Essays on the U.S. mutual fund industry

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Abstract

This thesis investigates three topics related to the research area of mutual funds in the U.S. market. Our first essay analyzes flow patterns in retail corporate bond mutual funds across the direct- and broker-sold segments. While a concave flow-to-performance relation (outflows are more sensitive to poor performance) is documented, such a relation exists only among broker-sold funds and increases with fund and market illiquidity. The concave relation is stronger among broker-sold funds with higher distribution costs, where brokers have greater incentives to advise redemptions and investors are more reliant on financial advice. Finally, outflows from broker-sold funds due to poor performance predict inflows to other broker-sold funds during normal time and predict inflows to direct-sold funds during crisis time.

Furthermore, our second essay investigates the impact of ETF ownership on the firms' propensity to issue seasoned equity offerings (SEOs) and the post-market performance of these SEOs. We document that ETF ownership is positively related to SEO propensity, consistent with the market timing explanation. We also show that this positive relationship is more prevalent among firms that are younger, smaller, unprofitable, and non-dividend-paying. Finally, we find that ETF ownership reduces the severity of SEO underperformance over both the short- and long-run.

Our third essay investigates whether multi-fund managers engage in portfolio pumping activity. we examine that portfolio pumping activity is prevalent among multi-fund managers at the end of year and quarter. Moreover, these fund managers are more likely to inflate the value of funds who hold small and less liquid securities. Finally, we investigate that portfolio pumping behavior among multi-fund managers might be motivated by the convex relationship between fund flow and fund performance and the spillover effects.

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Chapter 1 Introduction

1.1 Background and motivation

The last few decades have witnessed a dramatic growth of the mutual fund industry in the United States. According to the Investment Company Institute ICI (2022), the total net assets under management for the U.S. market stand at $27.0 trillion at the end of year 2021, making it the largest mutual fund industry around the worldwide. An approximately 102.6 million individual investors in 59.0 million households (45.4%) hold ownership of mutual funds in 2021, with different financial objectives, such as education, retirement preparation. There is no doubt that mutual funds play an important role in today's U.S. financial market. Not only do mutual funds significantly affect household wealth, but they are also important for the stability of financial market.

Among different types of mutual funds, equity funds have been the most important one in the U.S. market during recent years, with equity mutual funds alone making up 55% of U.S. mutual fund net assets in 2021. However, there are several important changes in the U.S. mutual fund industry that took place in the 21st Century. In this thesis, we investigates three topics related to different changes related to the mutual funds in the U.S. market.

First, corporate bond funds experience fast growth in recent years, becoming the second-largest category in U.S. mutual fund industry, with 21% of the total net assets being invested in corporate bond mutual funds. The increasing importance of corporate bond mutual funds leads to a concern about its influence on the financial market stability. Unlike the equity mutual funds, corporate bond mutual funds may lead to financial instability due to its concave flow-to-performance relationship, i.e., investor flows are more sensitive to poor performance than to good performance. Because of the liquidity mismatch of corporate bond mutual funds, poor performance of corporate bond mutual funds may result in investor's redemption incentive as the redemption costs will be borne mostly by the investors who stay with the funds (Chen et al., 2010). Thus, corporate bond mutual fund investors are more likely to redeem their shares at an early stage following the poor fund performance to obtain a first-mover advantage, which consequently result in a run-like behavior, hurting the financial market stability. Furthermore, as the key players in the mutual fund industry, retail investors invest through different distribution channels according to their preferences and degree of financial sophistication. This contributes to a difference in fund flow dynamics across the two segments. Thus, our first essay aims at explore the flow-to-performance relationship in corporate bond mutual funds across the direct- and broker-sold segments. Understanding the corporate bond mutual fund investor behavior has an important implications for financial stability. The relationship between fund flows and fund performance across different distribution channels helps regulators to make targeted strategy to avoid financial market instability.

Second, over the last decades, investors have proved a strong and growing preference for passive investment, given that active asset managers generally fail to outperform the market net of expense. In the meantime, most of the growth in passive investment has taken place by the increasing popularity of ETFs. Because ETFs are cheaper, more liquid and well diversified, they are more attractive for investors than index mutual funds (Moroz and Naruta, 2019). From 2000 to 2021, the U.S. exchange-traded fund industry grew from 80 ETFs managing $66 billion to 2,570 funds with $7.2 trillion in asset under management (ICI, 2022). Such a rapid development of ETFs has attracted increasing attention from practitioners and researchers, raising the questions about the important influence of ETFs on financial markets, particularly the impact on price informativeness and liquidity of underlying stocks associated with ETF arbitrage mechanism. This further raises our interest in examining the impact of ETF ownership on a firm's propensity of seasoned equity offerings. Since equity issuance is an important tool for firms to exploit information advantage to raise capital, when ETF ownership have an influence on the price efficiency and liquidity of underlying stocks, it may also influence firm's corporate decision on equity issuance. To investigate such a relationship, we are able to provide a new insight about how ETF ownership influence the firm's equity issuance decision and its post-issuance performance. This is helpful for investors to make their investment decisions and enables regulators to introduce relevant policies related to equity issuance.

Third, as mentioned above, it is well documented that active asset managers generally fail to outperform the market net of expense. In this case, fund managers may use illegal trading activity to improve fund performance, given that a convex relationship between fund flow and fund performance implies a disproportionately large amount of inflows associated with better fund performance. Portfolio pumping is one of the illegal trading activities used by fund manager to inflate their fund value. Through portfolio pumping, fund managers tend to purchase a significant amount of the securities they already held at the year- or quarter-ends, to artificially inflate the fund value, but experience a return reversal on the following trading day. With the increasing attention from regulators and practitioners[1] in the early 21st Century, portfolio pumping activity has become increasingly evasive. For instance, some studies document that fund managers can inflate their fund value at the month-end rather than year- or quarter-ends (Kim, 2020) and through depressed selling strategy rather than excessive buying (Hu et al., 2014). In the meantime, the asset under management captured by multi-fund managers has increased significantly since 2000

[1] The first regulatory action was taken by the Ontario Securities Commission (OSC), who accuses the RT Capital of repeated and intentional portfolio pumping activities at month-, quarter-, and year-ends (OSC, 2000). Ultimately, the Royal Bank of Canada paid a $3 million penalty and public an apology in newspapers. Similarly, the SEC also strengthens its regulation against portfolio pumping, with a senior SEC office announcing that the SEC is examining the possibility of portfolio pumping among dozens of mutual funds (Burns, 2001). A few months later, the commission fined Oechsle International Advisor and ABN AMRO because of market manipulation (SEC, 2001).

(Fu, 2020), when regulators began to focus more attention on portfolio pumping. Also, the prevalence of multi-fund managers is overlooked in literature. This coincidence raise our interest in investigating whether portfolio pumping among multi-fund managers is a new form in response to the increasing attention from the regulators. To investigate this phenomenon, we may provide regulators and practitioners a new type of portfolio pumping that they may not be aware of.

1.2 Research gaps and key research questions

Our first essay investigates the flow-to-performance relationship in corporate bond mutual funds across direct- and broker-sold distribution channels. Within the research area investigating the flow-to-performance relationship in mutual funds, numerous prior studies document a convex relation between fund flows and performance among equity mutual funds (see, e.g., Ippolito, 1992; Chevalier and Ellison, 1997; Lynch and Musto, 2003; Sirri and Tufano, 1998). However, relatively few empirical studies have investigated the flow-to-performance relation for fixed income mutual funds and their results are mixed. Recently, Chen and Qin (2016) and Goldstein et al. (2017) find that the flow-to-performance relation of corporate bond mutual funds is not as convex as in equity mutual funds. Instead, corporate bond mutual funds exhibit a concave flow-to-performance relation, i.e., the sensitivity of outflows to bad performance is greater than the sensitivity of inflows to good performance. A concave relationship between fund flow and fund performance may have negative implications for financial stability. For corporate bond mutual funds, investors are more likely to withdraw their shares after poor performance because investors remained in the funds will bear the redemption costs, which consequently result in a run-like risk and threaten the financial market.

In the mutual fund industry, bond funds are sold through two main distribution channels, either directly from the fund underwriter or indirectly through a broker, and these two segments differ in several major ways. First, direct-sold funds only provide portfolio management services whereas broker-sold funds provide investment advisory services and ongoing assistance for their investors. Second, direct-sold investors have more investment experience and financial knowledge and care more about risk-adjusted performance whereas novice and less-sophisticated investors choose to invest in broker-sold funds due to a lack of investment experience and knowledge (Del Guercio et al., 2010; Hortacsu and Syverson, 2004). Existing studies on fixed income mutual funds have yet to explore how such heterogeneity in market segments may influence the relation between fund flow and performance. Thus, our first essay fills this empirical gap and examine which retail market segments are more subject to the risks of fund runs and instability.

Our second essay investigates the impact of ETF ownership on the propensity of firm's seasoned equity offerings. Driven by the dramatic growth of ETFs, a nascent literature has begun to examine the impact of ETF ownership on their underlying securities, including volatility (Ben-David et al., 2018), return co- movement (Da and Shive, 2017), pricing inefficiency (Israeli et al., 2017), illiquidity (Hamm, 2014), price discovery in earnings (Glosten et al., 2021), and overvaluation (Zou, 2019). While most studies to date focus on the capital market implications of ETFs, a new line of inquiry has begun to examine the implications of ETFs for corporate decisions, such as investment (Antoniou et al., 2022) and cash holdings (El Kalak and Tosun, 2022). In our second essay, we aim to fill this research gap in the literature by investigating the role of ETF ownership for corporate equity financing decisions, specifically the likelihood of seasoned equity offerings and post-issue performance.

Our third essay examines whether portfolio pumping activity is prevalent among multi-fund managers. Portfolio pumping is a well documented illegal fund trading activity in the literature (see., e.g., Ben-David et al., 2013; Carhart et al., 2002; Duong and Meschke, 2020). The existing literature suggests that with the increasing attention from regulators, portfolio pumping has become more evasive. For instance, some studies document that fund managers can inflate their fund value at the month-end rather than year- or quarter-ends (Kim, 2020) and through depressed selling strategy rather than excessive buying (Hu et al., 2014). In the meantime, the prevalence of mutual fund managers who operate multiple funds simultaneously is often overlooked in the literature (see., e.g., Abdesaken, 2019; Fu, 2020). Given that multi-fund managers have the resources to conduct cross-fund subsidization at a lower coordination costs, we aim to fill the research gap in portfolio pumping literature by examining whether portfolio pumping activity is existed among fund managers who operate multiple funds simultaneously.

1.3 Thesis contributions

Our first essay makes several contributions to the literature. First, it contributes to the growing body of literature on the fund flow dynamics of fixed income mutual funds (see, e.g., Zhao, 2005; Chen and Qin, 2016; Goldstein et al., 2017). Chen and Qin (2016) argue that there is no significant convexity in the flow-to-performance relation for corporate bond mutual funds. Goldstein et al. (2017) document a concave relation between investor flows and fund performance. To the best of our knowledge, we are the first to analyze the patterns of fund flows of corporate bond funds in different retail market segments and find that the concave relation is evident only in the broker-sold segment.

Furthermore, our first essay adds to the body of research on the link between mutual funds and stability. Chen et al. (2010) argue that strategic complementarities among fund investors is conducive to financial fragility. Others suggest that strategic complementarities play a key role in the run-like behaviors in money market mutual funds (Schmidt et al., 2016) and in corporate bond funds (Goldstein et al., 2017). Feroli et al. (2014) document a feedback loop between decreasing fund returns and large fund redemptions that threatens financial stability. Complementing the above studies, our study investigates whether fund and market illiquidity may amplify the potential run behaviors among two distribution channels, which in turn, destabilizes the market.

Our second essay makes several important contributions to the literature. First, our findings add to the growing body of research examining the effect of ETF ownership on the underlying securities (e.g., Ben-David et al., 2018; Israeli et al., 2017). Prior studies mainly focus on the asset pricing implications of ETS, showing that higher ETF ownership increases return volatilities (Ben-David et al., 2018), decreases pricing efficiency (Israeli et al., 2017), and impairs stock liquidity (Hamm, 2014) of the underlying securities. We complement the existing literature by providing evidence on the implications of ETFs to corporate decision making, such as SEO decisions.

Second, our study extends the literature on the motivation behind security issuance (e.g., Masulis and Korwar, 1986; Myers and Majluf, 1984). Previous studies suggest that firm managers time the market and conduct equity issuance when their stocks are overvalued (Baker and Wurgler, 2002, Loughran and Ritter, 1995). Our research suggests that ETF ownership leads to decreasing informational efficiency and persistent demand for underlying securities, thereby offering an opportunity for firms to time the market and increasing the SEO probability among those firms.

Finally, our study also relates to the literature on post-issue performance (see, e.g., Corwin 2003; Kim and Purnanandam, 2014). Prior work suggests that firms exhibit negative performance both in the short-run (Asquith and Mullins, 1986; Masulis and Korwar, 1996) and in the long-run (Loughran and Ritter, 1995). Our evidence advances this literature by documenting that although the underperformance exists, firms with higher ETF ownership outperform their counterparts with lower ETF ownership. This evidence implies that higher ETF ownership implies higher market participation, which generates persistent demand for the underlying stocks, and imporves the post-issuance performance.

Our third essay primarily contributes to the literature on portfolio pumping activity in the mutual fund industry (see, e.g., Carhart et al., 2002; Duong et al., 2020; Wang, 2019). Prior studies have found a decline in portfolio pumping activity as a result of increased regulatory monitoring (Duong et al., 2020). In response to this, several studies provide evidence that portfolio pumping has become more evasive. For instance, portfolio pumping experience a shift from fund level to fund family level (Wang, 2019), from year- and quarter-ends to month-ends (Kim, 2020). To the best of our knowledge, this study is the first relating portfolio pumping to multi-fund managers. Our third essay complements the literature by documenting that portfolio pumping activity among fund managers who operate multiple funds simultaneously is another type of portfolio pumping activity that regulators may not be aware of.

The third essay is also related to the literature on cross-fund subsidization and agency conflicts. Agarwal et al. (2018) show that multitasking leads to an improved fund performance for newly assigned funds at the sacrifice of the performance of incumbent funds. Gaspar et al. (2016) confirm the agency problem of cross-subsidization, documenting that fund families transfer the performance of less profitable funds to those more profitable funds. Del Guercio et al. (2018) find that fund managers tend to maximize the hedge funds rather than mutual funds, because their compensation is more directly and heavily related to hedge funds. Our study adds to this area of research by suggesting that multi-fund managers exploit the cross-fund subsidization mechanism to inflate their fund performance through portfolio pumping.

1.4 Thesis structure

This thesis consists of six chapters. Chapter 1 is a general introduction of the study, highlighting the research background, motivation, research questions and research gaps. Chapter 2 is our first essay investigating the behavior of flows in corporate bond funds across direct- and broker-sold segments. Chapter 3 is our second essay investigating the impact of ETF ownership on the propensity of seasoned equity offerings. Chapter 4 is our third essay investigating whether portfolio pumping exists among multi-fund managers. Chapter 5 gives a general conclusion of the study.

Chapter 2 The behaviors of flows in retail corporate bond mutual funds

2.1 Introduction

Triggered by credit market stresses or changing interest rates, large redemptions from fixed income mutual funds with illiquid holdings may pose threat to systemic stability (see, e.g., Feroli et al., 2014; Goldstein et al., 2017).[2] In particular, the uncertainty surrounding the credit markets after the Federal Reserve's announcement of its intention to taper monetary policy in 2013 (the so-called "the Taper Tantrum") had led to massive outflows from bond mutual funds, causing widespread panic about fund runs. Another recent example is the concerns about illiquidity in bond funds raised by the Securities and Exchange Commission's (SEC) suspension of redemptions in December 2015 for the Third Avenue Focused Credit Fund, after the fund had announced its liquidation plan due to prolonged poor performance (Raza, 2015).

A recent, seminal study by Goldstein et al. (2017) shows evidence that redemptions from bond funds with illiquid holdings create incentives to "run" the funds and finds that investor flows are more sensitive to poor performance than to good performance, or, a concave flow-to-performance relation (as opposed to the widely-documented convex relation in equity mutual funds (Chevalier and Ellison, 1997)). A notable finding in their study is that such concave patterns in fund flows are more evident among retail funds.

