epsilon^2}(r_{i,2} + cq_{i,1} + f). \tag{3.6}$$

Then I examine how the fund sizes at time 1 and 2 are determined based on the equilibrium condition shown in equation 3.4. 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:

$$q_{i,1} = \frac{\bar{\alpha} + \bar{e} - f}{c}. \tag{3.7}$$

Substituting equations 3.6 and 3.7 into equation (3.4), I have the dollar holdings of fund i at time 2 as follows,

$$q_{i,2} = \frac{\bar{\alpha} + \bar{e}}{c} + \frac{\sigma_\alpha^2 + \sigma_{esg}^2}{\sigma_\alpha^2 + \sigma_{esg}^2 + \sigma_\epsilon^2}\frac{r_{i,2}}{c} - \frac{f}{c}. \tag{3.8}$$

The fund flows at time 2 are represented as,

$$\text{Flows}_{i,2} = \frac{\sigma_0^2 + \sigma_{esg}^2}{\sigma_0^2 + \sigma_{esg}^2 + \sigma_\epsilon^2}\frac{r_2}{\alpha_0 + e_0 - f}. \tag{3.9}$$

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

[11] The proof is provided in Appendix C.1.

σ^2_{esg} at time 0 to maximise the expected utility. equation (3.5) can be written as,

$$\sigma^2_{esg} = \underbrace{\arg\max}_{\sigma^2_{esg} \geqslant \sigma^2_s} \mathbb{E}_{i,0}\left[\left(\mathbb{E}_{i,2}\left[\alpha_i + e_i \mid r_{i,2}\right] - f\right) \mid \alpha_i, s_i\right] - \frac{f}{2c}\mathbb{V}\text{ar}_{i,0}\left[\left(\mathbb{E}_{i,2}\left[\alpha_i + e_i \mid r_{i,2}\right] - f\right) \mid \alpha_i, s_i\right]. \tag{3.10}$$

The mutual fund managers form their posterior expectation and variance of the ESG factor through Bayesian updating. The posterior ESG factor is expressed by,[12]

$$\hat{e}_i = e_i \mid s_i \sim N(e_s, \sigma^2_s), \tag{3.11}$$

where

$$e_s = \frac{\sigma^2_\eta \bar{e} + \sigma^2_e s_i}{\sigma^2_\eta + \sigma^2_e}, \quad \sigma^2_s = \frac{\sigma^2_\eta \sigma^2_e}{\sigma^2_\eta + \sigma^2_e}. \tag{3.12}$$

In the above expressions, e_s and σ^2_s 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 C).

In the Proposition 16, 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 16 *(flow-performance sensitivity): The flow-performance sensitivity increases with the investor uncertainty about the ESG factor:* $\frac{\partial Sensitivity_i}{\partial \sigma^2_{esg}} > 0$.

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

[12] This proof is provided in Appendix C.2.

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 17 *(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^2_{esg}; when $s_i \geqslant \bar{s}$, the fund optimally chooses not to disclose ESG risk to increase σ^2_{esg}; when $s_i \in (\underline{s}, \bar{s})$, there is a unique optimal σ^2_{esg} to maximise the expected utility, and $\frac{\partial \sigma^2_{esg}}{\partial s_i}$ is positive in equilibrium.*

According to this proposition, the optimal level of σ^2_{esg} 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 16 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 17 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 18 *(fund fee dampening effect): The cross derivative of the optimal σ^2_{esg} to s_i and f is:*

$$\frac{\partial^2 \sigma^2_{esg}}{\partial s_i \partial f} < 0 \tag{3.13}$$

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

$$\frac{\partial^2 \sigma^2_{esg}}{\partial s_i \partial \alpha_i} > 0 \tag{3.14}$$

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.

3.3 Data and Methodology

3.3.1 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.[13] 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.

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

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):

$$Flows_{it} = \frac{TNA_{it} - (1 + R_{it})TNA_{i,t-1}}{TNA_{i,t-1}}, \tag{3.15}$$

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 (3.15) 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.

3.3.2 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),[14] RepRisk takes an outside-in approach to access ESG risks by analysing information from public sources and stakeholders, e.g., print 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.[15] Reprisk collects news on 28 types of ESG incidents,[16] and calculates RepRisk Index (RRI) based on the news to measure the ESG risk exposure.[17] RRI ranges from 0 (the lowest) to 100 (the highest), which dynamically captures

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

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

[16] For details of the 28 different incidents, see Appendix C.7.1.

[17] 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

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.[18] 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 et al. (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) 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.[19]

of the incidents. The RRI decays if there is no new risk exposure. See details at: `https://www.reprisk.com/news-research/resources/methodology`.

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

[19] Similarly, the "strengths" and "concerns" have been examined separately in many papers (e.g., Chatterji et al. (2009); McGuire et al. (2012); Walls et al. (2012); Zyglidopoulos et al. (2012)).

3.3.3 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.[20] 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, 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.".

[20]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.

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 et al. (2017)). In this paper, I use *Bidirectional Encoder Representations from Transformers (BERT)* to build the language model.[21] 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. 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

[21]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).

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.

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.[22] Table 3.1 compares accuracy, recall, and overall F-value for classifying the same evaluation sample under deep learning and dictionary approaches.[23] The deep learning-based

[22]I use the word list defined in Baier et al. (2020) to implement the dictionary-based methodology, see Appendix C.8.

[23]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

Table 3.1: Text Classification Results Using Different Methods

Table 3.1 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 $F\text{-}score = 2 * \frac{Precision*Recall}{Precision+Recall}$.

Panel 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

Panel 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

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.

3.3.4 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,[24]

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 $F\text{-}score = 2 * \frac{Precision*Recall}{Precision+Recall}$.

[24]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

Figure 3.1: The Word Cloud of Mutual Fund ESG Disclosure

Figures 3.1a and 3.1b 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

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,[25] as shown in Figure 3.1.

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 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.

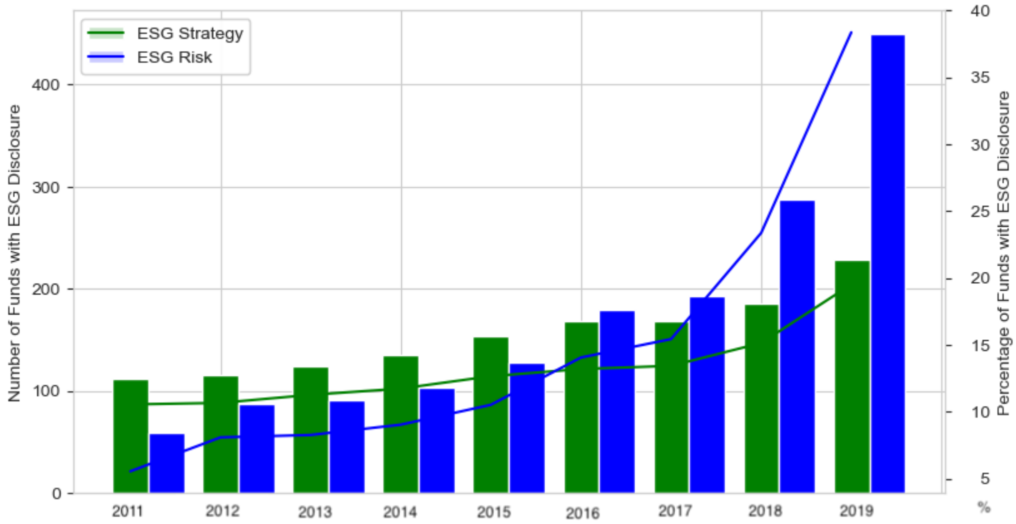
My final sample includes 1371 domestic diversified actively managed equity mutual funds with non-missing strategy and risk descriptions. As shown in Figure 3.2, from 2011 to 2019, the number and percentage of funds with ESG strategies and risk descriptors increased year-on-year from 2011 to 2019. Specifically, the number of funds with ESG investment strategy disclosure

a set of documents.