Retail investors are the key players in the mutual fund industry — as of 2017, more than 90 percent of total net assets (TNAs) of the U.S. mutual fund industry are held by

[2] As pointed out by the International Monetary Fund (IMF) (2015), "large redemptions from these funds – possibly triggered by an external event, such as a faster-than-anticipated rise in interest rates in the United States – may have a widespread market impact".

retail investors (Investment Company Institute, 2018, p.60) — and they invest through different distribution channels according to their preferences and degree of financial sophistication.[3] A recent, growing body of studies point to the importance of separately examining the direct- and broker-sold segments, finding that the two segments differ in clientele, incentives, performance, and flow dynamics (see, e.g., Bergstresser et al., 2009; Del Guercio and Reuter, 2014).[4] Given the essential role of distribution channels in understanding fund flow behaviors, we offer new empirical evidence on the stability concerns about fixed income mutual funds by examining the patterns of fund flows across the direct- and broker-sold segments.

A concave flow-to-performance relation may exist in fixed income mutual funds in either direct- or broker-sold segments under two competing views. First, under the investor-sophistication view, because direct-sold fund investors are more financially sophisticated, their superior skills in processing information and analyzing investment returns may prompt them to redeem shares earlier following poor performance, in turn driving greater outflows. As such, the first view predicts a more concave flow-to-performance relation in direct-sold funds than in broker-sold funds. By contrast, under the incentive-based view, because brokers in broker-sold funds receive commissions for fund sales, they may have incentives to advise investors to redeem from underperforming funds and switch to other funds for increased compensation. Thus, the flow-to-performance relation would be more concave for broker-sold funds under the second view.

To distinguish between the competing hypotheses, we construct a large sample of retail corporate bond mutual funds using data from the CRSP Survivor-Bias-Free U.S.

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[3] 79 percent American households rely on financial professionals to purchase funds, in which 37 percent investors only rely on financial professionals to purchase funds and other 42 percent investors also purchase funds independently. Furthermore, only 14 percent investors solely purchase funds directly from the fund company (ICI, 2018, p.151).

[4] Direct-sold funds only provide their investors portfolio management service, while broker-sold funds provide investors portfolio management bundled with financial advisory service.

Mutual Fund Database, and we analyze the flow dynamics of both direct- and broker-sold funds. Following the Investment Company Institute (ICI) (2018, p.131), we use the presence of sales loads plus the level of 12b-1 fees to classify direct- and broker-sold funds. Specifically, a fund share class is defined as direct-sold if it has neither front load nor rear load, and has an annual 12b-1 fee of no more than 25 bps, and it is defined as broker-sold otherwise.[5]

Our first test compares the sensitivity of investor flows to risk-adjusted and net returns between the two segments. Our results show that investors of direct-sold funds are sensitive to risk-adjusted performance only, while those of broker-sold funds chase both risk-adjusted and net returns. Further, the sensitivity of flows to risk-adjusted returns is significantly lower for broker-sold funds, consistent with their investors having a lower degree of financial sophistication.

We next examine the sensitivity of outflows to poor performance, or, a concave flow-to-performance relation, and whether such relation differs between the two segments. While a concave flow-to-performance relation is documented in our full sample consistent with Goldstein et al. (2017), an important result is that such relation exists only in the broker-sold segment but not among the direct-sold funds. In terms of magnitude, the sensitivity of outflows to poor performance is almost three times as strong as the sensitivity of inflows to good performance. Our evidence suggests that investors of broker-sold funds may exhibit potential run behaviors following poor fund performance.

To gain further insights into the stability implications of our findings, we explore whether the sensitivity of outflows to poor performance varies with the degree of fund and market illiquidity. Our results show that underperformed broker-sold funds experience significantly greater outflows during illiquid periods, as measured by the

[5] Sun (2017) shows that this classification approach captures the distribution channels according to the Financial Research Corporation (FRC) with an 88-percent accuracy.

VIX index or the TED spreads.[6] Additionally, outflows are shown to be significantly larger for underperformed broker-sold funds that hold less liquid assets. Further, the two dimensions of illiquidity appear to reinforce each other — the sensitivity of outflows to poor performance is found to be most evident among funds with illiquid assets during illiquid periods, thus revealing precisely the types of broker-sold funds and the time periods in which potential runs and market fragility are most likely to arise.

Having shown that outflows are more sensitive to poor performance in broker-sold funds, a follow-up question is whether brokers have a role in driving the relation of question. To answer this question, we exploit the level of distribution fees charged by the broker-sold funds to capture the incentives of their brokers and the extent of trust investors placed on the brokers' investment advice and suggestions. Because distribution fee is used for compensating broker for offering advice and ongoing assistance, brokers with higher fees are likely have greater incentives to advise investors to redeem shares from underperforming funds to earn transaction-based compensations. Besides, investors who are more willing to pay for financial advice tend to rely more on and have more trustful relationships with brokers and/or advisors (Sun, 2017). Our results show that the concave relation between flows and performance is more pronounced in broker-sold funds with high distribution fees, consistent with brokers having a role in driving the concave relation of question.

A potential concern is that for some fund families, switching between funds intra-family incurs no or reduced sales loads (Reid and Rea, 2003), implying that the incentives for brokers to advise fund switching may be minimal or low for funds in certain fund families. If our results are purely driven by such intra-family fund switching, our interpretation that brokers and their advice playing an economic role could not be true. To address this issue, among the broker-sold funds, we exclude all

[6] TED spreads is defined as the differences between the 3-month London Interbank Offered Rate and the interest rate of 3-month Treasury bill.

share classes from fund families managing more than one fund, confirming that our baseline results continue to hold.

There are at least two ways in which our findings can be interpreted. The first is that given that brokers have incentives to suggest redemptions to increase commissions, investors who trust their brokers and rely on their advice would follow their suggestions and redeem underperforming broker-sold funds. If this view is true, we expect that investors who redeem shares after poor performance may channel their money into other funds within the broker-sold segment. The second is that due to the realization of poor fund performance, investors who have been charged with high sales loads and fees may become especially upset and unsatisfied with their brokers, lose trust and faith in their advice, and terminate services and relationships with them. If that is the case, we expect a majority of investors redeeming shares after poor fund performance to leave the broker-sold segment and perhaps switch into funds in the alternative direct-sold segment. To shed some light on these interpretations, we explore whether outflows from broker-sold funds due to poor performance predict net flows to direct-sold funds and/or to the outperforming broker-sold funds. Empirical support is documented for both interpretations; the former effect exists during the normal time and the latter is evident during the crisis period.

Our paper contributes to the growing body of literature on the fund flow dynamics of fixed income mutual funds (see, e.g., Zhao, 2005; Chen and Qin, 2016; Goldstein et al., 2017). Chen and Qin (2016) argue that there is no significant convexity in the flow-to-performance relation for corporate bond mutual funds. Goldstein et al. (2017) document a concave relation between investor flows and fund performance. To the best of our knowledge, we are the first to analyze the patterns of fund flows of corporate bond funds in different retail market segments and find that the concave relation is evident only in the broker-sold segment.

Our findings add to the body of research on the link between mutual funds and stability. Chen et al. (2010) argue that strategic complementarities[7] among fund investors is conducive to financial fragility. Others suggest that strategic complementarities play a key role in the run-like behaviors in money market mutual funds (Schmidt et al., 2016) and in corporate bond funds (Goldstein et al., 2017). Feroli et al. (2014) document a feedback loop between decreasing fund returns and large fund redemptions that threatens financial stability. Complementing the above studies, our evidence suggests that fund and market illiquidity may amplify the potential run behaviors among broker-sold investors, destabilizing the market.

Finally, our paper relates to the literature on the economic implications of financial advice. Egan et al. (2017) find evidence of repeated misconduct that highlights the conflicts of interest between financial advisor and retail investors. Bergstresser et al. (2009) and Del Guercio and Reuter (2014) find that broker-sold funds underperform their direct-sold counterparts, arguing that broker-sold funds provide less tangible benefits to their investors. Christoffersen et al. (2013) show that mutual funds' sales loads and other revenues paid to brokers significantly influence fund inflows. Our findings suggest that brokers and their advice is likely to have an important role in driving the concave patterns in flows of corporate bond mutual funds.

The remainder of this essay is organized as follows. Section 2 reviews the literature and develops our hypotheses. Section 3 describes the data and variable constructions. Section 4 reports the empirical results and Section 5 concludes.

2.2 Literature review and hypothesis development

The structure of this sub-section will be organized as follows. First, studies investigating the relationship between fund flows and fund performance and the

[7] Investors who withdraw money will generate a cost to the fund and that cost will be borne mostly by the investors who stay in the funds.

effects of fund flows on market stability will be reviewed. Second, we will describe the investor heterogeneity between broker-sold channel and direct-sold channel in the literature. Finally, we develop the hypotheses on the shape of the flow-to-performance relationship between these two distribution channels and its potential effect on the market fragility.

2.2.1 Fund flow and past fund performance

In the mutual fund literature, one important strand of studies investigates the relationship between fund flows and fund performance. Within this area, numerous prior studies document a convex relation between fund flows and performance among equity mutual funds (see, e.g., Ippolito, 1992; Chevalier and Ellison, 1997; Lynch and Musto, 2003; Sirri and Tufano, 1998). For instance, Sirri and Tufano (1998) find that investors are more likely to make purchase decision based on fund past performance, i.e., buy funds with superior past performance, whereas fail to flee under-performed funds, showing an asymmetry in buying and selling behavior. The main implication of their findings is that when fund performance is good, the funds would experience a disproportionately larger amount of inflows, whereas poor performance is not followed by similarly large outflows.

Several studies offer explanations for the convex flow-to-performance relation in equity mutual funds. From a rational perspective, one explanation is that following poor fund performance, personnel replacement may take place. Lynch and Musto (2003) argue that the strategy or managers of poorly performing funds would be replaced and the current poor performance is expected to be non-persistent, consequently resulting in less sensitivity of fund outflows to poor performance. Similarly, Heinkel and Stoughton (1994) argue that fund managers will be fired unless they could beat the benchmark by a certain amount. A second explanation for the flow-to-performance relation is concerned with the participation costs. According to Huang et al. (2007), participation costs can be classified into information costs and transaction costs. To be specific, the information costs, for an individual investor, is the cost of collecting and analyzing fund information, whereas for a given fund, this means that fund past performance should be sufficiently good to overcome investors' participation barriers and attract investors as investors have different levels of financial sophistication. Taken together, higher information costs force investors to concentrate their investment portfolios in a relatively few funds with superior past performance. On the other hand, the transaction costs, i.e., the costs incurred in the buying and selling of funds, lead investors to expect a higher return. This suggests that investors would prefer to purchase funds with superior performance rather than those with medium level of past performance given that transaction cost is high. Thus, the participation costs theory suggests higher sensitivity of fund inflows to good performance (Huang et al., 2007). Similarly, Ferreira et al. (2012) find a more convex flow-to-performance relation in less developed financial markets because it is less convenient for investors in a less developed country to obtain information. This further confirms the participation cost explanation of Huang et al. (2007). In addition, from a behavioral perspective, Goetzmann and Peles (1997) attribute the flow-to-performance convexity to the cognitive dissonance of investors. In other words, investors tend to have biased perceptions and may overestimate the performance of their invested funds.

Relatively few empirical studies have investigated the flow-to-performance relation for fixed income mutual funds and their results are mixed. For example, Zhao (2005) documents that bond fund flows are related to risk-adjusted fund performance rather than raw returns. More recent studies begin to investigate the asymmetry in investors' subscription and redemption behaviors. For instance, Chen and Qin (2016) point out that investors' purchasing behavior of corporate bond funds with good performance is similar to their selling behaviors of funds with poor performance, implying that the flow-to-performance relation of corporate bond mutual funds is not as convex as in equity mutual funds. Furthermore, Goldstein et al. (2017) confirm the different patterns between bond and equity mutual funds, suggesting that corporate bond mutual funds exhibit a concave flow-to-performance relation, i.e., the sensitivity of outflows to bad performance is greater than the sensitivity of inflows to good performance. In addition, Leung and Kwong (2018) examine the flow-to-performance for bond mutual funds in the emerging market. The results show that past performance is a significant factor driving fund inflows when the fund return is positive while its influence vanishes when the return is negative, displaying a convex flow-to-performance relationship.

Goldstein et al. (2017) attribute the concave flow-to-performance relation in corporate bond mutual funds to the illiquidity of assets held by bond mutual funds and the strategic complementarities among individual investors. To be specific, unlike equity that investors typically trade many times throughout the day, corporate bonds are not traded frequently, whereas corporate bond mutual funds are highly liquid and allow investors to trade on a daily basis (Goldstein et al., 2017). This generates a liquidity mismatch between corporate bond mutual funds and their underlying assets. In general, for a given fund, investors' redemption behavior would hurt the fund performance. For example, Edelen (1999) argue that transaction costs caused by fund outflows lead to a negative abnormal fund return of up to -1.4% annually. Similarly, stocks sold by mutual funds due to liquidity needs experience a higher annual return of 1.55% than those sold through normal trading, which means that these underlying securities sold for liquidity reasons are underpriced (Alexander et al., 2007). Furthermore, redemption costs cannot be correctly reflected in fund net asset values as mutual funds generally make trades in response to these redemptions on the following day. Instead, these costs will be borne mostly by the investors who stay with the funds (Chen et al., 2010). In the case of corporate bond mutual funds, redemption behavior impose higher cost than equity funds that hold more liquid assets, which in turn, leads bond mutual fund investors face a higher degree of strategic complementarities. Thus, when corporate bond mutual funds experience poor performance, investor's redemption incentive will increase the expectation that other investors will take the same action, which leads to a multiplier effect and amplifies the fund outflows. In other words, the liquidity mismatch between corporate bond mutual funds and their underlying assets encourages investors to redeem their holdings early following poor fund performance in order to obtain a first-mover advantage. Consequently, the increase in the overall amount of redemptions following poor performance yields a concave flow-to-performance relation.

2.2.2 Asymmetry in Flow-to-performance relations and financial instability

All of the studies reviewed in the previous section provide insights into the two types of asymmetry in the relationship between fund flow and fund performance. Another strand of related studies expresses concern about the potential financial instability caused by asymmetry in flow-to-performance relations (see, e.g. Chevalier and Ellison, 1997; Feroli et al., 2014; Goldstein et al., 2017).

On the one hand, a convex relationship between fund flow and fund performance would incentivize the fund manager to take the excessive risk of their portfolios (Chevalier and Ellison, 1997). In this case, the high risk-taking strategy will reward the fund manager with a large amount of inflow for fund good performance, but will not result in substantial outflow for fund poor performance. This, in turn, could potentially influence the market stability by increasing the risk of asset bubbles.

On the other hand, a concave relationship between fund flow and fund performance may also have negative implications for financial stability. Given that fixed income mutual funds could provide liquidity transformation, these funds provide liquidity service by allowing daily redemptions and holding relatively illiquid assets, there is also a potential risk of runs when investors massively redeem shares of their funds. To be specific, massive redemptions create disruptions in the underlying assets of the fund, the cost will be borne by investors who remained in the fund (Chen et al., 2010).

Due to the anticipation and fear that outflows of other investors will generate costs for investors themselves, investors will have economic incentives to redeem ahead of the anticipated outflows, which is the first-mover advantage (Goldstein et al., 2017). This behavior will increase the overall amount of redemptions, resulting in the risk of runs. This is similar to the widespread withdrawal of investors in bank runs proposed by Diamond and Dybvig (1983). Thus, a negative shock may trigger a large scale of redemptions, which could result in investors' run behaviors and further worsen the negative shock as the liquidity transformation service is unable to be provided for everybody simultaneously.

Following the collapse of Lehman Brothers, existing literature on run-behavior risk has focused on commercial banks and money market mutual funds. For instance, Schmidt et al. (2016) document that such run-behavior risk mainly results from institutional investors, i.e., sophisticated investors, in money market mutual funds during the crisis. Also, this run-like phenomenon is more pronounced among funds holding relatively less liquid assets.

Unlike banks and money market mutual funds, corporate bond mutual funds have a floating net asset value, which means that investors are not guaranteed a minimum amount when they redeem their shares. This is to prevent the strategic complementarities among investors (Goldstein et al., 2017). However, it is not the case since investors can redeem their shares at any trading day and their redemption behavior would impose a negative externality on other investors remaining in the same funds. This, in turn, still generates strategic complementarities and could potential cause financial fragility.

More recently, several studies confirm that outflows of corporate bond funds may give rise to financial fragility. For example, Goldstein et al. (2017) provide evidence that the sensitivity of fund outflows to poor fund performance is greater in funds with less liquid asset holdings and during illiquid and stressed market conditions, implying potential run behaviors among fund investors. Furthermore, Feroli et al. (2014) find that an unexpected monetary policy shock would result in large outflows in fixed income mutual funds, with fund redemptions triggering a further reduction of fund returns. This implies that there is a feedback loop between decreasing fund returns and a large amount of fund outflows, which worsens the shocks and threatens financial stability.

Given this backdrop, regulators are drawing increasing concern about the impact of corporate bond fund on financial market stability. For instance, the expansion of corporate bond mutual funds are regarded as a potential threat to financial stability by the Financial Stability Oversight Council in its 2015 annual report (FSOC, 2015). Also, the Securities and Exchange Commission has published a new rule 22e-4, to promote effective liquidity risk management in the open-end mutual fund industry in 2017 (SEC, 2017). Similarly, the Financial Stability Board (FSB, 2017) also mentions that liquidity mismatch of open-end mutual funds is a potential structural vulnerability and provides several recommendation about the liquidity disclosure.

2.2.3 Mutual funds distribution channels and investor heterogeneity

A growing body of research examines the dynamics of fund flows of different types of investors (see, e.g., Del Guercio and Reuter, 2014; Keswani and Stolin, 2012). Some investigate the differential sensitivities of fund flows from institutional and retail investors to performance. Notably, Del Guercio and Tkac (2002) examine the flow-to-performance relations between mutual funds and pension funds, finding that retail investors' flows are more sensitive to fund performance than those of institutional investors. However, the authors document that only institutional investors would tend to withdraw assets from underperforming funds, revealing a less convex flow-to-performance pattern. Recent studies focus on the differences in fund flow dynamics among different categories of retail investors, including those who purchase funds through brokers and those purchase funds directly through fund underwriters (see, e.g., Bergstresser et al. 2009; Del Guercio and Reuter, 2014). Bergstresser et al. (2009) argue that brokers do not deliver tangible benefits to their investors as broker-sold funds underperform their direct-sold counterparts by more than the differences in distribution fees. Similarly, Del Guercio and Reuter (2014) confirm the underperformance of equity mutual funds actively managed by brokers. Del Guercio and Reuter (2014) also find that fund flows in the direct-sold channel are sensitive to the fund's risk-adjusted performance, whereas those of the broker-sold funds are sensitive to raw returns only. Such a difference in return-chasing behaviors suggests that direct-sold funds have more incentives to generate alpha and put more effort in portfolio management, whereas broker-sold funds have more incentive to improve the client service.

In the mutual fund industry, bond funds are sold through two main distribution channels, either directly from the fund underwriter or indirectly through a broker, and these two segments differ in several major ways. First, direct-sold funds only provide portfolio management services, and, thus, retail-sold fund investors have to make investment decisions based on their own research. Although all investors expect a higher after-fee return, advisory needs take precedence over the needs of maximizing fund returns for some investors. For example, professional advisors may help investors allocate or rebalance assets, and help investors ease their mind during extreme market situations (Del Guercio and Reuter, 2014). To target this type of investors, broker-sold funds provide investment advisory services and ongoing assistance for their investors. Second, the fee structure differs between direct- and broker-sold funds. Specifically, since broker-sold funds provide additional financial services to their investors, they charge more, in the form of sales loads and 12b-1 fees, to compensate their financial professionals (Reid and Rea, 2003). In general, broker-sold funds charge investors a one-time front load or rear load at the time of purchasing or redeeming funds based on different fund share classes, whereas direct-sold fund investors do not pay such fees. Furthermore, broker-sold funds charge higher 12b-1 fees as distribution or marketing costs from their investors than direct-sold funds. Third, the level of investors' financial sophistication differs between the direct- and broker-sold fund segments. Investors with more investment experience and financial knowledge may not need as much help and advice from brokers and advisors, and care more about risk-adjusted performance. As such, such investors are more likely to invest in direct-sold funds. On the other hand, due to a lack of investment experience and knowledge, novice and less-sophisticated investors place a greater value on the financial services provided by broker-sold funds and are therefore more likely to select broker-sold funds (Del Guercio et al., 2010; Hortacsu and Syverson, 2004).

Despite these differences between the two segments, existing studies on fixed income mutual funds have yet to explore how such heterogeneity in market segments may influence the relation between fund flow and performance. We fill this empirical gap and examine which retail market segments are more subject to the risks of fund runs and instability.

2.2.4 Hypotheses development

On the one hand, the flow-to-performance relation in the direct-sold fund may be more concave (or less convex) as direct-sold fund investors are sensitive to risk-adjusted performance (Del Guercio and Reuter, 2014) and may, therefore, react more strongly to poor performance than broker-sold fund investors. This is confirmed by Christoffersen and Musto (2002), who show that performance-sensitive investors leave funds with poor performance. Investor sophistication may also influence the relationship between fund flows and fund performance. Evans and Fahlenbrach (2012) argue that, because of their superior monitoring skills, institutional investors tend to be more responsive to poor risk-adjusted performance than their retail counterparts. These arguments suggest that poor performance would result in relatively more outflows from the direct-sold segment than the broker-sold segment.

Hypothesis 1a: *The flow-to-performance relation is more concave in the direct-sold segment*.

On the other hand, the flow-to-performance relation in broker-sold funds could be more concave, to the extent that brokers and advisors of broker-sold funds, who are compensated by the transaction-based sale loads, have incentives to advise investors to redeem from underperformed funds for increased compensations (Keswani and Stolin, 2012). Moreover, direct-sold fund investors may exhibit a weaker reaction to poor performance, as direct-sold funds have the incentives to invest more in portfolio management (Del Guercio and Reuter, 2014) and investors expect these funds to replace their strategy or managers subsequent to poor performance (Lynch and Musto, 2003). Moreover, from a behavioral perspective, well-informed individual investors who exhibit cognitive dissonance may resist poor performance that conflicts with their past investment decisions (Goetzmann and Peles, 1997). As such, direct-sold fund investors may react more slowly to poor performance than broker-sold fund investors who rely on the help and advice from brokers and advisors.

Hypothesis 1b: *The flow-to-performance relation is more concave in the broker-sold segment*.

2.2.5 Conclusion

To sum up, in this sub-section, we review the literature on the flow-to-performance relation in mutual funds and different distribution channels for mutual funds. Existing studies document that compared with equity mutual funds, the sensitivity of outflows to bad performance is greater than the sensitivity of inflows to good performance for corporate bond mutual funds, indicating a concave flow-to-performance relation. More importantly, the concave flow-to-performance relation for the corporate bond mutual fund has a potential run-behavior risk on the fragility of the financial market. Also, the investor heterogeneity between direct- and broker-sold segments leaves a question on the investors' sensitivity to fund performance. Thus, the shape of the flow-to-performance relations in the direct- and broker-sold distribution channels as well as which segment is more susceptible to fund runs are ultimately open empirical questions on which we intend to shed light.

2.3 Research design

In this sub-section, the first section introduces the data source used and discusses the sample selection process. Next, we discuss how we construct our key variables in detail. Finally, descriptive statistics are presented.

2.3.1 Data source and sample selection

To investigate the relationship between fund flow and fund performance in corporate bond mutual funds, we construct a large sample of corporate bond mutual funds using data collected from the CRSP Survivor-Bias-Free US Mutual Fund Database. Since monthly data of fund size is available only after 1991, our fund data cover the period from January 1991 to December 2017.[8] The unit of observation in our study is at the fund-share-class level.

To construct our sample, we apply the objective codes to identify corporate bond funds[9] and exclude all index funds, exchange traded funds, and exchange traded notes. In addition, we exclude institutional-oriented funds (that is, funds with more than 80% of their assets held by institutional share classes) from our sample because such funds are less subject to fund runs and thus are less likely to exhibit a concave

[8] Since alphas are estimated using data of the previous 12 months, the sample period for our main analysis on the flow-to-performance relation begins in January 1992.

[9] Specifically, a corporate bond fund is defined as the funds with a Lipper objective code of "A", "BBB", "HY", "SII", "SID", "IID", or a Strategic Insight objective code of "CGN", "CHQ", "CHY", "CIM", "CMQ", "CPR", "CSM", or a Wiesenberger objective code of "CBD", "CHY", or a CRSP objective code of "IC" as the first two characters.

flow-to-performance sensitivity.[10] Furthermore, we remove all institutional share classes in the remaining funds.[11] To avoid potential data biases, such as incubation biases associated with new and small funds, funds with age less than three and total net assets (TNA) less than $10 million are excluded from our sample (Chen and Qin, 2016; Evans, 2010). Also, we exclude fund share classes with missing values. Our final sample includes a total of 1,564 fund share classes from 833 corporate bond funds.

Since the CRSP database does not classify funds into direct- and broker-sold ones, we follow ICI (2018, p.131) and use front load, rear load, and 12b-1 fees to distinguish between the two types of funds.[12] Sun (2017) shows that this fee-based classification approach captures the distribution channel classification of Financial Research Corporation (FRC) with an 88-percent accuracy. Specifically, we define a retail fund share as direct-sold if it has neither front load nor rear load, and has an annual 12b-1 fee of no more than 25 bps, and as broker-sold otherwise.

2.3.2 Key variable construction

2.3.2.1 Mutual fund flows

Following the literature (see, e.g., Chen et al., 2008; Coval and Stafford, 2007; Goldstein et al., 2017), mutual fund flows are calculated as the percentage change in

[10] In institutional-oriented funds, institutional investors who are large and hold large proportion of fund assets are inclined to internalize the liquidation costs associated with their outflows and thus have less incentives to “run” the funds (Chen et al., 2010; Goldstein et al., 2017).

[11] Evans and Fahlenbrach (2012) define retail funds as those with only include retail share classes or those that have both retail and institutional share classes. Goldstein et al. (2017) find that outflows of retail-oriented funds are more sensitive to poor performance when market or fund is illiquid, while the outflow-to-poor-performance sensitivity for institutional-oriented funds do not significantly vary with the degree of fund liquidity and between illiquid and liquid periods. Our approach is more conservative than theirs.

[12] Previous paper of Del Guercio and Reuter (2014) uses FRC distribution channel indicator to classify broker-sold funds and direct-sold funds. However, historical data of fund distribution channel is not available since FRC is acquired by Strategic Insight.

the fund's TNA minus the percentage change in TNA due to fund return in a given month. Specifically, the net flow of a corporate bond fund *i* in month *t* is defined as:

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

where $R_{i,t}$ is the return of fund *i* over month *t* and $TNA_{i,t}$ is the TNA of fund *i* at the end of month t. To reduce the potential effect of outliers, fund flows are winsorized at the 1% and 99% levels.

2.3.2.2 Fund performance and factor models

To measure risk-adjusted fund performance, we use data of the past 12 months and estimate rolling-window regressions to estimate the monthly alphas for each bond fund. Following Elton et al. (1995) and Chen and Qin (2016), we estimate the four-factor model to measure the risk-adjusted performance of each fund:

$$R_{i,t} - R_{ft} = \alpha + \beta_1 STK_t + \beta_2 BOND_t + \beta_3 DEF_t + \beta_4 OPTION_t + e_t \quad (2)$$

where $R_{i,t}$ is the return of fund *i* over month *t*; R_{ft} is the risk-free rate proxied by the 30-days Treasury bill rate; *STK* is the excess return on the CRSP value-weighted stock index; *BOND* is the excess return on the Barclays US aggregate bond index; *DEF* is the return spread between the Barclays US high-yield bond index and the Barclays US intermediate government bond index; and *OPTION* is the return spread between the Barclays US mortgage-backed security index and the Barclays US intermediate government bond index. The estimated alpha represents the risk-adjusted performance for each fund. The bond indexes are collected from the Bloomberg database.

2.3.2.3 Measuring illiquidity

Following Goldstein et al. (2017), we use both market- and fund-based measures of liquidity. We use the VIX index from the Chicago Board Options Exchange (COBE) (Bao et al., 2011; Goldstein et al., 2017) and TED spreads, that is, the differences between the 3-month London Interbank Offered Rate (LIBOR) and the interest rate of

3-month Treasury bill (Goldstein et al., 2017), as proxies for aggregate market illiquidity.

In addition to the aggregate market illiquidity, we also measure liquidity at the fund level. Scholes (2000) argues that when liquidation problems arise fund managers tend to sell liquid assets first. Since cash represents the most liquid asset class, we use the percentage of cash holdings for each fund as a proxy for fund-level liquidity. For robustness, we also use the sum of cash and government bond holdings as an additional measure of fund liquidity.

2.3.3 Summary statistics

Table 2-1 provides the Descriptive statistics for our sample of corporate bond mutual funds. As Panel A of Table 2-1 shows, there are 462 (420) and 1,225 (612) fund share classes in the direct- and broker-sold segments, respectively. Panel B of Table 2-1 shows that the number of retail fund share classes increases dramatically during the period of 1992-2004 and stabilizes thereafter. The average total net assets (TNA) exhibits a continuous increase over the sample period, reflecting the growing importance of the retail corporate bond mutual fund industry. On average, there are more share classes of small funds in the broker-sold segment than in the direct-sold segment.

Figure 2-1 plots the average net flows for all retail funds and the two market segments, showing that they move in different directions most of the time, suggesting that investor behaviors may differ across the two types of funds. Notably, direct-sold funds experienced a dramatic inflows between 1996 and 1997. This might be related to the movement in interest rate. ICI (1996) documents that corporate bond mutual funds experience a weak fund flow due to the rising interest rates before 1995 when the Federal Reserve tightened monetary policy, whereas inflows have reversed outflows since 1996 due to the downward movement in interest rates.

Table 2-1 Descriptive statistics

This table reports descriptive statistics. Panel A describes the overall sample for all retail corporate bond funds, direct- and broker-sold segments. Panel B describes the number of share classes (funds) and average TNA in detail by the end of each year. The sample period is from January 1992 to December 2017.