[25] 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.

Figure 3.2: The Trend of Funds with ESG-related Disclosure

In Figure 3.2, 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.



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.

Table 3.2 presents summary statistics on fund variables, with cross-sectional statistics for the entire sample of funds in Table Panel A, the time-series averages of cross-sectional statistics for the funds with ESG strategy disclosure in Table Panel B, and the time-series averages of cross-sectional statistics for the funds with ESG risk disclosure in Table Panel C. 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 3.2, 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%).

Table 3.2: Mean Statistics by ESG Disclosure

Table 3.2 reports fund characteristics based on ESG disclosure. Panels Panel A, Panel B, and Panel C 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.

Panel 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

Panel 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

Panel 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 3.3: Industry Allocation of Fund Portfolios

Table 3.3 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 3.3 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,[26] 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 3.3 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.

3.4 Empirical Results

3.4.1 ESG Risk Disclosure and Fund Flows

Proposition 16 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:

$$\begin{aligned} Flows_{it} =& a + \beta_1 * ESGRisk_{i,t-1} + \beta_2 * ESGRisk_{i,t-1} * Performance_{i,t-1} \\ &+ \beta_3 * Performance_{i,t-1} + b * Controls_{i,t-1} + \epsilon_{i,t}, \end{aligned} \tag{3.16}$$

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 as well as fund family size, and $\epsilon_{i,t}$ is the regression error term. I also include style-by-time fixed effects.

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

Table 3.4: Regressions of Fund Flows on ESG Risk Disclosure Variable, Past Performance, and Interaction Terms

Table 3.4 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	$\text{ESGRisk}_{\text{Dummy}}$ (1)	(2)	$\text{ESGRisk}_{\text{Weight}}$ (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

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.

Table 3.4 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.

3.4.2 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 (3.16) 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

Table 3.5: Regressions of Fund Flows on ESG Investing Disclosure Variable, Past Performance, and Interaction Terms

Table 3.5 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 Measure	ESG Strategy Dummy (1)	(2)	ESG Investing Dummy (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

the variable $ESGInvest$ equals to one.

Table 3.5 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.

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

The evidence in Section 3.4.1 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 (3.16). 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:

$$\begin{aligned} Flows_{it} =& a + \beta_1 * Treat * Post * Performance_{i,t-1} \\ &+ \beta_3 * Performance_{i,t-1} + b * Controls_{i,t-1} + \epsilon_{i,t}, \end{aligned} \tag{3.17}$$

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

Table 3.6 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 16 and validates the empirical results in Section 3.4.1.

3.4.4 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

Table 3.6: Difference-in-Difference Regressions of Fund Flows on Interaction Terms between ESG Risk Disclosure Variable and Past Performance

Table 3.6 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

the relationship between ESG disclosure and fund actual ESG risk. Proposition 17 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:

$$\begin{aligned} ESGActualRisk_{it} =& a + \beta_1 * ESGStr_{i,t-1} + \beta_2 * ESGRisk_{i,t-1} \\ & + \beta_3 * ESGStr_{i,t-1} * ESGRisk_{i,t-1} + b * Controls_{i,t-1} + \epsilon_{i,t}, \end{aligned} \tag{3.18}$$

Table 3.7: Regressions of Fund Actual ESG Risk Exposure on ESG Disclosure Variable

Table 3.7 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 Panel A, Panel B, and Panel C, 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.

Panel 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*** (34.66)	24.68*** (33.93)	26.182*** (34.72)	24.645*** (34.3)
ESGStr	-0.41*** (3.46)	-0.1102 (-0.98)	-0.4434*** (-3.92)	-0.1661 (-1.55)
ESGRisk	0.9126*** (7.25)	0.4016*** (3.63)	6.2861*** (7.15)	3.0235*** (3.86)
ESGRisk*ESGStr	-2.2152*** (8.78)	-1.7432*** (7.49)	-18.089*** (-9.84)	-13.299*** (-8.14)
Loglength	0.0148 (-0.14)	-0.0061 (-0.006)	0.0925 (0.88)	0.0031 (0.03)
Logtna	-0.1268*** (-4.65)	-0.1009*** (-4.07)	-0.125*** (-4.58)	-0.0996*** (-4.01)
LogfamilySize	0.2821*** (14.06)	0.1842*** (10.06)	0.2795*** (13.94)	0.1825*** (9.98)
Performance	-0.1463 (-1.11)	0.0557 (0.46)	-0.1488 (-1.13)	0.0561 (0.46)
Volatility	-187.7*** (-26.87)	-147.6*** (-21.19)	-188.45*** (-26.99)	-148.1*** (-21.28)
Logage	0.9362*** (14.9)	0.6616*** (11.64)	0.9416*** (15)	0.6694*** (11.78)
ExpRatio	-214.29*** (-13.06)	-135.19*** (-9.02)	-214.16*** (-13.01)	-135.3*** (-9.01)
TurnRatio	-0.2699*** (-4.16)	-0.1774*** (-2.86)	-0.2759*** (-4.25)	-0.1783*** (-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

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 (3.16).

Panel B: Actual ESG Risk Measure: Peak RRI

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

Panel C: Actual ESG Risk Measure: Severity Score

ESGRisk Measure	Severity Score			
	$ESGRisk_{Dummy}$		$ESGRisk_{Weight}$	
	(1)	(2)	(3)	(4)
Const	0.5845*** (31.76)	0.5367*** (31.03)	0.5758*** (31.76)	0.5366*** (31.37)
ESGStr	-0.007*** (-2.45)	-0.0011 (-0.41)	-0.0078*** (-2.84)	-0.0024 (-0.92)
ESGRisk	0.0199*** (6.59)	0.0077*** (2.87)	0.1313*** (6.19)	0.0539*** (2.85)
ESGRisk*ESGStr	-0.0503*** (-8.1)	-0.0379*** (-6.62)	-0.4095*** (-9.08)	-0.286*** (-7.15)
Loglength	0.0017 (0.63)	0.0011 (0.46)	0.0034 (1.33)	0.0012 (0.51)
Logtna	-0.0016** (-2.45)	-0.0015** (-2.43)	-0.0016** (-2.39)	-0.0014** (-2.38)
LogfamilySize	0.0052*** (10.78)	0.0031*** (7.12)	0.0052*** (10.66)	0.0031*** (7.04)
Performance	-0.0054 (-1.67)	0.0000 (0.03)	-0.0054 (-1.69)	0.0000 (0.03)
Volatility	-4.975*** (-28.79)	-3.7931*** (-21.94)	-4.9929*** (-28.9)	-3.8045*** (-22.01)
Logage	0.0218*** (14.32)	0.0153*** (11.06)	0.022*** (14.41)	0.0155*** (11.19)
ExpRatio	-4.7111*** (-11.76)	-3.1107*** (-8.54)	-4.7064*** (-11.72)	-3.1114*** (-8.53)
TurnRatio	-0.0084*** (-5.43)	-0.0059*** (-3.98)	-0.0086*** (-5.53)	-0.0059*** (-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 3.7 presents the estimation results of regressions of funds' actual ESG risk exposure against funds' ESG disclosure. In Tables Panel A, Panel B, and Panel C, 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 3.7 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 17, 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 (3.18).

Table 3.8 presents consistent estimation results with Table 3.7, 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.

Table 3.8: Regressions of Fund MSCI Concern Score on ESG Disclosure Vairable

Table 3.8 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	$ESGRisk_{Dummy}$		$ESGRisk_{Weight}$	
	(1)	(2)	(3)	(4)
Const	1.1662*** (24.26)	1.1259*** (23.76)	1.1679*** (24.66)	1.1395*** (24.34)
ESGStr	-0.0223*** (-3.15)	-0.0166** (-2.42)	-0.0269*** (3.92)	-0.0211*** (-3.14)
ESGRisk	0.0199** (2.52)	-0.008 (-1.1)	0.1094** (2.17)	-0.0637 (-1.35)
ESGRisk*ESGStr	-0.1071*** (-6.27)	-0.0762*** (-4.49)	-0.6737*** (6.31)	-0.4459*** (-3.98)
Loglength	-0.0098 (-1.38)	-0.0101 (-1.47)	-0.01 (-1.45)	-0.0126* (-1.88)
Logtna	-0.0132*** (-7.72)	-0.011*** (-6.67)	-0.0132*** (-7.72)	-0.0109*** (-6.66)
LogfamilySize	0.0064*** (5.12)	0.0034*** (2.81)	0.0064*** (5.09)	0.0034*** (2.79)
Performance	-0.0196** (-2.35)	-0.0068 (-0.84)	-0.0197** (-2.36)	-0.0068 (0.84)
Volatility	-7.4897*** (-17.67)	-6.543*** (15.29)	-7.4965*** (-17.68)	-6.5436*** (-15.29)
Logage	0.0106*** (2.81)	0.006 (1.66)	0.011*** (2.92)	0.0064 (1.78)
ExpRatio	-4.639*** (-4.8)	-2.3815** (-2.47)	-4.6649*** (-4.83)	-2.3904** (-2.48)
TurnRatio	-0.0015 (-0.38)	-0.0051 (-1.39)	-0.0015 (-0.38)	-0.0049 (-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

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.

3.4.5 The Determinant of Fund ESG Disclosure

The Actual ESG Risk Effect

The results in Section 3.4.4 show that ESG-related disclosure is informative in predicting funds' actual ESG risks. In this section, I directly test Proposition 17 and investigate how ESG disclosure of mutual funds is determined. Based on the results in Table 3.7 and Proposition 17, 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:

$$ESGRisk_{it} = a + \beta_1 * PeakRRI_{i,t-1} + b * Controls_{i,t-1} + \epsilon_{i,t}, \tag{3.19}$$

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.

Table 3.9 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 17.That is, funds with a high ESG risk exposure are motivated to disclose the corresponding risk in their

Table 3.9: The Choice of Fund ESG Disclosure

Table 3.9 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.

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

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.

The Cross-Sectional Effects

In this section, I test Propositions 18 and 19 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 18 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 19 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:

$$
\begin{aligned}
ESGRisk_{it} =& a + \beta_1 * PeakRRI_{i,t-1} + \beta_2 * CharacterDummy_{i,t-1} * PeakRRI_{i,t-1} \\
&+ b * Controls_{i,t-1} + \epsilon_{i,t},
\end{aligned}
\tag{3.20}
$$

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 (3.19).

Table 3.10: Cross-sectional Effects of Fund Characteristics on ESG Disclosure Choices

Table 3.10 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	$\text{ESGRisk}_{\text{Dummy}}$					
	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 3.10 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 18, 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 19 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.

3.4.6 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:

$$\begin{aligned} Trade_{ij,t} =& a + \beta_1 * ESGDisclosure_{j,t-1} + \beta_2 * ESGDisclosure_{j,t-1} * Post \\ &+ b * FundControl_{j,t-1} + c * StockControl_{i,t-1} + \epsilon_{it}, \end{aligned} \tag{3.21}$$

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 3.11. 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

Table 3.11: The Trading of Funds on ESG incidents

Table 3.11 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*** (14.86)	1.8068*** (14.85)	1.8119*** (14.83)	1.8074*** (14.81)	1.8117*** (14.86)	1.8094*** (14.85)
ESGDisclosure	0.0202 (1.17)	0.0971*** (4.19)	-0.0246 (-0.2)	0.5832*** (2.96)	0.0128 (0.79)	0.0363* (1.68)
Post*ESGDisclosure		-0.1121*** (-3.45)		-0.8227*** (-3.34)		-0.0434 (-1.37)
PRC	-0.0971*** (-5.77)	-0.0962*** (-5.73)	-0.097*** (-5.76)	-0.0964*** (-5.73)	-0.0972*** (-5.79)	-0.0969*** (-5.77)
Stocksize	0.0311* (1.92)	0.0301* (1.86)	0.031* (1.92)	0.0304* (1.88)	0.031* (1.92)	0.0308* (1.91)
Shrout	-0.0542*** (-3.06)	-0.0534*** (-3.02)	-0.0539*** (-3.05)	-0.0533*** (-3.02)	-0.054*** (-3.06)	-0.0537*** (-3.04)
Vol	-0.0267*** (-4.68)	0.0058 (1.52)	-0.0268*** (-4.7)	-0.0268*** (-4.71)	-0.0269*** (-4.7)	-0.0269*** (-4.72)
Performance	-0.1055*** (-11.97)	-0.0267*** (-4.69)	-0.1059*** (-12.01)	-0.1058*** (12)	-0.1057*** (-12)	-0.1056*** (-11.99)
Volatility	0.4482*** (4.26)	-0.1056*** (-11.98)	0.4496*** (4.28)	0.45*** (4.28)	0.4488*** (4.27)	0.4466*** (4.25)
Logtna	0.0056 (1.48)	0.4481*** (4.26)	0.0057 (1.49)	0.0054 (1.41)	0.0058 (1.52)	0.0057 (1.48)
LogfamilySize	-0.0304*** (-10.6)	-0.0303*** (-10.6)	-0.0302*** (-10.54)	-0.03*** (-10.48)	-0.0302*** (-10.48)	-0.0301*** (10.45)
TurnRatio	-0.2004*** (-12.12)	-0.1994*** (12.09)	-0.2006*** (-12.15)	-0.2002*** (12.14)	-0.2011 (-12.2)	-0.2008*** (-12.17)
Cashflows	1.8778*** (18.59)	1.8793*** (18.67)	1.8789*** (18.62)	1.8772*** (18.63)	1.8788*** (18.63)	1.8786*** (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

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 3.11 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).