Panel A: Descriptive statistics (full sample, direct- and broker-sold subsamples)

	Number of fund share classes	Number of funds	Observations
All retail	1,564	833	197,054
Direct-sold	462	420	49,589
Broker-sold	1,225	612	147,465

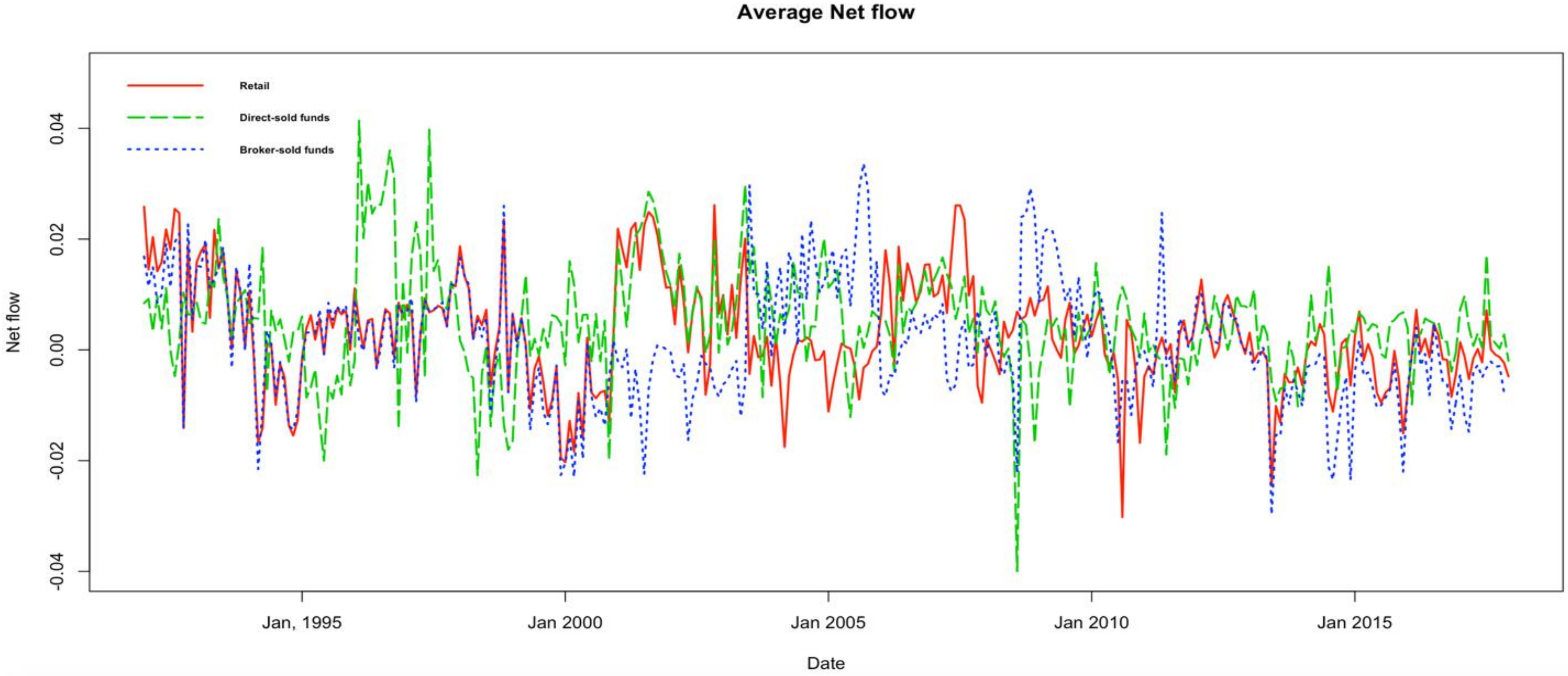
Panel B: Descriptive statistics by year (end of December)

	Number of share classes (funds)			Average TNA (millions)		
	All retail	Direct-sold	Broker-sold	All retail	Direct-sold	Broker-sold
1992	243 (221)	75 (75)	168 (147)	370.39	425.56	345.76
1993	298 (257)	94 (93)	204 (166)	402.36	397.69	404.51
1994	325 (274)	101 (101)	224 (175)	332.45	318.25	338.85
1995	383 (293)	120 (119)	263 (177)	348.23	326.42	358.18
1996	424 (316)	130 (128)	294 (192)	360.03	343.22	367.46
1997	471 (341)	150 (148)	321 (196)	391.05	352.58	409.03
1998	550 (385)	172 (170)	378 (220)	365.93	365.08	366.32
1999	593 (404)	180 (174)	413 (237)	335.96	354.81	327.75
2000	611 (409)	170 (168)	441 (247)	291.66	373.92	259.95
2001	689 (415)	161 (158)	528 (271)	308.50	459.73	262.38
2002	757 (428)	156 (151)	601 (295)	336.75	533.83	285.59
2003	811 (435)	156 (148)	655 (304)	387.70	636.22	328.51

2004	815 (431)	151 (142)	664 (311)	397.11	717.04	324.35
2005	781 (410)	147 (136)	634 (291)	402.94	755.59	321.18
2006	756 (401)	146 (137)	610 (281)	453.34	873.00	352.90
2007	760 (403)	149 (139)	611 (288)	500.90	1,062.77	363.88
2008	732 (385)	164 (143)	568 (274)	454.63	973.17	304.91
2009	800 (392)	188 (160)	612 (278)	630.01	1,202.6	454.12
2010	788 (385)	191 (165)	597 (272)	724.00	1,345.38	525.20
2011	741 (377)	191 (166)	550 (259)	793.64	1,379.81	590.08
2012	752 (383)	204 (175)	548 (263)	912.16	1,620.84	648.35
2013	734 (375)	198 (170)	536 (268)	879.70	1,594.55	615.64
2014	733 (379)	204 (179)	529 (270)	890.31	1,768.89	551.50
2015	708 (380)	195 (169)	513 (271)	862.75	1,845.73	489.11
2016	700 (380)	198 (169)	502 (272)	892.76	1,777.03	543.99
2017	650 (358)	182 (160)	468 (263)	967.68	1,784.55	650.02

Figure 2-1 Average net flows for retail corporate bond funds and direct- and broker-sold segments

Figure 3-1 shows the average net flow for retail corporate bond funds and its two market segments from January 1992 to December 2017. The red solid line, green long dashed line and blue dashed line represent the retail funds, direct-sold funds, broker-sold funds, respectively.



Panel A of Table 2-2 provides summary statistics for our corporate bond mutual fund sample from January 1992 to December 2017 and Panel B compares between the direct- and broker-sold funds. The average (median) fund flow and fund return for our sample are 0.66% (-0.32%) and 0.41% (0.43%).[13] The average (median) risk-adjusted performance and fund flows for the direct-sold funds are -0.04% (-0.02%) and 0.95% (0.02%), respectively, which are significantly higher than their broker-sold counterparts. However, the median monthly return associated with the direct channel (0.40%) is significantly lower than that of the broker-sold channel (0.45%). The direct-sold funds also have larger fund size and relative younger than the broker-sold funds. The fees charged by direct-sold funds are lower than those by broker-sold funds, with an average (median) expense ratio of 0.74% (0.74%) and 1.30% (1.25%) for these two distribution channels, respectively. Finally, direct-sold funds tend to hold more cash on average than the broker-sold funds (4.52% vs. 3.60%).

[13] This is similar to the study of Goldstein et al. (2017) in which the average (median) fund flow and fund return are 0.82% (-0.20%) and 0.42% (0.47%) during the sample period of 1992-2014. In addition, the summary statistics for other control variables, such as expense ratio, cash holding, are also comparable to Goldstein et al. (2017).

Table 2-2 Summary statistics

This table reports the summary statistics. Panel A shows various fund characteristics for our full sample of retail corporate bond funds. Panel B provides univariate comparison between direct-sold funds and broker-sold funds. Fund flow (%) is the percentage fund flow in a given month, Alpha (%) is the risk-adjusted performance which is the intercept of the four-factor model in equation (2) using the past 12 month of data, Return (%) is the monthly net return in percent, log TNA is the natural logarithm of fund total net asset (TNA), log Age is the natural logarithm of fund age in years, Expense ratio (%) is the fund expense ratio in percent, Front load (%) is the fund front load in percent, Rear load (%) is the fund rear load in percent, 12b-1 fee (%) is the fund 12b-1 fee in percent, Cash holdings (%) is the proportion of cash held by fund in percent.

Panel A: Summary statistics (full sample)

	Obs.	Mean	Stdev	0.25	Median	0.75
Fund flow (%)	196,793	0.66	6.03	-1.82	-0.32	1.63
Alpha (%)	191,742	-0.06	0.34	-0.15	-0.05	0.05
Return (%)	197,054	0.41	1.75	-0.18	0.43	1.14
log TNA	197,054	4.82	1.57	3.59	4.62	5.85
log Age	197,054	2.10	0.77	1.61	2.20	2.71
Expense ratio (%)	197,054	1.16	0.47	0.81	1.05	1.58
Front load (%)	197,054	0.77	1.15	0	0	1.96
Rear load (%)	197,054	0.37	0.64	0	0	0.33
12b-1 fee (%)	197,054	0.41	0.39	0	0.25	0.84
Cash holdings (%)	197,054	3.83	11.36	0.60	2.83	5.73

Table 2-2 - continued

Panel B: Univariate comparison

	Direct-sold			Broker-sold			Difference			
	N	Mean	Median	N	Mean	Median	Mean	sig.	Median	sig.
Fund flow (%)	49,501	0.95	0.02	147,292	0.57	-0.47	0.000	***	0.000	***
Alpha (%)	47,965	-0.04	-0.02	143,777	-0.07	-0.06	0.000	***	0.000	***
Return (%)	49,589	0.41	0.40	147,465	0.40	0.45	0.333		0.000	***
log TNA	49,589	5.19	4.96	147,465	4.70	4.51	0.000	***	0.000	***
log Age	49,589	2.05	2.20	147,465	2.12	2.30	0.000	***	0.000	***
Expense ratio (%)	49,589	0.74	0.74	147,465	1.30	1.25	0.000	***	0.000	***
Front load (%)	49,589	0.00	0.00	147,465	1.03	0	0.000	***	0.000	***
Rear load (%)	49,589	0.00	0.00	147,465	0.50	0.33	0.000	***	0.000	***
12b-1 fee (%)	49,589	0.05	0.00	147,465	0.53	0.35	0.000	***	0.000	***
Cash holdings (%)	49,589	4.52	2.82	147,465	3.60	2.84	0.000	***	0.000	***

2.4 Findings and discussions

2.4.1 The flow-to-performance relation

In this section, we first analyze whether the sensitivity of fund flows to fund performance differs significantly between the direct- and broker-sold funds using the following regression:

$$Flow_{i,t} = \alpha + \beta_1 Alpha_{i,t-12\rightarrow t-1} + \gamma Control_{i,t} + e_{i,t} \qquad (3)$$

where $Flow_{i,\,t}$ is the net flow of fund i in month t, estimated by equation (1); $Alpha_{i,\,t-12\rightarrow t-1}$ is the risk-adjusted performance of fund i, the intercept of the four-factor model of equation (2) using data of the past 12 months; $Control_{i,t}$ is a vector of control variables, including net flows in the previous month, the natural logarithm of fund TNA, age, and expense ratios. Month fixed effects are included and standard errors are clustered at the fund-share-class level.

Table 2-3 reports the regression results. Column (1) shows that risk-adjusted performance is positively and significantly associated with fund flows. Columns (3) and (5) show that investors of both direct- and broker-sold funds chase risk-adjusted performance: coefficients for alphas are 1.713 and 0.894, respectively. This implies that a one-standard-deviation increase in alpha is expected to increase fund size by approximately 47.86 million dollars in the direct-sold channel and 16.24 million dollars in the broker-sold channel, respectively.[14] Therefore, relatively less revenue from portfolio management is expected in broker-sold funds than in direct-sold funds. Furthermore, the difference in coefficients for alpha between the two segments is 0.819 and statistically significant, suggesting that investors of the direct-sold funds are more sensitive to risk-adjusted performance than those of the broker-sold funds.

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[14] The approximately increase in fund size in the following one year is calculated as follow, the standard deviations of alpha are 0.24% and 0.36% for direct- and broker-sold funds, and the mean TNA for two segments are 970.2 million and 420.5 million, thus, the increase in fund size for direct-sold funds is 1.713 * 0.24% * 12 * 970.8 and for broker-sold funds is 0.894 * 0.36% * 12 * 420.5.

Using a sample of equity funds, Del Guercio and Reuter (2014) find that flows of broker-sold funds are more sensitive to raw returns, whereas those of the direct-sold funds are more sensitive to the four-factor alpha. Their results suggest a difference in return-chasing behavior between investors of the two market segments. Motivated by this evidence, we test the relation between fund flow and raw returns by replacing fund alpha in equation (6) with raw returns.

The results are reported in columns (2), (4), and (6). The coefficient on net return in column (2) is positive (0.050) and significant (*t*-value = 3.24), implying that retail investors chase raw returns. However, columns (4) and (6) show that the flow-to-net-return sensitivity is only significant in the broker-sold segment. Moreover, the coefficient for net returns is significantly different across the broker- (0.065) and direct-sold (-0.092) segments.

Overall, our results suggest that investors in both direct- and broker-sold funds are sensitive to risk-adjusted performance, but the sensitivity of fund flows to risk-adjusted performance is significantly stronger in direct-sold funds. We also find that broker-sold fund investors are sensitive only to fund net returns. Our results are consistent with the findings of Del Guercio and Reuter (2014), implying that broker-sold fund investors are less financially sophisticated and may not fully appreciate the differences between risk-adjusted and raw returns. In addition, the different reactions to risk-adjusted performance and net returns between these two types of investors confirm our assumption about the investor heterogeneity across direct- and broker-sold segments, which lays a foundation for the following empirical tests.

Table 2-3 Flow to performance relations

This table reports the regression results of the flow-to-performance relations. The dependent variable is monthly net fund flow. The main independent variables are fund alpha of past 12 months in columns (1), (3), (5), and fund net return in the previous month in columns (2), (4), (6). Other independent variables include fund net flows in the previous month, the natural logarithm of fund age in years, the natural logarithm of fund TNA, fund expense ratios. Month fixed effects are included. T-statistics based on fund-share-class-clustered standard errors are reported in parentheses. The sample period is from January 1992 to December 2017. ***, ** and * denote the statistical significance at the level of 1%, 5% and 10%, respectively.

	Net flow					
Sample	All retail		Direct-sold funds		Broker-sold funds	
	(1)	(2)	(3)	(4)	(5)	(6)
Alpha	1.033***		1.713***		0.894***	
	(6.13)		(7.11)		(5.18)	
Net return (t-1)		0.050***		-0.092		0.065***
		(3.24)		(-1.29)		(4.30)
Lagged net flows	0.339***	0.387***	0.191***	0.243***	0.403***	0.449***
	(26.02)	(31.35)	(8.73)	(10.93)	(30.52)	(37.66)
Log(Age)	-0.012***	-0.014***	-0.014***	-0.016***	-0.011***	-0.013***
	(-21.86)	(-23.80)	(-12.63)	(-12.68)	(-18.91)	(-21.70)
Log(TNA)	0.000***	0.000***	0.001	0.000	0.000**	0.000***
	(3.70)	(3.06)	(1.57)	(0.73)	(2.73)	(2.78)
Expense	-0.330***	-0.330***	-0.165	-0.279	-0.351***	-0.340***
	(-6.07)	(-6.36)	(-0.55)	(-0.87)	(-5.58)	(-5.79)
The difference in coefficient of lagged net flows between direct- and broker-sold funds					-0.212***	-0.206***
					(-8.33)	(-8.22)
The difference in coefficient of lagged net return between direct- and broker-sold funds						-0.157**

						(-2.17)
The difference in coefficient of alpha between direct- and broker-sold funds					0.819***	
					(2.77)	
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.156	0.210	0.061	0.097	0.206	0.268
Obs.	191,103	196,475	47,785	49,399	143,318	147,076

2.4.2 Non-linearity in the flow-to-performance relation

Although we find that investors in the direct-sold segment are more sensitive to risk-adjusted performance than their broker-sold counterparts, the question of whether the relation of question is linear in both segments remains unexplored. In this section, we explore whether investors in both segments react to poor performance in a similar way as good performance. To test this, we formulate the following regression model following Goldstein et al. (2017)[15]:

$$Flow_{i,t} = \alpha + \beta_1 Alpha_{i,t-12\to t-1} + \beta_2 Alpha_{i,t-12\to t-1} \times D\left(Alpha_{i,t-12\to t-1} < 0\right) + \beta_3 D\left(Alpha_{i,t-12\to t-1} < 0\right) + \gamma Control_{i,\,t} + e_{i,\,t} \tag{4}$$

where $D\left(Alpha_{i,\ t-12\to t-1} < 0\right)$ is a dummy that equals one if fund i's alpha is negative and zero otherwise; all other variables are as defined previously. The interaction term $Alpha_{i,t-12\to t-1} \times D\left(Alpha_{i,t-12\to t-1} < 0\right)$ is our main variable of interest. A positive (negative) β_2 indicates a greater sensitivity of outflows (inflows) to poor (good) performance, that is, a concave (convex) flow-to-performance relation. Month fixed effects are included and standard errors are clustered at the fund-share-class level.

Table 2-4 reports the regression results. Column (1) reports the full-sample results. Unlike the usual convex relation found in equity mutual funds, we document a concave flow-to-performance relation for retail corporate bond funds, entirely consistent with those reported by Goldstein et al. (2017). Specifically, the estimated coefficient of the interaction term is positive (0.471) and significant, suggesting that the sensitivity of outflows to poor performance is more than two times as strong as the sensitivity of inflows to good performance (0.858 versus 0.387). Columns (2) and (3)

[15] We also conduct a test for the non-linearity relation between fund flow and net returns, the results are similar. In subsequent sections, we report results based on risk-adjusted performance as it is a better measure of managerial performance.

report the results for the direct- and broker-sold segments, respectively. The coefficient of the interaction term is insignificant for the direct-sold segment and significantly positive for the broker-sold segment. These findings indicate that the flow-to-performance relation is linear in the direct-sold segment but is concave for the broker-sold funds. For the broker-sold funds, the sensitivity of outflows to poor performance is 0.799 (0.524 + 0.275), which is almost three times as strong as the sensitivity of inflows to good performance.

Taken together, our results suggest that the sensitivity of outflow to poor performance is stronger than the sensitivity of inflow to good performance for retail corporate bond funds, that is, a concave flow-to-performance relation. This is consistent with the findings of Goldstein et al. (2017). Such a concave relation is only present among the broker-sold funds. This result supports the hypothesis *1b*, suggesting that brokers and advisors of broker-sold funds might play a role in the concave flow-to-performance relation through advise investors to redeem from underperformed funds.

Table 2-4 Flow to performance relations (non-linearity)

This table reports the regression results of the non-linearity in flow-to-performance relations. The dependent variable is monthly net fund flow. The independent variables include fund alpha of past 12 months, the interaction term between fund alpha and negative alpha dummy, fund net flows in the previous month, the natural logarithm of fund age in years, the natural logarithm of fund TNA, fund expense ratios. The negative alpha dummy equals one if the fund alpha is negative and zero otherwise. Month fixed effects are included. T-statistics based on fund-share-class-clustered standard errors are reported in parentheses. The sample period is from January 1992 to December 2017. ***, ** and * denote the statistical significance at the level of 1%, 5% and 10%, respectively.

	Net flow		
Sample	All retail	Direct-sold	Broker-sold
	(1)	(2)	(3)
Alpha	0.387	1.216***	0.275
	(1.53)	(3.15)	(1.17)
Alpha × Negative Alpha	0.471*	-0.092	0.524**
	(1.69)	(-0.19)	(2.01)
Negative Alpha	-0.006***	-0.005***	-0.005***
	(-10.96)	(-5.52)	(-10.05)
Lagged net flows	0.336***	0.189***	0.400***
	(25.90)	(8.66)	(30.36)
Log(Age)	-0.012***	-0.014***	-0.010***
	(-21.80)	(-12.68)	(-18.76)
Log(TNA)	0.000***	0.001	0.000**
	(3.04)	(1.47)	(1.97)
Expense	-0.287***	-0.151	-0.309***
	(-5.23)	(-0.51)	(-4.88)
The difference in coefficient of alpha × negative alpha between direct- and broker-sold funds			-0.616
			(-1.13)
Month FE	Yes	Yes	Yes
Adj. R^2	0.157	0.062	0.208
Obs.	191,103	47,785	143,318

2.4.3 The role of illiquidity

In the previous section, we find that the sensitivity of outflows to poor performance in retail corporate bond funds is mainly driven by the broker-sold segment. This leads to the concern that a negative shock may trigger large redemptions, consequently resulting in run behaviors, amplifying the impact of negative shocks, and threatening market stability. In this section, we examine the effect of illiquidity on investors' redemption behavior.

2.4.3.1 Market-level illiquidity

We first examine the effect of market illiquidity on the outflow-to-poor-performance relation. Since we focus on the investors' redemption behaviors, we estimate the following regression for the subsample of funds that have negative alphas in time *t-1*:

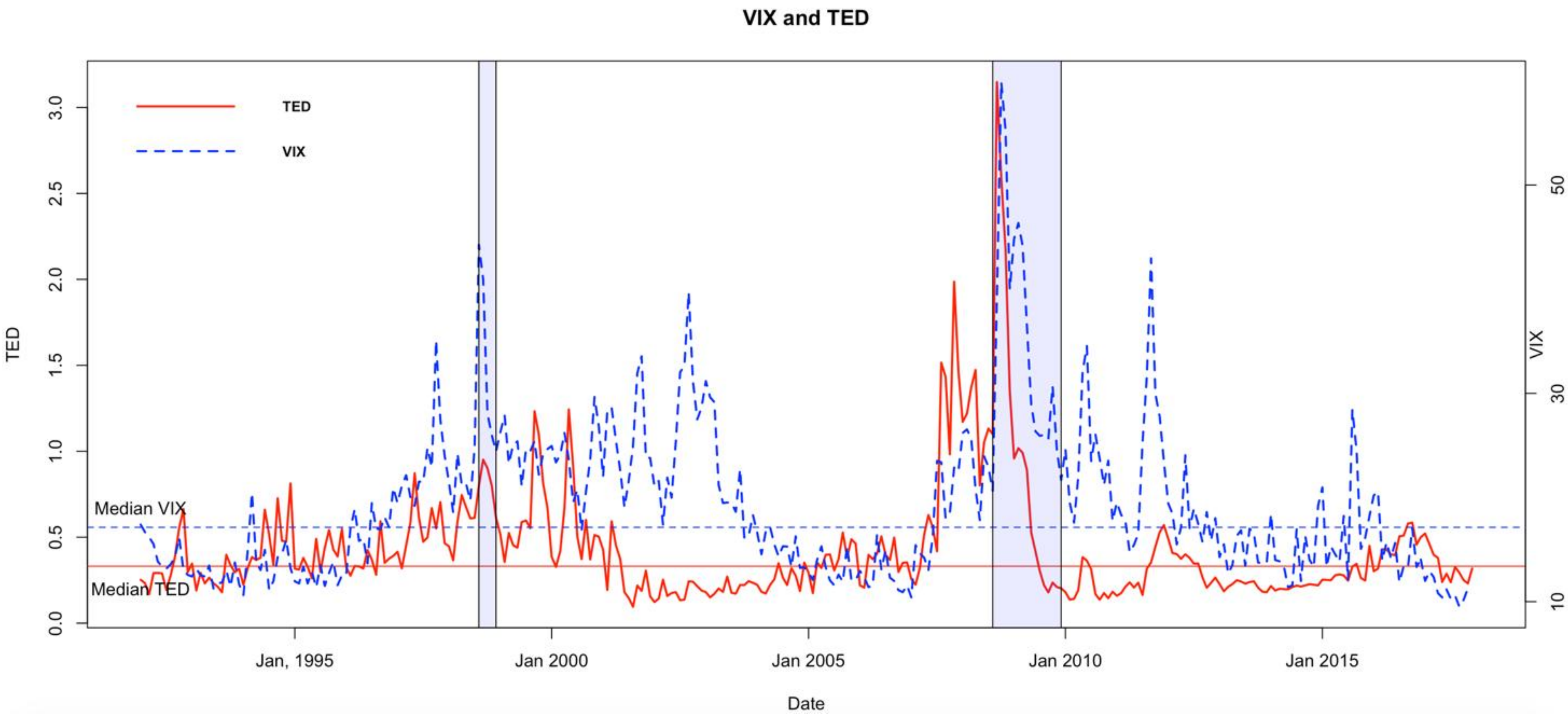
$$Flow_{i,t} = \alpha + \beta_1 Alpha_{i,t-12\to t-1} + \beta_2 Alpha_{i,t-12\to t-1} \times Market\ illiquidity_{i,t} + \beta_3 Market\ illiquidity_{i,t} + \gamma Control_{i,t} + e_{i,t} \quad (5)$$

where $Market\ illiquidity_{i,t}$ is a dummy variable equal to one if the proxy for corporate bond market illiquidity is above the sample median and zero otherwise; both the VIX index and TED spreads are used as proxies for market illiquidity; all other variables are as defined previously. The interaction term $Alpha_{i,t-12\to t-1} \times Market\ illiquidity_{i,t}$ is our main variable of interest. A positive (negative) β_2 indicates that outflows are more (less) sensitive to poor performance during illiquid periods. We cluster standard errors at the fund-share-class level.

Figure 2-2 plots the VIX index and TED spreads from January 1992 to December 2017. The illiquid periods (above-sample medians) are consistent across the two proxies. Further, both the VIX index and TED spreads are considerably higher during financial crises, especially the recent global financial crisis.

Figure 2-2 VIX and TED spreads

Figure 2-2 shows the VIX and TED spreads from January 1992 to December 2017. The red solid line and blue dashed line represent TED spreads and VIX, respectively. The horizontal lines show the sample median of VIX and TED spreads and the shaded regions represent the crisis period.



Panel A of Table 2-5 reports the estimation for equation (5). Columns (1) to (3) present the results based on the VIX index as a proxy of market illiquidity. Column (1) shows that market illiquidity does not affect the relation between outflows and poor performance in retail corporate bond funds. Columns (2) and (3) report results for the direct- and broker-sold segments, respectively. Broker-sold funds exhibit a greater sensitivity of outflows to poor performance during illiquid periods, with a 1% decrease in risk-adjusted performance leading to 0.503% (0.178 + 0.325) increase in fund outflows. Interestingly, the effect of poor performance on outflows in broker-sold funds disappears during the period with above-median liquidity. By contrast, we find that the sensitivity of outflow to poor performance is weaker during illiquid periods (0.257 for high-VIX vs. 1.497 for low-VIX) for direct-sold funds. We also find that the difference in outflow-to-poor-performance sensitivity during illiquid periods between the direct- and broker-sold segments is statistically significant at 5% significant level.

Next, the results based on TED spreads are reported in columns (4) to (6). As shown in column (5), the coefficient on the interaction term between alpha and TED spreads is insignificant, suggesting that the outflow-to-poor-performance sensitivity does not depend on market illiquidity in the direct-sold funds. However, results in column (6) show that broker-sold funds experience higher sensitivity of outflows to poor performance during illiquid periods (0.383 for high-TED vs. 0.054 for low-TED).

Since illiquidity indicators capture most of the past crises (Ben-Rephael, 2017), we perform further tests to isolate the effect of illiquidity from that of crises on the sensitivity of outflows to poor performance. We include a crisis dummy that equals one for the Long-term Capital Management (LTCM) crisis between August and December 1998 (Fahlenbrach et al., 2012; Goldstein et al., 2017) and the global financial crisis between August 2008 and December 2009, and zero otherwise. As Panel B of Table 2-5 shows, after controlling for the crisis effects, market illiquidity remains significant in determining the sensitivity of outflows to poor performance only among the broker-sold funds.

Overall, we find that the sensitivity of outflow to poor performance is higher for broker-sold funds during illiquid periods, consistent with the view that large redemptions and run behaviors may occur in the broker-sold segment when market conditions are unfavorable.

Table 2-5 Market illiquidity effect on flow-to-performance relations

This table reports the regression results of the market illiquidity effect on flow-to-performance relations for subsample of fund records with negative alpha. The dependent variable is monthly net fund flow. The independent variables include fund alpha of past 12 months, the interaction term between fund alpha and the dummy variable for market illiquidity, fund net flows in the previous month, the natural logarithm of fund age in years, the natural logarithm of fund TNA, fund expense ratios. The dummy of market illiquidity equals one if the market illiquidity proxy is above the sample median and zero otherwise, market illiquidity proxies includes VIX and TED spreads. In panel B, we also control the interaction variable between fund alpha and crisis dummy. The crisis dummy is equal to one during the period between August and December 1998 (the LTCM crisis) and the period between August 2008 and December 2009 (the financial crisis) and zero otherwise. T-statistics based on fund-share-class-clustered standard errors are reported in parentheses. The sample period is from January 1992 to December 2017. ***, ** and * denote the statistical significance at the level of 1%, 5% and 10%, respectively.

Panel A: VIX + TED

	Net flow					
Sample	All retail	Direct-sold	Broker-sold	All retail	Direct-sold	Broker-sold
Alpha < 0	(1)	(2)	(3)	(4)	(5)	(6)
Alpha	0.402***	1.497***	0.178	0.067	0.155	0.054
	(2.64)	(3.28)	(1.07)	(0.56)	(0.34)	(0.53)
Alpha × VIX	0.083	-1.240**	0.325*			
	(0.49)	(-2.14)	(1.84)			
VIX	0.006***	0.001	0.007***			
	(16.16)	(1.20)	(16.85)			
Alpha × TED				0.371***	0.583	0.329***
				(2.71)	(1.06)	(2.69)
TED				0.000	0.001	0.000
				(0.72)	(0.97)	(0.30)
Lagged net flows	0.333***	0.168***	0.401***	0.337***	0.168***	0.408***
	(50.17)	(13.59)	(51.97)	(51.00)	(13.61)	(53.09)
Log(Age)	-0.009***	-0.010***	-0.008***	-0.009***	-0.010***	-0.008***

	(-37.23)	(-18.92)	(-31.02)	(-37.35)	(-18.62)	(-31.42)
Log(TNA)	0.000***	0.001***	0.000***	0.000***	0.001***	0.000***
	(4.80)	(3.80)	(3.22)	(4.23)	(3.59)	(2.91)
Expense	-0.243***	0.096	-0.242***	-0.255***	0.049	-0.235
	(-6.95)	(0.50)	(-5.97)	(-7.29)	(0.26)	(-5.82)
The difference in coefficient of alpha × VIX			-1.565**			
between direct- and broker-sold funds			(-2.57)			
The difference in coefficient of alpha × TED						0.254
between direct- and broker-sold funds						(0.40)
Adj. R^2	0.148	0.049	0.205	0.145	0.048	0.201
Obs.	122,606	28,331	94,275	122,606	28,331	94,275

Table 2-5 - continued

Panel B: VIX and TED + Crisis

Sample	All retail	Direct-sold	Broker-sold	All retail	Direct-sold	Broker-sold
Alpha < 0	(1)	(2)	(3)	(4)	(5)	(6)
Alpha	0.418***	1.518***	0.192	0.184	0.717**	0.108
	(2.74)	(3.33)	(1.16)	(1.50)	(2.13)	(0.89)
Alpha × VIX	0.198	-0.631	0.376**			
	(1.15)	(-1.13)	(2.06)			
VIX	0.005***	0.001	0.006***			
	(13.97)	(1.43)	(14.34)			
Alpha × TED				0.401***	0.660	0.360***
				(2.92)	(1.29)	(2.82)
TED				-0.000	0.000	-0.001*

				(-1.36)	(0.45)	(-1.75)
Alpha × Crisis	0.040	-1.061	0.224	0.285	-1.141	0.508***
	(0.22)	(-1.33)	(1.58)	(1.61)	(-1.54)	(3.67)
Crisis	0.006***	0.003	0.007***	0.010***	0.004*	0.011***
	(7.24)	(1.24)	(7.91)	(11.59)	(1.93)	(12.65)
Lagged net flows	0.331***	0.167***	0.399***	0.334***	0.167***	0.403***
	(50.03)	(13.51)	(51.83)	(50.64)	(13.50)	(52.69)
Log(Age)	-0.009***	-0.011***	-0.008***	-0.009***	-0.011***	-0.009***
	(-37.78)	(-19.16)	(-31.52)	(-38.38)	(-19.09)	(-32.35)
Log(TNA)	0.001***	0.001***	0.000***	0.000***	0.001***	0.000***
	(5.30)	(3.89)	(3.76)	(5.02)	(3.74)	(3.74)
Expense	-0.232***	0.121	-0.230***	-0.240***	0.097	-0.225***
	(-6.61)	(0.63)	(-5.68)	(-6.87)	(0.51)	(-5.56)
The difference in coefficient of alpha × VIX between direct- and broker-sold funds			-1.007* (-1.73)			
The difference in coefficient of alpha × TED between direct- and broker-sold funds						0.300 (0.48)
The difference in coefficient of alpha × Crisis between direct- and broker-sold funds			-1.285* (-1.86)			-1.649** (-2.49)
Adj. R^2	0.149	0.050	0.206	0.147	0.049	0.203
Obs.	122,606	28,331	94,275	122,606	28,331	94,275

2.4.3.2 Fund-level illiquidity

In addition to proxies of market illiquidity, in this section we examine whether fund-specific illiquidity determines the sensitivity of outflows to poor performance. To this end, we perform the following regression on the subsample of funds with negative alphas:

$$Flow_{i,t} = \alpha + \beta_1 Alpha_{i,t-12\to t-1} + \beta_2 Alpha_{i,t-12\to t-1} \times Fund\ illiquidity_{i,t} + \beta_3 Fund\ illiquidity_{i,t} + \gamma Control_{i,t} + e_{i,t} \quad (6)$$

Where $Fund\ illiquidity_{i,t}$ is a dummy that equals one if our fund illiquidity measure is below the 25th quantile within an investment style in a given month, and zero otherwise[16]; we use both cash holdings and the holdings of cash and government bonds to capture fund illiquidity; all other variables are as defined previously. The interaction term $Alpha_{i,t-12\to t-1} \times Fund\ illiquidity_{i,t}$ is our main variable of interest. A positive (negative) β_2 indicates that outflows are more (less) sensitive to poor performance for illiquid funds. Month fixed effects are included and standard errors are clustered at the fund-share-class level. Because Lipper objective codes are only available from 1999 onwards, the sample we use for this set of tests covers the period from January 1999 to December 2017.