3.5 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.

APPENDICES

A. Appendix for Chapter 1

A.1 Proof of Proposition 1

Let $s = [s_1, ..., s_n]$ be the information the informed investor possesses at time 2. The price does not reflect more information about fundamental than s. The mean vector and variance-covariance matrix of the $n+1$ dimensional normal random variable $(v, s) \sim N(0, \Sigma)$, with the variance-covariance matrix $\Sigma \in \mathbb{R}^{(n+1)\times(n+1)}$. The mean vector and variance-covariance matrix can be partitioned as $\mu = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$, and

$$\Sigma = \begin{bmatrix} \Sigma_{v,v} & \Sigma_{v,s} \\ \Sigma_{s,v} & \Sigma_{s,s} \end{bmatrix} = \begin{bmatrix} 1/\tau & 1/\tau & ... & 1/\tau \\ 1/\tau & 1/\tau + 1/\tau_\epsilon & ... & 1/\tau + \rho/\tau_\epsilon \\ \vdots & \vdots & \ddots & \vdots \\ 1/\tau & 1/\tau + \rho/\tau_\epsilon & ... & 1/\tau + 1/\tau_\epsilon \end{bmatrix} \tag{A.1}$$

.

The conditional mean is

$$E[v \mid s_1, ..., s_n] = \Sigma_{v,s}\Sigma_{s,s}^{-1}s = \frac{\tau_\epsilon \sum_{i=1}^{n} s_i}{\tau + (n-1)\rho\tau + n\tau_\epsilon} \tag{A.2}$$

and the variance-covariance matrix

$$Var[v \mid s_1, ..., s_n] = \Sigma_{v,v} - \Sigma_{v,s}\Sigma_{s,s}^{-1}\Sigma_{s,v} = \frac{1 + (n-1)\rho}{\tau + (n-1)\rho\tau + n\tau_\epsilon} \tag{A.3}$$

Thus the demand of an informed trader is:

$$D_{inf}\left(\sum_{i=1}^{n} s_i, p\right) = \frac{\gamma\tau_\epsilon}{1 + (n-1)p}\sum_{i=1}^{n} s_i - \gamma\frac{\tau + (n-1)\rho\tau + n\tau_\epsilon}{1 + (n-1)p}p \tag{A.4}$$

The uniformed trader extract signal from price:

$$w = \lambda\frac{\gamma\tau_\epsilon}{1 + (n-1)p}\sum_{i=1}^{n} s_i + x$$

I define I as the aggregate trading intensity of informed traders, where

$$I = \lambda\gamma\frac{\tau_\epsilon}{1 + (n-1)\rho}$$

Thus we can write w as

$$w = In\left(v + \frac{I\sum_{i=1}^{n}\epsilon_i + x}{In}\right)$$

Because of the multivariate normal distribution of ϵ_i, I have

$$\text{Var}\left(\sum_{i=1}^{n}\epsilon_i\right) = \frac{n\big(1 + \rho(n-1)\big)}{\tau_\epsilon} = \frac{n^2}{D} \tag{A.5}$$

and the precision of public signal given the fundamental v is

$$\left(\text{Var}\left(\frac{I\sum_{i=1}^{n}\epsilon_i + x}{In}\right)\right)^{-1} = \frac{I^2n^2}{\frac{1}{\tau_x} + I^2\frac{n\big(1+\rho(n-1)\big)}{\tau_\epsilon}} = \frac{1}{\frac{1}{n^2I^2\tau_x} + \frac{1}{D}} \tag{A.6}$$

So the variance of fundamental v given the information set of the uninformed traders is:

$$\text{Var}[v \mid p] = \left(\tau + \frac{1}{\frac{1}{n^2 I^2 \tau_x} + \frac{1}{D}}\right)^{-1} \tag{A.7}$$

Under the conjecture that $p = nI\eta(v + \frac{I\sum_{i=1}^{n}\epsilon_i + x}{In})$, the expectation of fundamental v given the information set of the uninformed traders is:

$$\text{E}[v \mid p] = \left(\tau + \frac{I^2 n^2}{\frac{1}{\tau_x} + I^2 \frac{n\left(1+\rho(n-1)\right)}{\tau_\epsilon}}\right)^{-1} \frac{I^2 n^2}{\frac{1}{\tau_x} + I^2 \frac{n\left(1+\rho(n-1)\right)}{\tau_\epsilon}} \frac{\eta}{nI} p \tag{A.8}$$

Substitute the expressions above into $D_{uninf}(p) = \frac{\gamma(E[v|p]-p)}{\text{Var}[v|p]}$, and the market clearing condition. I get the coefficients:

$$\eta = \frac{\big(1 + (-1+n)\rho\big)\big(1 + (-1+n)\rho + n\gamma^2\lambda\tau_x\tau_\epsilon\big)}{\gamma\Big(\big(1 + (-1+n)\rho\big)^2\tau + n\lambda\big(1 + (-1+n)\rho\big)(1 + \gamma^2\lambda\tau\tau_x)\tau_\epsilon + n^2\gamma^2\lambda^2\tau_x\tau_\epsilon^2\Big)} \tag{A.9}$$

And thus I can get the demand of the uniformed trader as

$$D_{uninf}(p) = bp$$

where

$$b = -\frac{\gamma\tau}{1 + \gamma^2\lambda\tau_x D}$$

□

A.2 Proof of Proposition 5

According to Proposition 3, in the interior equilibrium,

$$\lambda = \sqrt{\frac{-A\tau + D}{A\tau_x\gamma^2(\tau D + D^2)}} \tag{A.10}$$

I take the derivative of λ with respect to D:

$$\frac{d\lambda}{dD} = \frac{1}{2A\tau_x\gamma^2}\left(\frac{-A\tau + D}{A\tau_x\gamma^2(\tau D + D^2)}\right)^{-1/2}\frac{-D^2 + 2A\tau D + A\tau^2}{(\tau D + D^2)^2} \tag{A.11}$$

The sign of $\frac{d\lambda}{dD}$ depends on the sign of $(-D^2+2A\tau D+A\tau^2)$. When $D \in \left[A\tau, A\tau\left(1+\sqrt{1+\frac{1}{A}}\right)\right)$, $\frac{d\lambda}{dD} > 0$; when $D \in \left[A\tau\left(1+\sqrt{1+\frac{1}{A}}\right), +\infty\right)$, $\frac{d\lambda}{dD} < 0$. $\square$