The results are presented in Table 2-6. Columns (1) to (3) report the regression results based on cash holdings. Column (1) shows the full-sample results that funds with high cash holdings exhibit lower sensitivity of outflows to poor performance than those with low cash holdings. A 1% decrease in alpha increases outflows from funds with high (low) level of cash by 0.930% (1.476%). Comparing the relation between cash holdings and outflow-to-poor-performance sensitivity between the direct- and broker-sold funds, we find little evidence of significant difference between the two market segments. However, in the broker-sold segment, we find that low cash funds

[16] To allow fund holdings information to be available to the public, our fund illiquidity measure is constructed using holdings data in the previous month. The investment style is defined using fund Lipper objective codes.

experience 76.6 percent (1.524 vs. 0.863) more outflows after poor performance than their high cash counterparts.

Columns (4) to (6) reports the results based on the holdings of cash and government bonds. Similar to the results in columns (1) to (3), we find that the effect of poor performance on outflows is more pronounced in broker-sold funds with low liquidity, as measured by holdings of cash and government bonds.

Table 2-6 Fund illiquidity effect on flow to performance relations

This table reports the regression results of the fund illiquidity effect on flow-to-performance relations for subsample of fund records with negative alphas. The dependent variable is monthly net fund flow. The independent variables include fund alpha of past 12 months, the interaction term between fund alpha and the dummy variable for fund illiquidity, fund net flows in the previous month, the natural logarithm of fund age in years, the natural logarithm of fund TNA, fund expense ratios. We use fund cash holding and fund holdings of cash and government bonds to capture the fund illiquidity, the dummy of fund illiquidity equals one if the fund liquid asset holdings is below the 25th quantile within the same investment style in each month and zero otherwise. Month fixed effects are included. T-statistics based on fund-share-class-clustered standard errors are reported in parentheses. The sample period is from January 1999 to December 2017. ***, ** and * denote the statistical significance at the level of 1%, 5% and 10%, respectively.

	Net flow					
Sample	All retail	Direct-sold	Broker-sold	All retail	Direct-sold	Broker-sold
Alpha < 0	(1)	(2)	(3)	(4)	(5)	(6)
Alpha	0.930***	1.183***	0.863***	0.965***	1.368***	0.909***
	(6.96)	(3.09)	(6.42)	(7.11)	(3.41)	(6.62)
Alpha × Cash	0.546***	-0.470	0.660***			
	(2.67)	(-0.35)	(3.55)			
Cash	-0.002***	-0.004**	-0.001**			
	(-2.86)	(-2.14)	(-2.35)			
Alpha × Cash & Govt				0.325	-1.403	0.395**
				(1.58)	(-1.29)	(1.96)
Cash & Govt				-0.002**	-0.004**	-0.001**
				(-2.51)	(-2.26)	(-2.10)
Lagged net flows	0.300***	0.156***	0.362***	0.300***	0.157***	0.362***
	(19.60)	(5.85)	(23.51)	(19.62)	(5.86)	(23.54)
Log(Age)	-0.009***	-0.012***	-0.008***	-0.009***	-0.012***	-0.008***
	(-15.00)	(-8.76)	(-13.34)	(-14.96)	(-8.77)	(-13.30)
Log(TNA)	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***

	(4.58)	(2.86)	(3.82)	(4.55)	(2.86)	(3.78)
Expense	-0.344***	0.486	-0.373***	-0.349***	0.488	-0.376***
	(-5.24)	(1.23)	(-5.04)	(-5.33)	(1.23)	(-5.09)
The difference in coefficient of alpha × cash between direct- and broker-sold funds			-1.130			
			(-0.83)			
The difference in coefficient of alpha × cash & govt between direct- and broker-sold funds						-1.798
						(-1.61)
Month FE	YES	YES	YES	YES	YES	YES
Adj. R^2	0.124	0.039	0.171	0.124	0.039	0.170
Obs.	103,997	22,921	81,076	103,997	22,921	81,076

2.4.3.3 The complementary effect of fund and market illiquidity

In this section, we further test whether market and fund illiquidity complement each other in determining the sensitivity of flows to poor performance. We divide sample funds into two groups based on the sample median of their holdings of cash and government bonds and estimate the flow regression of equation (5).

Table 2-7 reports the results. In Panel A, columns (1) and (2) report the results for the full sample and show that a 1% decrease in alpha leads to a 0.451% (0.484 – 0.033) increase in outflows during illiquid periods (based on the VIX index) for illiquid funds. Furthermore, the effect of market illiquidity on outflow-to-poor-performance sensitivity is insignificant for their liquid counterparts. In columns (3) and (4) of Panel A, we find that the effect of market illiquidity on the flow-to-performance relation is not significantly different across the liquid and illiquid funds within the direct-sold segment. Columns (5) and (6) show the results for the broker-sold funds. The effect of market illiquidity as measured by the VIX index on the outflow-to-poor-performance relation is only significant for the illiquid funds. Specifically, outflows increase by 0.432% (0.420 + 0.012) given a 1% decrease in alpha. We also examine the effect of market illiquidity measured by the TED spreads in panel B of Table 2-7, finding consistent results.

Overall, our results show that market and fund illiquidity complement each other in determining the sensitivity of outflow to poor performance in the broker-sold segment, consistent with the widespread stability concerns about fixed income mutual funds.

Table 2-7 The flow-to-performance relation of illiquid funds during illiquidity periods

This table reports the regression results of the joint effect of market and fund illiquidity on flow-to-performance relations for subsample of fund records with negative alphas. We split funds into high and low cash and government bond holdings subsamples for all retail corporate bond funds, retail-sold segment and broker-sold segment. We further run the regression in which the dependent variable is monthly net fund flow and the independent variables include fund alpha of past 12 months, the interaction term between fund alpha and the dummy variable for market illiquidity, fund net flows in the previous month, the natural logarithm of fund age in years, the natural logarithm of fund TNA, fund expense ratios. The dummy of market illiquidity equals one if the market illiquidity proxy is above the sample median and zero otherwise, market illiquidity proxies includes VIX and TED spreads. T-statistics based on fund-share-class-clustered standard errors are reported in parentheses. The sample period is from January 1992 to December 2017. ***, ** and * denote the statistical significance at the level of 1%, 5% and 10%, respectively.

Panel A: VIX

	Net flow					
Sample	All retail		Direct-sold		Broker-sold	
Alpha < 0	High cash & govt holdings	Low cash & govt holdings	High cash & govt holdings	Low cash & govt holdings	High cash & govt holdings	Low cash & govt holdings
	(1)	(2)	(3)	(4)	(5)	(6)
Alpha	0.860***	-0.033	2.258***	1.051*	0.361	0.012
	(4.06)	(-0.16)	(3.07)	(1.85)	(1.55)	(0.06)
Alpha × VIX	-0.369	0.484**	-1.487	-1.066	0.215	0.420*
	(-1.56)	(2.14)	(-1.37)	(-1.55)	(0.88)	(1.81)
VIX	0.006***	0.006***	0.000	0.002	0.007***	0.006***
	(11.43)	(11.72)	(0.03)	(1.15)	(13.66)	(10.96)
Lagged net flows	0.291***	0.344***	0.131***	0.186***	0.386***	0.380***
	(31.70)	(36.94)	(7.54)	(10.90)	(35.87)	(34.99)
Log(Age)	-0.009***	-0.008***	-0.011***	-0.009***	-0.008***	-0.008***
	(-28.30)	(-23.95)	(-13.37)	(-12.39)	(-22.95)	(-21.10)

Log(TNA)	0.001***	0.001***	0.001**	0.002***	0.001***	0.000***
	(7.07)	(5.03)	(2.08)	(4.97)	(6.32)	(3.28)
Expense	-0.082	-0.310***	-0.127	0.456*	0.002	-0.405***
	(-1.60)	(-6.70)	(-0.42)	(1.91)	(0.04)	(-7.33)
Adj. R^2	0.123	0.160	0.038	0.055	0.199	0.193
Obs.	61,525	60,602	14,119	14,114	47,800	46,094

Table 2-7 – continued

Panel B: TED						
Sample	All retail		Direct-sold		Broker-sold	
Alpha < 0	High cash & govt holdings	Low cash & govt holdings	High cash & govt holdings	Low cash & govt holdings	High cash & govt holdings	Low cash & govt holdings
	(1)	(2)	(3)	(4)	(5)	(6)
Alpha	0.223	-0.040	0.589	-0.178	0.223**	-0.062
	(1.22)	(-0.26)	(0.60)	(-0.37)	(1.99)	(-0.39)
Alpha × TED	0.326	0.369**	1.215	0.510	0.223	0.389**
	(1.56)	(2.08)	(1.10)	(0.83)	(1.46)	(2.17)
TED	0.001*	-0.000	-0.000	0.002*	0.001**	-0.001*
	(1.73)	(-0.76)	(-0.12)	(1.93)	(2.10)	(-1.85)
Lagged net flows	0.296***	0.348***	0.131***	0.188***	0.394***	0.385***
	(32.26)	(37.50)	(7.50)	(10.94)	(36.75)	(35.57)
Log(Age)	-0.009***	-0.008***	-0.011***	-0.009***	-0.008***	-0.008***
	(-28.18)	(-24.03)	(-13.29)	(-12.29)	(-23.11)	(-21.30)
Log(TNA)	0.001***	0.001***	0.001*	0.002***	0.001***	0.000***
	(6.57)	(4.69)	(1.87)	(5.03)	(6.34)	(2.84)

Expense	-0.085*	-0.319***	-0.194	0.432*	0.034	-0.419***
	(-1.68)	(-6.93)	(-0.64)	(1.81)	(0.61)	(-7.61)
Adj. R^2	0.119	0.157	0.038	0.054	0.194	0.191
Obs.	61,525	60,602	14,119	14,114	47,800	46,094

2.4.4 Broker advice and the flow-to-performance relation

Previous sections document that the concave flow-to-performance relation and the potential run behaviors associated with illiquidity exist only in the broker-sold segment. Since investors in broker-sold funds likely rely more and place greater value on brokers' advice and suggestions due to a lack of investment experience, knowledge, and skills (Del Guercio et al., 2010), a follow-up question we ask is whether broker advice plays a role in determining the flow-to-performance sensitivity.

In principle, distribution fee is used to compensated for financial advice and ongoing assistance (Reid and Rea, 2003; Sun, 2017). Advisors also have incentives to advise fund redemption because they earn additional compensation from increased transactions (Keswani and Stolin, 2012). Therefore, to the extent that brokers in funds with higher distribution fees have greater incentives to advise redemption following poor performance, we expect to find the concave flow-to-performance relation only among those funds. Likewise, in a competitive environment, underperforming funds tend to spend more in distribution costs to attract investors, which in turn drive broker-sold funds more expensive (Gil-Bazo and Ruiz-Verdu, 2009; Sun, 2017). Thus, investors who invest in funds with higher distribution fees are willing to pay more for advisory services and thus are likely to have higher trust in their brokers/advisors.

We use distribution costs to measure the brokers/advisors' incentives and the trust investors place on brokers and separate broker-sold funds into two subsamples based on the sample medians of distribution fees, calculated as the sum of 12b-1 fee and amortized loads (Sun, 2017). The flow regression of equation (4) is estimated on the two groups.

Columns (1) and (2) in Table 2-8 report the results. We find that the coefficient of the interaction term is positive (0.665) and significant, suggesting a concave flow-to-performance relation in broker-sold funds with high distribution fees. However, little evidence of non-linearity in the flow-to-performance is documented in broker-sold funds with low distribution fees. To further ascertain the role of broker advice, we examine the impact of portfolio management efforts (measured by non-marketing fees) on the relation of question.[17] Columns (3) and (4) show that the flow-to-performance relation is not different across funds with high and low non-marketing fees, showing that this relation is unrelated to the fund's portfolio management effort.

However, one may argue that higher distribution fees does not necessarily reflect low portfolio management effort, a fund can put more effort in the distribution and portfolio management simultaneously. Thus, we also compare the flow-to-performance relation across funds with high and low proportion of distribution fees in columns (5) and (6).[18] The results are consistent with the results in columns (1) and (2), implying that broker advice plays a role in the concave relation between fund flow and performance. Overall, our results show that funds with higher distribution fees, i.e., investors rely more on financial advisors and advisors have more incentive to earn transaction-based compensation, reveal a concave flow-to-performance relation. This provides further support for our hypothesis *1b.*

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[17] Non-marketing fee is calculated as the expense ratios minus 12b-1 fee, which is mainly used to invest in portfolio management (Sun, 2017), the subsamples are also divided based on the sample median of non-marketing fee.

[18] Proportion of distribution fees is calculated as distribution fees divided by the sum of distribution fees and non-marketing fees, the subsamples are divided based on the sample median.

Table 2-8 Comparison between high and low distribution fees within broker-sold funds (non-linearity)

This table reports the regression results of the non-linearity in flow-to-performance relations for broker-sold funds with high and low fund distribution and non-marketing fees. The dependent variable is monthly net fund flow. The independent variables include fund alpha of past 12 months, the interaction term between fund alpha and negative alpha dummy, fund net flows in the previous month, the natural logarithm of fund age in years, the natural logarithm of fund TNA, fund expense ratios. The negative alpha dummy equals one if the fund alpha is negative and zero otherwise. Month fixed effects are included. Distribution fee is calculated as the sum of 12b-1 fee and amortized loads, the non-marketing fees is calculated as expense ratios minus 12b-1 fee (Sun, 2017). We also calculate the proportion of distribution fees in total fees, and compare the high and low proportion subsamples in columns (5) and (6). T-statistics based on fund-share-class-clustered standard errors are reported in parentheses. The sample period is from January 1992 to December 2017. ***, ** and * denote the statistical significance at the level of 1%, 5% and 10%, respectively.

	Net flow					
Sample	High distribution fees	Low distribution fees	High non-marketing fees	Low non-marketing fees	High proportion of distribution fees	Low proportion of distribution fees
	(1)	(2)	(3)	(4)	(5)	(6)
Alpha	0.057	0.889***	0.214	0.641*	0.002	0.935***
	(0.32)	(2.68)	(0.84)	(1.89)	(0.01)	(3.09)
Alpha × Negative Alpha	0.665***	-0.009	0.431	0.366	0.789***	-0.107
	(2.79)	(-0.03)	(1.44)	(1.11)	(3.43)	(-0.33)
Negative Alpha	-0.004***	-0.006	-0.006***	-0.005***	-0.004***	-0.006***
	(-6.31)	(-8.82)	(-8.04)	(-7.35)	(-7.46)	(-8.22)
Lagged net flows	0.491***	0.312***	0.375***	0.422***	0.488***	0.325***
	(25.30)	(20.30)	(19.85)	(26.88)	(28.06)	(19.41)
Log(Age)	-0.009***	-0.010***	-0.012***	-0.009***	-0.009***	-0.011***
	(-12.59)	(-13.21)	(-14.45)	(-12.95)	(-12.89)	(-13.24)
Log(TNA)	0.000	0.000	-0.000	0.000**	0.000	0.000

	(0.46)	(0.16)	(-0.55)	(2.51)	（0.82)	(0.62)
Expense	-0.235**	-0.609***	-0.192**	-0.339***	-0.417***	-0.170
	(-1.97)	(-3.81)	(-2.16)	(-3.76)	(-5.17)	(-1.42)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.294	0.137	0.188	0.226	0.293	0.146
Obs.	72,198	71,120	73,798	69,520	71,733	71,585

Another potential concern is that for some funds, investor switching funds within the same family does not trigger sale loads, whereas switching to funds in other families does (Reid and Rea, 2003). If exchange between funds intra-family are free or incur reduced loads, brokers may have little or no incentives to ask investors to redeem following poor performance. In this case, our previous results for the role of broker advice in the concave flow-to-performance relation might be biased and driven by other reasons. To address this concern, we exclude all fund share classes belonging to fund families that manage more than one fund and perform the flow regressions of equation (4). Table 2-9 shows that the coefficient on the interaction term is positive (0.582) and statistically significant, indicating that the sensitivity of outflows to poor performance is greater than the sensitivity of inflows to good performance. This finding offer some more support for our hypothesis that broker advice plays a role in the concave flow-to-performance relation in the broker-sold segment.

Table 2-9 Further test for the role of broker advice in the concave relation

This table reports the regression results of the non-linearity in flow-to-performance relations for a subsample of broker-sold funds in which fund family only manage one fund. The dependent variable is monthly net fund flow. The independent variables include fund alpha of past 12 months, the interaction term between fund alpha and negative alpha dummy, fund net flows in the previous month, the natural logarithm of fund age in years, the natural logarithm of fund TNA, fund expense ratios. The negative alpha dummy equals one if the fund alpha is negative and zero otherwise. Month fixed effects are included. T-statistics based on fund-share-class-clustered standard errors are reported in parentheses. The sample period is from January 1992 to December 2017. ***, ** and * denote the statistical significance at the level of 1%, 5% and 10%, respectively.

	Net flow
Sample	fund family only manage one fund
Broker-sold funds	(1)
Alpha	0.166
	(0.73)
Alpha × Negative Alpha	0.582**
	(2.05)
Negative Alpha	-0.005***
	(-8.79)
Lagged net flows	0.420***
	(23.97)
Log(Age)	-0.010***
	(-13.88)
Log(TNA)	0.001***
	(2.97)
Expense	-0.369***
	(-4.44)
Month FE	Yes
Adj. R^2	0.224
Obs.	82,956

2.4.5 Losing trust in advisors versus following brokers' advice

In this section, we propose two possible explanations for the role of the brokers' advice in the concave relation between fund flow and performance. Brokers' advice can influence the flow-to-performance relation because brokers receive additional compensation when investors switch funds and therefore have incentives to encourage investors to redeem underperforming funds (Christoffersen et al., 2013; Keswani and Stolin, 2012). If investors trust their brokers, we would expect broker-sold fund investors who redeem underperforming funds to remain in the broker-sold segment. In other words, the net flows of outperforming broker-sold funds would be affected by the outflows of underperforming broker-sold funds. However, brokers' advice may also affect the sensitivity of outflows to performance as investors may find it unacceptable to pay high commissions for bad performing funds and therefore lose trust in brokers' advice. Sun (2017) argues that some broker-sold fund investors may choose to terminate the consumption of financial advice and switch to direct-sold funds because the fee difference between two segments exceeds their marginal value for the broker advice. Thus, we expect investors who lose trust in their brokers' advice to leave broker-sold segment completely after redeeming underperforming funds. In other words, the net flows of direct-sold funds would be affected by the outflows of underperforming broker-sold funds.

To distinguish between these two explanations, we apply the regression in equation (3) to broker-funds with negative alphas and estimate the fitted outflows by multiplying the fund's alpha with the coefficient on alpha (or β_1). We then construct the time series data for the size weighted predicted outflows of underperforming funds within the broker-sold segment.[19] Secondly, we construct the time series data for direct-sold funds and broker-sold funds with positive alphas and divide broker-sold funds with

[19] The size weighted predicted outflow in month t is calculated as the sum of the product of fund fitted outflows in month t and fund TNA in month t-1, divided by the sum of total TNA in month t-1.

positive alphas into two subsamples: funds with high distribution fees and funds with low distribution fees.[20]

The predicted outflows of broker-sold funds with negative alphas and the net flows of direct-sold funds and broker-sold funds with positive alphas are plotted in Figure 2-3 and the net flows between high and low distribution fee subsamples in broker-sold funds with positive alphas are plotted in Figure 2-4. Figure 2-3 shows that, in general, outperforming broker-sold funds experience more inflows than direct-sold funds when underperforming broker-sold funds have large outflows, whereas Figure 2-4 shows that the net flows of outperforming broker-sold funds with high distribution fee tend to change more dramatically than their low distribution fee counterparts.

[20] Fund net flow, alpha, expense ratio is calculated as the size weighted average in each month, TNA is the sum of fund's TNA in each month.

Figure 2-3 Fitted flow of broker-sold funds with negative alphas and net flows of direct-sold funds and broker-sold funds with positive alpha

This figure shows the predicted outflows of broker-sold funds with negative alphas, and the net flows of direct-sold funds and broker-sold funds with positive alpha from January 1992 to December 2017. The red solid line and blue long dashed line represent the net flows of direct-sold funds and broker-sold funds with positive alpha, respectively. The green dashed line represents our predicted flow of broker-sold funds with negative alphas. The shaded regions represent the crisis period

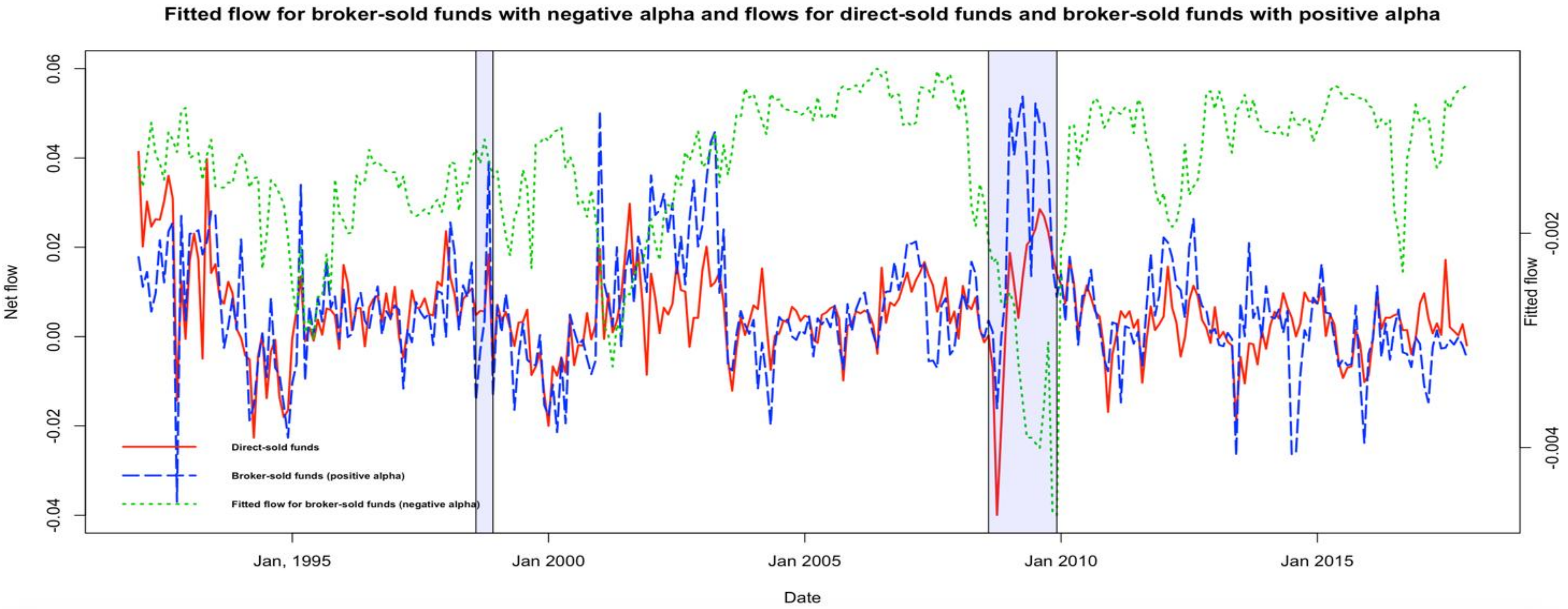
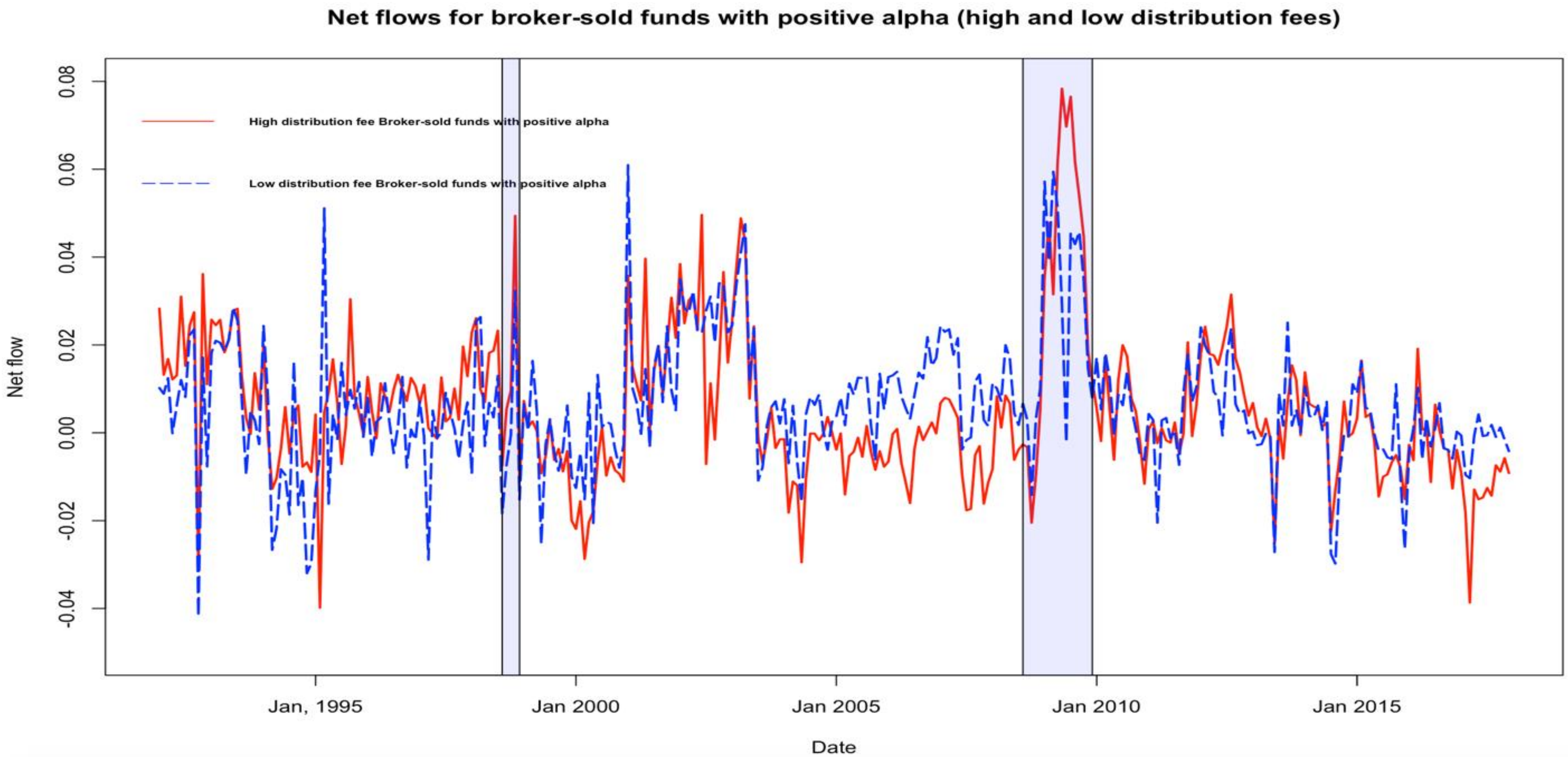


Figure 2-4 Net flows of broker-sold funds with positive alpha with high and low distribution fees

Figure 2-4 shows the net flows of two subsamples of broker-sold funds with positive alpha with high and low distribution fees from January 1992 to December 2017. The red solid line and blue dashed line represent high and low distribution fee subsamples, respectively. The shaded regions represent the crisis period.



We also use the following time series regression to examine whether the outflows from broker-sold funds go to the direct-sold segment or remain in the broker-sold segment:

$$Flow_t = \alpha + \beta_1 Fitted\,flow_t + \gamma Control_t + e_t \tag{7}$$

where $Flow_t$ is the net flow in month *t* in each segment; $Fitted\,flow_t$ is the predicted outflow in broker-sold funds with negative alphas in month *t*; $Control_t$ is a vector of control variables, including alpha, net flow in month t-1, the natural logarithm of the sum of fund TNA, expense ratios, GDP growth, CPI growth, the yield spread between Moody's BAA and AAA corporate bond.

Table 2-10 reports the parameter estimates of equation (10) and Newey-West adjusted t-statistics. Columns (1) and (3) compare direct-sold funds and broker-sold funds with positive alphas. The predicted outflows have a significant effect on the fund flow in the direct-sold segment (the coefficient is -1.401), suggesting that some outflows from underperforming broker-sold funds go to direct-sold funds, consistent with the second explanation. In contrast, we do not find the significant effect of predicted outflows from underperforming broker-sold funds on fund flows of broker-sold funds with positive alphas. We further split broker-sold funds with positive alphas into high and low distribution fee subsamples and report the results in columns (5) and (7). We find a significant relation between predicted outflows from underperforming broker-sold funds and inflows to outperforming broker-sold funds with high distribution fees, but this effect is not present in broker-sold funds with low distribution fees. This suggests that some investors may follow their broker advice to redeem and they are still willing to pay high fees for advice, revealing high trust in broker advice and supporting the first explanation. Also, the insignificant effect of predicted outflows on fund flows of broker-sold funds with positive alphas may be attributed to the fact that the effect in the high and low distribution fee subsamples offset each other.

Table 2-10 The movement of outflows in underperforming broker-sold funds

This table reports the regression results of the effect of predicted outflow of underperforming broker-sold funds on net flow in direct-sold segment, broker-sold funds with positive alpha, and its subsample with high and low distribution fees. The dependent variable is monthly net fund flow. The independent variables include predicted fund outflow of underperforming broker-sold funds, fund alpha, fund net flows in the previous month, the natural logarithm of fund TNA, fund expense ratios, GDP growth, CPI growth and the yield spread between Moody's BAA and AAA corporate bonds. We also further interact the predicted flow with crisis dummy and non-crisis dummy in columns (2), (4), (6), (8). The predicted outflow is estimated as the product of fund alpha and the coefficient of alpha β_1 in the regression equation (6) for broker-sold funds with negative alphas. We further estimate the size weighted predicted outflow in each month, which is calculated as the sum of the product of fund predicted outflows in month t and fund TNA in the previous month, divided by the sum of total TNA in the previous month. For time series data of direct-sold funds and broker-sold funds with positive alpha, fund net flow, alpha, expense ratio is calculated as the size weighted average in each month, TNA is the sum of fund's TNA in each month. The crisis dummy is equal to one during the period between August and December 1998 (the LTCM crisis) and the period between August 2008 and December 2009 (the financial crisis) and zero otherwise, non-crisis dummy is created as 1 minus crisis dummy. The sample period is from January 1992 to December 2017. The t-statistics are based on Newey-West standard error and reported in parentheses. ***, ** and * denote the statistical significance at the level of 1%, 5% and 10%, respectively.

	Net flow							
Sample	Direct-sold funds		Broker-sold funds (Positive alpha)		Broker-sold funds with positive alpha (High distribution fees)		Broker-sold funds with positive alpha (Low distribution fees)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fitted flow	-1.401*		-0.765		-3.008**		-0.388	
	(-1.90)		(-0.53)		(-2.10)		(-0.25)	
Fitted flow × Crisis		-1.555*		-0.993		-3.109		-0.572
		(-1.86)		(-0.53)		(-1.56)		(-0.29)
Fitted flow × Non-Crisis		-1.123		-0.490		-2.903**		-0.123
		(-1.26)		(-0.36)		(-2.33)		(-0.08)
Alpha	1.156	1.019	0.525	0.483	0.431	0.412	0.124	0.095

	(1.48)	(1.18)	(0.67)	(0.61)	(0.41)	(0.38)	(0.18)	(0.14)
Lagged Net flows	0.513***	0.512***	0.422***	0.421***	0.538***	0.537***	0.343***	0.343***
	(7.62)	(7.49)	(4.90)	(4.84)	(7.08)	(6.97)	(4.16)	(4.17)
Log(TNA)	-0.002**	-0.002**	-0.003**	-0.003**	-0.002	-0.002	-0.002	-0.002
	(-2.27)	(-2.23)	(-2.51)	(-2.59)	(-1.09)	(-1.11)	(-1.47)	(-1.49)
Expense	-2.771**	-2.633**	-0.221	-0.224	0.135	0.143	0.082	0.032
	(-2.15)	(-2.04)	(-0.36)	(-0.37)	(0.20)	(0.21)	(0.08)	(0.03)
GDP	0.053	0.053	0.151	0.151	0.206	0.207	0.201	0.201
	(0.66)	(0.65)	(1.36)	(1.36)	(1.59)	(1.60)	(1.50)	(1.50)
CPI	0.187	0.184	0.171	0.171	0.399	0.399	0.215	0.214
	(0.86)	(0.85)	(0.47)	(0.47)	(1.17)	(1.17)	(0.51)	(0.51)
BAA - AAA spread	0.002	0.001	0.009***	0.009***	0.008***	0.008***	0.011***	0.011***
	(0.95)	(0.66)	(4.44)	(3.63)	(3.90)	(3.58)	(4.44)	(3.69)
Adj. R^2	0.340	0.338	0.365	0.363	0.497	0.495	0.266	0.264
Obs.	311	311	311	311	311	311	311	311

We further examine the movement of outflows of poor-performing broker-sold funds during crisis and non-crisis period by interacting the fitted flows in equation (7) with crisis dummy and non-crisis dummy.[21] We find that the predicted outflows in broker-sold funds with negative alphas have significant effect on inflows to direct-sold funds during the crisis period (column (2)) and have a significant effect on inflows to outperforming broker-sold funds with high distribution fees during non-crisis period (column (6)).