A.3 Proof of Proposition 8

The demand of uninformed naive traders:

$$\begin{aligned} D_{uninf2}(p) &= \frac{\gamma\big(E_b[v \mid p] - p\big)}{\mathrm{Var}_b[v \mid p]} \\ &= b_2 p \end{aligned} \tag{A.12}$$

where

$$\mathrm{Var}_b[v \mid p] = \frac{1}{\tau + \frac{1}{\frac{1}{n\tau} + \frac{1}{n^2\lambda_2^2\gamma^2\tau_\epsilon^2\tau_x}}} \tag{A.13}$$

$$\mathrm{E}_b[v \mid p] = \frac{\frac{1}{\frac{1}{n\tau} + \frac{1}{n^2\lambda_2^2\gamma^2\tau_\epsilon^2\tau_x}}}{\tau + \frac{1}{\frac{1}{n\tau} + \frac{1}{n^2\lambda_2^2\gamma^2\tau_\epsilon^2\tau_x}}}\frac{\lambda_2\gamma(\tau + n\tau_\epsilon) - (1-\lambda_2)b_2}{n\lambda_2\gamma\tau_\epsilon}p \tag{A.14}$$

b_2 is solved from the following function:

$$\frac{b_2}{\gamma} = \frac{1}{\frac{1}{n\tau_\epsilon} + \frac{1}{n^2\lambda_2^2\gamma^2\tau_\epsilon^2\tau_x}}\frac{\lambda_2\gamma(\tau + n\tau_\epsilon) - (1-\lambda_2)b_2}{n\lambda_2\gamma\tau_\epsilon} - \tau - \frac{1}{\frac{1}{n\tau_\epsilon} + \frac{1}{n^2\lambda_2^2\gamma^2\tau_\epsilon^2\tau_x}} \tag{A.15}$$

I solve the equation above and get:

$$b_2 = -\frac{\gamma\tau}{1 + n\gamma^2\lambda_2\tau_x\tau_\epsilon}$$

The actual market clearing condition is:

$$\begin{aligned}\beta\lambda_2\gamma\tau_\epsilon\sum_{i=1}^{n}s_i-\lambda_2\beta\gamma(\tau+n\tau_\epsilon)p+(1-\beta)\lambda_1\gamma\frac{D}{n}\sum_{i=1}^{n}s_i-(1-\beta)\lambda_1\gamma(\tau+D)p\\ +(1-\beta)(1-\lambda_1)b_1p+\beta(1-\lambda_2)b_2p+x=0\end{aligned} \tag{A.16}$$

The price is pinned down by the market clearing condition, and the general form of price is:

$$\begin{aligned}p&=\eta I\sum_{i=1}^{n}s_i+\eta x\\ &=\underbrace{\eta Inv}_{\text{fundamental}}+\underbrace{\eta I\sum_{i=1}^{n}\epsilon_i}_{\text{Signal erros}}+\underbrace{\eta x}_{\text{Liquidity trading noise}}\\ &=Wv+Y\sum_{i=1}^{n}\epsilon_i+\eta x\end{aligned} \tag{A.17}$$

where $W=\eta In$, $Y=\eta I$.

The demand function of uninformed rational traders extract noise signal:

$$\begin{aligned}D_{uninf1}(p)&=\frac{\gamma\big(E[v\mid p]-p\big)}{\mathrm{Var}[v\mid p]}\\ &=b_1p\end{aligned} \tag{A.18}$$

Substitute the expression of $E[v \mid p]$ and $\mathrm{Var}[v \mid p]$ into the equation above, and solve b_1.

$$\mathrm{E}[v\mid p]=\frac{\frac{1}{\frac{1}{D}+\frac{1}{n^2I^2\tau_x}}\frac{\lambda_2\beta\gamma(\tau+n\tau_\epsilon)+(1-\beta)\lambda_1\gamma(\tau+D)-(1-\beta)(1-\lambda_1)b_1-\beta(1-\lambda_2)b_2}{nI}}{\tau+\frac{1}{\frac{1}{D}+\frac{1}{n^2I^2\tau_x}}} \tag{A.19}$$

$$\mathrm{Var}[v\mid p]=\frac{1}{\tau+\frac{1}{\frac{1}{D}+\frac{1}{n^2I^2\tau_x}}} \tag{A.20}$$

where

$$\mathrm{nI}=\begin{cases}\sqrt{\frac{-A\tau D+D^2}{A\tau_x(\tau+D)}} & \lambda_1>0\\ \lambda_2\gamma n\tau_\epsilon & \lambda_1=0.\end{cases}$$

$$\frac{b_1}{\gamma} = \frac{1}{\frac{1}{D}+\frac{1}{n^2I^2\tau_x}} \frac{\lambda_2\beta\gamma(\tau+n\tau_\epsilon)+(1-\beta)\lambda_1\gamma(\tau+D)-(1-\beta)(1-\lambda_1)b_1-\beta(1-\lambda_2)b_2}{nI}$$
$$-\tau-\frac{1}{\frac{1}{D}+\frac{1}{n^2I^2\tau_x}} \tag{A.21}$$

b_1 is solved from equation above. □

A.4 Proof of Proposition 8

I get the expression of price informativeness:

$$\text{PI} = \begin{cases} \frac{\tau+D}{A+1} & \lambda_1 > 0 \\ \tau+\frac{1}{\frac{1}{D}+\frac{1}{n^2\beta^2\lambda_2^2\gamma^2\tau_\epsilon^2\tau_x}} & \lambda_1 = 0. \end{cases}$$

Only when $\tau+\frac{1}{\frac{1}{D}+\frac{1}{n^2\beta^2\lambda_2^2\gamma^2\tau_\epsilon^2\tau_x}} > \frac{\tau+D}{A+1}$, $\lambda_1 = 0$. And I have $\partial(\frac{\tau+D}{A+1})/\partial\beta = 0$, and

$$\partial\left(\tau+\frac{1}{\frac{1}{D}+\frac{1}{n^2\beta^2\lambda_2^2\gamma^2\tau_\epsilon^2\tau_x}}\right)/\partial\beta > 0$$

. □

A.5 Proof of Proposition 10

$$\lambda_2\Delta-\sqrt{\frac{D-\tau A}{A\tau_x\gamma^2(\tau D+D^2)}} = \frac{\Delta}{\sqrt{A\tau_x\gamma^2}}\left(\sqrt{\frac{n\tau_\epsilon-\tau A}{\tau n\tau_\epsilon+n^2\tau_\epsilon^2}}-\sqrt{\frac{D-\tau A}{\Delta\tau n\tau_\epsilon+n^2\tau_\epsilon^2}}\right) \tag{A.22}$$

Let

$$\Psi(\rho) = \sqrt{\frac{n\tau_\epsilon-\tau A}{\tau n\tau_\epsilon+n^2\tau_\epsilon^2}}-\sqrt{\frac{D-\tau A}{\Delta\tau n\tau_\epsilon+n^2\tau_\epsilon^2}}$$

Because $\frac{\partial\Psi(\rho)}{\partial\rho} > 0$, thus $\Psi(\rho) > \Psi(0) = 0$, and the second term is positive and increases in ρ.

□

A.6 Proof of Proposition 12

When $\lambda_1 > 0$, I have

$$\frac{b_1}{\gamma} = \frac{1}{\frac{1}{D} + \frac{1}{n^2 I^2 \tau_x}} \frac{\eta^{-1}}{nI} - \tau - \frac{1}{\frac{1}{D} + \frac{1}{n^2 I^2 \tau_x}} \tag{A.23}$$

The aggregate trading intensity I is unrelated to β, so $\frac{db_1}{d\beta}$ have the same sign with $\frac{d\eta^{-1}}{d\beta}$. To study how β influences market depth (η^{-1}), I can study how β influences b_1 instead.

When $\lambda_1 > 0$, I have $nI = \sqrt{\frac{-A\tau D + D^2}{A\tau_x(\tau + D)}}$.

According to the definition of I,

$$nI = \gamma\lambda_2\beta D\Delta + (1-\beta)\lambda_1\gamma D \tag{A.24}$$

I rewrite

$$\lambda_2\beta\gamma(\tau + n\tau_\epsilon) + (1-\beta)\lambda_1\gamma(\tau + D) = nI + \frac{\tau nI}{D} - \gamma\tau\lambda_2\beta(n-1)\rho \tag{A.25}$$

Substitute equation (A.29) into equation (A.25), take the derivative of both sides of equation with respect to β, and rearrange it, I get

$$\begin{aligned} \left[\frac{(\frac{1}{D} + \frac{1}{n^2 I^2 \tau_x})nI}{\gamma} + (1-\beta)(1-\lambda_1)\right] \frac{\partial b_1}{\partial \beta} &= (1-\lambda_1)b_1 \\ &- \gamma\tau\lambda_2(n-1)\rho - (1-\lambda_2)b_2 + (1-\beta)b_1\frac{\partial \lambda_1}{\partial \beta} \end{aligned} \tag{A.26}$$

Take the derivative of both sides with respect to β, I solve

$$\frac{\partial \lambda_1}{\partial \beta} = -\frac{\lambda_2\Delta - \lambda_1}{1-\beta} \tag{A.27}$$

Substitute equation (A.31) into equation (A.30), and I get

$$\left[\frac{(\frac{1}{D}+\frac{1}{n^2I^2\tau_x})nI}{\gamma}+(1-\beta)(1-\lambda_1)\right]\frac{\partial b_1}{\partial\beta}=-\gamma\tau\lambda_2(n-1)\rho-\lambda_2 b_1(n-1)\rho \\ +(1-\lambda_2)b_1-(1-\lambda_2)b_2 \tag{A.28}$$

I have $\gamma\tau > -b_1$, so the term $-\gamma\tau\lambda_2(n-1)\rho-\lambda_2 b_1(n-1)\rho < 0$. If I assume there exits a β satisfying $\frac{\partial b_1}{\partial\beta} > 0$, and I assume β^* is the minimum among all the value of β satisfying the condition. I can conclude $(1-\lambda_2)b_1-(1-\lambda_2)b_2 > 0$. Because $\frac{\partial b_1}{\partial\beta} < 0$ when $\beta \in (0,\beta^*)$, thus $(1-\lambda_2)b_1-(1-\lambda_2)b_2 < (1-\lambda_2)(-\frac{\gamma\tau}{1+\gamma^2\lambda_0\tau_x D}+\frac{\gamma\tau}{1+n\gamma^2\lambda_2\tau_x\tau_\epsilon}) < 0$, which contradicts to the original assumption that $\frac{\partial b_1}{\partial\beta} > 0$, I can prove $\frac{\partial\eta^{-1}}{\partial\beta} < 0$ when $\lambda_1 > 0$.

When $\lambda_1 = 0$, market depth is expressed by:

$$\eta^{-1}=\beta\lambda_2(\gamma\tau+\gamma n\tau_\epsilon)-\beta(1-\lambda_2)b_2-(1-\beta)b_1 \tag{A.29}$$

Take the derivative with the respect to β:

$$\frac{\partial\eta^{-1}}{\partial\beta}=\lambda_2(\gamma\tau+\gamma n\tau_\epsilon)-(1-\lambda_2)b_2+b_1-(1-\beta)\frac{\partial b_1}{\partial\beta} \tag{A.30}$$

when $\rho\to 0$, because $\beta \geqslant \frac{\lambda_0}{\lambda_2\Delta}$, $\beta\to 1$, and $b_1\to b_2$. $\frac{\partial b_1}{\partial\beta}$ have finite bounds. Thus $\frac{\partial\eta^{-1}}{\partial\beta}\to \lambda_2(\gamma\tau+\gamma n\tau_\epsilon+b_2)$, which is larger than zero.

Denote $q=nI=\beta\lambda_2$, I solve b_1 from equation (A.27),

$$b_1=\frac{-\tau-\frac{1}{\frac{1}{D}+\frac{1}{q^2\tau_x}}+\frac{\beta\gamma\lambda_2(\tau+n\tau_\epsilon)}{q(\frac{1}{D}+\frac{1}{q^2\tau_x})}-\frac{\beta(1-\lambda_2)b_2}{q(\frac{1}{D}+\frac{1}{q^2\tau_x})}}{\frac{1}{\gamma}+\frac{1-\beta}{q(\frac{1}{D}+\frac{1}{q^2\tau_x})}} \tag{A.31}$$

When $\beta\to 1$, $b_1\to -\gamma\tau+\gamma\frac{\gamma\lambda_2\tau-(1-\lambda_2)b_2}{q(\frac{1}{D}+\frac{1}{q^2\tau_x})}$, $\frac{\partial b_1}{\partial\beta}$ have finite bounds. Thus $\frac{\partial\eta^{-1}}{\partial\beta}\to\gamma\lambda_2\tau-(1-\lambda_2)b_2-\gamma\tau+\gamma\frac{\gamma\lambda_2\tau-(1-\lambda_2)b_2}{q(\frac{1}{D}+\frac{1}{q^2\tau_x})}$.

$\gamma\lambda_2\tau-(1-\lambda_2)b_2-\gamma\tau+\gamma\frac{\gamma\lambda_2\tau-(1-\lambda_2)b_2}{q(\frac{1}{D}+\frac{1}{q^2\tau_x})}$ is an increasing function about D, and D decreases in ρ.

If $\gamma\lambda_2\tau-(1-\lambda_2)b_2-\gamma\tau+\gamma\frac{\gamma\lambda_2\tau-(1-\lambda_2)b_2}{q(\frac{1}{\tau_\epsilon}+\frac{1}{q^2\tau_x})}<0$, when $\rho>\rho^*$, where ρ^* is the solution of equation $\gamma\lambda_2\tau-(1-\lambda_2)b_2-\gamma\tau+\gamma\frac{\gamma\lambda_2\tau-(1-\lambda_2)b_2}{q(\frac{1}{D}+\frac{1}{q^2\tau_x})}=0$, and $q=\lambda_2\gamma n\tau_\epsilon$, market depth is decreasing in ρ as $\beta\to 1$.

A.7 Proof of Proposition 14

$$\begin{aligned}\mathrm{E}\left[(v-p)^2\right] &= \mathrm{Var}(v-p)\\ &= \frac{(1-\eta nI)^2}{\tau}+\frac{n^2I^2\eta^2}{D}+\frac{\eta^2}{\tau_x}\end{aligned}$$

(1) When $\lambda_1>0$, nI keeps the constant where $nI=\lambda_0\gamma D$. We have $\eta<\frac{1}{nI}$, and thus $1>\eta nI$.

$$\begin{aligned}\frac{d\mathrm{Var}(v-p)}{d\eta} &= \frac{2(1-\eta nI)(-nI)}{\tau}+\frac{2n^2I^2\eta}{D}+\frac{2\eta}{\tau_x}\\ &= -\frac{2nI}{\tau}+\Big(\frac{2n^2I^2}{\tau}+\frac{2n^2I^2}{D}+\frac{2}{\tau_x}\Big)\eta\end{aligned} \tag{A.32}$$

When $\eta>\frac{1}{nI+\frac{nI\tau}{D}+\frac{\tau}{nI\tau_x}}$, $\frac{d\mathrm{Var}(v-p)}{d\eta}>0$; otherwise, $\eta>\frac{1}{nI+\frac{nI\tau}{D}+\frac{\tau}{nI\tau_x}}$, $\frac{d\mathrm{Var}(v-p)}{d\eta}<0$.

According to Proposition 13, η is increasing in β when $\lambda_1>0$. When $\beta=0$, $\eta=\frac{1}{nI+\lambda_0\gamma\tau+\frac{(1-\lambda_0)\gamma\tau}{1+\gamma\tau_x nI}}$. Thus $\eta>\frac{1}{nI+\lambda_0\gamma\tau+\frac{(1-\lambda_0)\gamma\tau}{1+\gamma\tau_x nI}}$.

The threshold of η can be writen as $\frac{1}{nI+\frac{nI\tau}{D}+\frac{\tau}{nI\tau_x}}=\frac{1}{nI+\lambda_0\gamma\tau+\frac{\tau}{nI\tau_x}}$. Because $\frac{(1-\lambda_0)\gamma\tau}{1+\gamma\tau_x nI}<\frac{\tau}{nI\tau_x}$, thus $\eta>\frac{1}{nI+\frac{nI\tau}{D}+\frac{\tau}{nI\tau_x}}$. I can get $\frac{d\mathrm{Var}(v-p)}{d\eta}>0$.

A.8 Proof of Proposition 15

The expected utility of uninformed naive traders is:

$$\mathrm{E}\Bigg[-\exp\Bigg\{-\frac{b_2\sqrt{\mathrm{Var}[v-p]\mathrm{Var}[p]}}{\gamma}\frac{(v-p)p}{\sqrt{\mathrm{Var}[v-p]\mathrm{Var}[p]}}\Bigg\}\Bigg] \tag{A.33}$$

Let ρ_{xy} be the correlation between the two standard normally distributed variables: $\frac{v-p}{\sqrt{\text{Var}[v-p]}}$ and $\frac{p}{\sqrt{\text{Var}[p]}}$.

$$M_{xy}(t) = \frac{1}{\sqrt{[1-(1+\rho_{xy})t][1+(1-\rho_{xy})t]}}$$

Let $t = -\frac{b_2\sqrt{\text{Var}[v-p]\text{Var}[p]}}{\gamma}$, $\rho_{xy} = \frac{\text{Cov}(v-p,p)}{\sqrt{\text{Var}[v-p]\text{Var}[p]}}$. According to the linear expression of price function equation (A.21), $p = Wv + Y\sum_{i=1}^n \epsilon_i + \eta x$, we get $\text{Var}[p] = \frac{W^2}{\tau}$, $\text{Var}[v-p] = \frac{(1-W)^2}{\tau} + \frac{Y^2n^2}{D} + \frac{\eta^2}{\tau_x}$, and $\text{Cov}(v-p,p) = \frac{(1-W)W}{\tau} + \frac{Y^2n^2}{D} + \frac{\eta^2}{\tau_x}$.

$$CE_{uninf2} = \frac{\gamma}{2}\log\Big(\big[1-(1+\rho_{xy})t\big]\big[1+(1-\rho_{xy})t\big]\Big) \tag{A.34}$$

Similarly, I calculate the expected certainty of informed naive traders under the rational measure:

$$\text{E}\bigg[-\exp\bigg\{-\frac{1}{\gamma}\big[(v-p)x-c\big]\bigg\}\bigg] = \text{E}\bigg[-\exp\bigg\{-\frac{1}{\gamma}\Big[(v-p)D_{inf2}\Big(\sum_{i=1}^n s_i, p\Big)-c\Big]\bigg\}\bigg] \tag{A.35}$$

I have

$$\begin{aligned} D_{inf2}\left(\sum_{i=1}^n s_i, p\right) &= \gamma\tau_\epsilon\sum_{i=1}^n s_i - \gamma(\tau+n\tau_\epsilon)p \\ &= \gamma\tau_\epsilon\left(nv+\sum_{i=1}^n\epsilon_i\right) - \gamma(\tau+n\tau_\epsilon)\left(Wv+Y\sum_{i=1}^n\epsilon_i+\eta x\right) \\ &= \Big(\gamma\tau_\epsilon n - \gamma W(\tau+n\tau_\epsilon)\Big)v + \big(\gamma\tau_\epsilon - Y\gamma(\tau+n\tau_\epsilon)\big)\sum_{i=1}^n\epsilon_i - \gamma\eta(\tau+n\tau_\epsilon)x \end{aligned} \tag{A.36}$$

, which is a linear combination of v, $\sum_{i=1}^n \epsilon_i$ and p, thus $(v-p)D_{inf2}(\sum_{i=1}^n s_i, p)$ is the product of two correlated normally distributed variables.

$$CE_{inf2} = \frac{\gamma}{2}\log\Big(\big[1-(1+\rho_{xy})t\big]\big[1+(1-\rho_{xy})t\big]\Big) \tag{A.37}$$

where $t = -\frac{\sqrt{(v-p)D_{inf2}}}{\gamma}$, $\rho_{xy} = \frac{\text{Cov}(v-p, D_{inf2})}{\sqrt{(v-p)D_{inf2}}}$, given that

$$\text{Cov}(v-p, D_{inf2}) = \frac{\big(\gamma\tau_\epsilon n - \gamma W(\tau + n\tau_\epsilon)\big)(1-W)}{\tau} - \frac{\big(\gamma\tau_\epsilon - Y\gamma(\tau + n\tau_\epsilon)\big)Yn^2}{D} + \frac{\gamma\eta^2(\tau + n\tau_\epsilon)}{\tau_x}$$

$$\text{Var}(D_{inf2}) = \frac{\big(\gamma\tau_\epsilon n - \gamma W(\tau + n\tau_\epsilon)\big)^2}{\tau} + \frac{\big(\gamma\tau_\epsilon - Y\gamma(\tau + n\tau_\epsilon)\big)n^2}{D} + \frac{\big(\gamma\eta(\tau + n\tau_\epsilon)\big)^2}{\tau_x}$$

□

A.9 Proof of Proposition 15

Let $q = nI \in [\gamma D, \gamma n\tau_\epsilon]$, q increases in β.

$$\frac{\partial \text{Var}(p-v)}{\partial q} = \frac{\partial \frac{\gamma^2\tau + 1/\tau_x + q^2/D}{(\gamma\tau + q)^2}}{\partial q} = \frac{q\gamma\tau/D - \gamma^2\tau - 1/\tau_x}{(\gamma\tau + q)^3} \tag{A.38}$$

If $\rho < \frac{1}{\tau_x\gamma^2\tau(n-1)}$, $\frac{\gamma^2\tau+1/\tau_x+q^2/D}{(\gamma\tau+q)^2}\partial q < 0$ when $q \in [\gamma D, \gamma n\tau_\epsilon]$;

If $\rho > \frac{1}{\tau_x\gamma^2\tau(n-1)}$, $\frac{\gamma^2\tau+1/\tau_x+q^2/D}{(\gamma\tau+q)^2}\partial q < 0$ when $q \in [\gamma D, \gamma D + \frac{D}{\tau_x\gamma^2\tau}]$; $\frac{\gamma^2\tau+1/\tau_x+q^2/D}{(\gamma\tau+q)^2}\partial q > 0$ when

$q \in (\gamma D + \frac{D}{\tau_x \gamma^2 \tau}, \gamma n \tau_\epsilon]$. $\square$

B. Appendix for Chapter 2

B.1 Examples: Principal Investment Strategy (PIS)

B.1.1 AMG River Road Dividend All Cap Value Fund: High Fog Index 29.94

Under normal conditions, the fund invests at least 80% of its assets in equity securities. The fund invests in a diversified, all cap portfolio of income producing equity securities with yields that River Road asset management, LLC, the subadviser to the fund (River Road or the subadviser), believes will exceed that of the Russell 3000 value index. The fund invests primarily in dividend paying common stocks, publicly traded partnerships (Ptps), and real estate investment trusts (Reits). The fund may also invest in foreign securities (directly and through depositary receipts), convertible preferred stocks, and royalty income trusts. the subadvisers investment philosophy is based upon its proprietary absolute value approach, which seeks to provide attractive, sustainable, low volatility returns over the long term, while reducing downside portfolio risk. The subadviser uses systematic and dynamic proprietary research to analyze companies based on investment criteria such as one or more of the following: high, growing dividend financial strength security price that is at a discount to assessed valuation as determined by the subadvisers unique and proprietary absolute value approach attractive business model shareholder-oriented management undiscovered, underfollowed, misunderstood companies to seek to manage risk, the subadviser employs a structured sell discipline and a strategy of balanced diversification.

B.1.2 Oberweis Emerging Growth Fund: Low Fog Index 17.74

The Fund invests, under normal circumstances, at least 80% of its net assets in the securities of relatively small companies with a market capitalization of less than $1.5 billion at the time of investment which meet the Oberweis Octagon investment criteria described below. The Fund invests principally in the common stocks of companies that the Fund's investment adviser, Oberweis Asset Management, Inc. ("OAM"), believes have the potential for significant long-term growth in market value.

The Fund seeks to invest in those companies which OAM considers to have above-average long-term growth potential based on its analysis of eight factors, which OAM calls the "Oberweis Octagon." These factors are:

- At least 30% growth in revenues in the latest quarter. OAM prefers this to be generated from internal growth as opposed to acquisition of other businesses.
- At least 30% growth in pre-tax income in the latest quarter. There should also be rapid growth in earnings per share.
- There should be a reasonable price/earnings ratio in relation to the company's underlying growth rate. In order to be considered for investment, companies must generally have a price/earnings ratio not more than one-half of the company's growth rate.
- Products or services that offer the opportunity for substantial future growth. Such growth generally either stems from products in newer, high growth markets or products with the potential to grow market share within an existing market. In the latter case, such products typically grow market share due to competitive advantages over other market offerings. Examples of such advantages include new technologies, patents and niche market positions with high barriers to competitive entry.
- Favorable recent trends in revenue and earnings growth, ideally showing acceleration.
- Reasonable price-to-sales ratio based on the company's underlying growth prospects and profit margins.

- A review of the company's financial statements, with particular attention to footnotes, in order to identify unusual items which may indicate future problems.

- High relative strength in the market, in that the company's stock has outperformed at least 75% of other stocks in the market over the preceding twelve months.

B.1.3 BlackRock Small Cap Growth Fund Fund-overall Fog Index: 22.29, Fund-Specific Fog Index: 25.67

Small cap growth equity normally invests at least 80% of its net assets in equity securities issued by US small capitalization companies which fund management believes offer superior prospects for growth. Equity securities consist primarily of common stock, preferred stock, securities convertible into common stock and securities or other instruments whose price is linked to the value of common stock. The fund management team focuses on US small capitalization emerging growth companies. Although a universal definition of small capitalization companies does not exist, the fund generally defines these companies, at the time of the fund's investment, as those with market capitalizations comparable in size to the companies in the Russell 2000 growth index (between approximately $39 million and $2.536 billion as of June 30, 2010, the most recent rebalance date). In the future, the fund may define small capitalization companies using a different index or classification system. The fund primarily buys common stock but also can invest in preferred stock and convertible securities. From time to time the fund may invest in shares of companies through "new issues" or initial public offerings ("IPOS").

C. Appendix for Chapter 3

C.1 Investors' Bayesian Updating

According to equation (3.2), investors' prior about $\alpha_i + e_i$ is

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

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,

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

C.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,

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

and the conditional variance,

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

C.3 Proof of Proposition 16

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

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

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,

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

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

C.4 Proof of Proposition 17

Substituting equations (3.6), (3.7) and (3.12) into the objective function in equation (3.10), and using $\mathcal{L}$ to denote the objective function, I get the following expression:

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

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:

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

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,

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

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

$$\frac{\partial \sigma^2_{esg}}{\partial s} = \frac{\frac{\partial \tau}{\partial s}}{\frac{\partial \tau}{\partial \sigma^2_{esg}}} = \frac{\frac{\partial \tau}{\partial e_s}\frac{\partial e_s}{\partial s}}{\frac{\partial \tau}{\partial \sigma^2_{esg}}} > 0, \tag{C.10}$$

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

C.5 Proof of Proposition 18 and 19

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

$$\sigma^2_{esg} = \frac{c(\alpha_i + e_s - \bar{\alpha} - \bar{e})(\sigma^2_\alpha + \sigma^2_\epsilon) - \sigma^2_\alpha f(\sigma^2_\alpha + \sigma^2_\epsilon)}{f(\sigma^2_\epsilon + \sigma^2_s) - c(\alpha_i + e_s - \bar{\alpha} - \bar{e})}. \tag{C.11}$$

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

$$\frac{\partial \sigma^2_{esg}}{\partial s_i} = \frac{\partial e^2_{esg}}{\partial e_s}\frac{\partial e_s}{s_i} = \frac{c\sigma^2_\epsilon(\sigma^2_\epsilon + \sigma^2_s)}{\left(\sqrt{f}(\sigma^2_\epsilon + \sigma^2_s) - \frac{c(\alpha_i + e_s - \bar{\alpha} - \bar{e})}{\sqrt{f}}\right)^2}\frac{\sigma^2_e}{\sigma^2_\eta + \sigma^2_e}. \tag{C.12}$$

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

C.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,

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

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,

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

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

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

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

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

The fund flows at time 2 are represented as,

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

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

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

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.

C.7 RepRisk Risk Tag

C.7.1 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.

C.7.2 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.8 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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