Overall, we find evidence that some investors in underperforming broker-sold funds switch to the direct-sold segment and some remain in the broker-sold segment, supporting both explanations. We also find that investors who redeem underperforming broker-sold funds tend to follow their brokers during non-crisis period and distrust them during crisis period. One possible explanation for this results is that the widespread collapse of trust during the financial crisis leads investors to lose confidence in their financial advisors (Guiso, 2010). Furthermore, this collapse of trust would be more severe in the case that financial advisors recommend investors to purchase less diversified funds and cause substantial loss to investors during the crisis.

2.5 Conclusion

This paper investigates the flow-to-performance relation in corporate bond mutual funds. Our analysis focuses mainly on the difference of the sensitivity of fund flows to performance between the direct-sold segment and the broker-sold segment and yields several interesting results. Firstly, we find the concave flow-to-performance relation in corporate bond funds is only evident in the broker-sold segment, with the sensitivity of outflows to poor performance being almost three times as strong as the

[21] Crisis dummy equals one during the period between August and December 1998 (the LTCM crisis) and the period between August 2008 and December 2009 (the financial crisis) and zero otherwise. Non-crisis dummy is created as 1 minus crisis dummy.

inflow-to-good performance sensitivity. Secondly, we show that the redemption behavior subsequent to poor performance in the broker-sold segment is amplified by both market and fund illiquidity, suggesting a potential run behavior under unfavorable conditions. Finally, we investigate the possible explanations of the concave flow-to-performance relation in the broker-sold funds. We find that this concave relation only exists in broker-sold funds with high distribution fees, suggesting that broker advice may play a role in the concave relation between fund flow and fund performance due to the trust of investor and advisors' incentive to facilitate investor redemptions. We also find that investors of underperforming broker-sold funds are more likely to trust brokers and switch to other outperforming broker-sold funds during non-crisis period and mistrust them and switch to direct-sold funds during crisis period.

Our findings imply that the compensation that brokers receive when investors switch funds serves as an incentive to encourage transactions. Regulators should therefore try to restrain such incentive, as it may destabilize the market. Furthermore, the finding that trust relationships between brokers/advisors and investors are fragile during crisis time calls for more research on how investors' confidence in financial intermediaries can be restored.

Chapter 3 ETF ownership and seasoned equity offerings

3.1 Introduction

Driven by the dramatic growth of exchange-traded funds (ETFs) over the past few decades,[22] a growing body of studies examines the impact of ETF ownership on the underlying securities and finds inconclusive evidence. Some research documents that ETF ownership leads to increased volatility (Ben-David et al., 2018), higher return co-movement (Da and Shive, 2017), and reduced informational efficiency (Israeli et al., 2017) whereas others find that ETF ownership improves firms' price efficiency (Glosten et al., 2016) and governance (Appel et al., 2016). While most existing studies concentrate on the asset-pricing implications of ETFs, a new line in this area has begun to investigate the impact of ETFs on corporate financial decisions (see, e.g., Antoniou et al., 2022; El Kalak and Tosun, 2022), which has not yet to be fully exploited. In this paper, we investigate whether and how ETF ownership drives firms' seasoned-equity-offerings (SEOs) decisions.

ETF ownership may influence a firm's propensity to SEO issuance in several ways. First, existing models of information acquisition suggest that informed investors exploit their informational advantage to trade against their uninformed counterparts to make profit through information collection (see, e.g., Hirshleifer et al. 1994; Israeli et al., 2017). However, ETFs, as an investment vehicle with well-diversified portfolio and lower trading costs, attract noise traders to migrate to ETF markets from the individual stock market. With the migration of noise traders, a large proportion of shares outstanding are blocked in ETFs whereas relatively less shares are available for investors to trade. This implies a less opportunity for informed investors to trade on

[22] According to the Investment Company Institute (2018), there are 1,569 index-based ETFs with total net assets of 3.3 trillion dollar at the end of 2017, representing approximately 17% of the total net assets in long-term funds in the U.S, increased from 6% at the end of 2007.

their informational advantage and limited profitability of information collection, which further decrease the firm-level informational efficiency (Israeli et al., 2017). Second, aside from the migration of noise traders to the ETF markets, ETFs might also attract a new clientele of investors who would not otherwise trade in the stock market (Ben-David et al., 2018). This will lead to an increase in investor base for ETFs and higher equity market participation because the increased ETF trading activity will transmit a non-fundamental demand shock to the underlying securities. This increased ETF flows further put an upward price pressure and overvaluation on the underlying securities (Shleifer, 1986; Zou, 2019). Thus, both the migration view and market participation view provide firm managers a "window of opportunity" to exploit their informational advantage to issue equity when stock price are overvalued.

To examine the impact of ETF Ownership on a firm's propensity of SEO, we construct a comprehensive sample of US stocks between 2003 and 2018. First, we identify ETFs from the CRSP stock and mutual fund databases and calculate the firm-level ETF ownership using the CRSP mutual funds holding database. To measure ETF ownership, we employ two measures following the prior literature. The first is the ratio of the dollar value held by ETFs to the firm's market capitalization (Ben-David et al., 2018); the second is the proportion of shares held by ETFs in the firm's total number of shares outstanding (Israeli et al., 2017). We then match these data with the SEO data from Thomson One New Equity Issues Database and the security and quarterly accounting data from CRSP and Compustat. Consequently, our sample contains 120,737 firm-quarter observations for 5,122 firms.

Our first set of tests examines whether ETF ownership is associated with firms' propensity to issue SEO. To do so, we employ logit models where the dependent variable, SEO probability, is defined as one if a SEO announcement is observed for a given firm in a given quarter, and zero otherwise. Our main independent variable is ETF ownership calculated based on BFM and ILS measures. Our finding shows that firms with higher ETF ownership are significantly more likely to issue SEOs, suggesting that firm managers tend to time the market when firm's ETF ownership is high.

The baseline results might raise doubts that some factors, such as firm's investment opportunity, co-determine ETF ownership and SEO probability, and thus fail to identify a causal relation. To mitigate this potential endogeneity concerns, we implement an identification strategy based on S&P 500 index inclusion and deletion following the study of Aghion et al. (2013). Specifically, when a firm is added to (deleted from) S&P 500 index, its ETF ownership is likely to be increased (decreased) as ETFs passively track indexes. Thus, major index changes, such as S&P 500 index, reflect an exogenous variation in ETF ownership, which helps us to identify a causal relationship between ETF ownership and SEO probability. Our first-stage results confirm that the addition to the S&P 500 index leads to a significant increase in the firm's ETF ownership. The second-stage results confirm that ETF ownership significantly increases the firm's propensity to issue SEOs, suggesting that endogeneity is unlikely to drive our results.

A prediction of the market-timing view is that firms with more financial constraints would rely more heavily on equity issuance to raise external capital for future investment or financial deficit, and thus are more sensitive to stock mispricing.[23] The findings are consistent with our expectation, showing that with a high level of ETF ownership, younger, smaller, unprofitable, and non-dividend paying firms are more likely to issue SEOs. In other words, all four proxies for financial constraints significantly amplify the effect of ETF ownership on SEO probability. Among four financial constraints proxies, unprofitable firms show the greatest incentive to issue SEOs when their ETF ownership is high. More specifically, with a 1% increase in ETF ownership, the probability of SEO for unprofitable firms is almost 10% higher

[23] E.g. Baker and Wurgler (2003) document that the effect of stock mispricing on investment is more pronounced for financial constrained firms.

than their profitable counterparts.

Since firms are often shown to underperform after SEO issuance over the short- and long-run (e.g., Corwin, 2003; Loughran and Ritter, 1995), we analyze whether ETF ownership determines the firm's post-SEO performance. On the one hand, the migration view suggests that ETF ownership increases firm-level information asymmetry, which provides firm managers an opportunity to time the market and issue equity. However, the adverse selection model predicts, due to the asymmetry information, rational investors react negatively to SEOs as they perceive equity issuance as a signal of overvaluation (Myers and Majluf, 1984). Thus, increased information asymmetry associated with ETF ownership implies a stronger adverse reaction to SEO announcement, implying a higher level of underperformance. Alternatively, under the market participation hypothesis, ETF ownership provides persistent demand for the underlying equity. This liquidity shock from the demand side can, at least partly, offset the liquidity shock from the supply side caused by equity issuance, which further reduces the short-term underperformance.

Consistent with the market participation view, our tests show that firms with higher ETF ownership experience significantly less underpricing around SEO issuances. The evidence suggests that issuing firms experience a common underpricing after SEOs because equity issuance provides an immediate stock supply and leads to a downward price pressure. However, firms with higher ETF ownership suffer less from the SEO underpricing because ETF trading provides a liquidity shock from the demand side, which partially absorb the supply-side liquidity shock of SEOs.

To corroborate this explanation, we further test the competing hypothesis of adverse selection. An alternative framework of adverse selection is that investors react negatively to SEOs because of the belief that managers will squander the capital raised by equity issuance, i.e., agency problem (Ritter, 2003). Given the informational advantage of insiders and blockholders, selling secondary shares in a SEO may reflect their incentive to exploit this advantage and pursue personal goals, which is aversive for investors. Thus, we test whether including secondary offering as part of the SEO package amplifies underpricing.[24] Our results show that there is no significant difference between primary only offering and a combination of primary and secondary offering, indicating that adverse selection does not play a role in the relation between ETF ownership and SEO underpricing.

Finally, we examine the impact of ETF ownership on the long-term post-SEO performance. A common explanation for long-term underperformance is the successful market timing, which leads to a long-term correction for the overvaluation (Loughran and Ritter, 1995). Thus, On the one hand, the migration hypothesis, ETF ownership worsens firm's information efficiency, leading investors to react more negatively to SEO announcement. This further implies a relative longer time to correct the initial underpricing, consequently leading to poorer performance in the long-run. On the other hand, the market participation view suggests that firms with higher ETF ownership experience persistent demand from ETFs and the exodus of noise traders from individual stock market to ETFs results in a relatively lower cost for firms with higher ETF ownership to conduct SEOs. Thus, if issuers can conduct SEOs with lower costs and pursue their investment opportunities under the persistent demand, higher ETF ownership may lead to a lower level of long-term underperformance.

As prior studies that long-run performance are vulnerable to bad-model problem[25]

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[24] In SEOs, secondary offering is to sell existing shares, benefiting existing shareholders, such as insider and blockholders.

[25] Brav et al. (2000) suggest that long-term underperformance is attributed to model misspecification. Specifically, the authors find that SEO firms show some underperformance using buy-and-hold abnormal returns (BAHRs) whereas there is no evidence of underperformance for SEO-issuer when using time-series factor models. Fama (1998) also document that bad-model unavoidable and is more serious in the long-run for all asset pricing model, especially for BAHRs.

(Brav et al., 2000; Fama, 1998), we employ both event-time and calendar time approach to examine the long-run post-issue performance. Consistent with prior literature, we find that SEO firms generally underperform in the long-run. More importantly, we find that firms with higher ETF ownership experience weaker underperformance than those with lower ETF ownership, consistent with the market participation view suggesting that higher ETF ownership provides underlying securities persistent demand which lower the long-term underperformance.

Our study makes several important contributions to the literature. First, our findings add to the growing body of research examining the effect of ETF ownership on the underlying securities (e.g., Ben-David et al., 2018; Israeli et al., 2017). Prior studies mainly focus on the asset pricing implications of ETS, showing that higher ETF ownership increases return volatilities (Ben-David et al., 2018), decreases pricing efficiency (Israeli et al., 2017), and impairs stock liquidity (Hamm, 2014) of the underlying securities. We complement the existing literature by providing evidence on the implications of ETFs to corporate decision making, such as SEO decisions.

Second, our study extends the literature on the motivation behind security issuance (e.g., Masulis and Korwar, 1986; Myers and Majluf, 1984). Previous studies suggest that firm managers time the market and conduct equity issuance when their stocks are overvalued (Baker and Wurgler, 2002, Loughran and Ritter, 1995). Our research suggests that ETF trading facilitate the transmission of non-fundamental demand shocks to their constituent stocks, thereby offering an opportunity for firms to time the market and increasing the SEO probability among those firms. Our study is closely related to the work of Khan et al. (2012), who find that inflow-driven buying pressure from mutual funds leads to overpricing and thus increased probability of SEOs[26]and

[26] Unlike Khan et al. (2012) who focus on the flow-driven liquidity demand on the propensity of SEOs, our paper focuses on the impact of non-fundamental demand shock induced by ETFs' creation/redemption mechanisms – purchasing ETFs simultaneously triggers trading activity for the underlying securities and the demand for these stocks.

Dathan and Davydenko (2018), who show that firms are more likely to issue bonds when facing higher passive demand by bond ETFs.

Finally, our study also relates to the literature on post-issue performance (see, e.g., Corwin 2003; Kim and Purnanandam, 2014). Prior work suggests that firms exhibit negative performance both in the short-run (Asquith and Mullins, 1986; Masulis and Korwar, 1996) and in the long-run (Loughran and Ritter, 1995). Our evidence advances this literature by documenting that although the underperformance exists, firms with higher ETF ownership outperform their counterparts with lower ETF ownership. This evidence implies that ETFs offer some benefits to their underlying securities, such as permanent increase in stock price.

The remainder of this essay is organized as follows. Section 2 reviews the literature and develops the hypotheses. Section 3 describes the sample and key variable construction. Section 4 reports the empirical results and Section 5 makes a conclusion.

3.2 Literature review and hypothesis development

In this sub-section, we describe the ETF mechanism and provide a brief review of the literature on the impact of ETF ownership on the underlying securities. We then review the literature on SEO motivations and post-issue performance. Finally, we develop our hypotheses on the relation between ETF ownership and SEO decisions and performance.

3.2.1 Exchange traded funds mechanism

Under the Investment Company Act, ETFs possess the characteristics of both unit investment trusts and open-ended funds (Israel et al., 2017). Like unit investment trusts, investors can buy or sell ETFs on stock exchanges throughout the day whereas open-ended mutual funds are only traded at the end of the trading day. Like open-ended index mutual funds, ETFs are constructed to mimic a market index and can create and redeem shares at any time. Therefore, ETFs not only provide a convenient way for investors to trade them like common stocks on the exchange, but also enable investors to diversify their portfolios.

ETFs do not interact with investors directly. Specifically, large financial institutions or market makers, namely authorized participants (APs), deliver a basket of securities and/or cash to ETF managers or sponsors, in exchange for the creation of ETF units in the primary market. APs can also redeem ETF shares in exchange for the underlying securities. Afterwards, investors can trade ETF shares with APs in the secondary market in the same way as buying or selling common stocks on the exchange. Under this creation/redemption mechanism, the number of share outstanding of an ETF is adjusted based on the supply and demand, with "creations" indicating an increase in the supply whereas "redemptions" implying a decrease in the number of ETF's shares outstanding.

Furthermore, the demand and supply may cause the price of ETF shares to deviate from the net asset value (NAV) of the underlying securities (Israeli et al., 2017). However, the price deviation will be adjusted through an arbitrage process associated with ETF creation or redemption (Ben-David et al., 2018). To be specific, when ETF is traded at a price higher than its NAV (i.e., ETF premium), APs could deliver a basket of underlying securities to an ETF sponsor and receive ETF shares. Subsequently, APs sell these shares on the secondary market, providing new supply to meet the increasing demand for ETF shares. In contrast, when the ETF price is lower than its NAV (i.e., ETF is selling at a discount), APs buy ETF shares on the secondary market and then swap them for the underlying securities from the sponsor. In turn, APs sell the securities to investors on the exchange. Other investors can also perform arbitrage by exploiting the price discrepancy between an ETF and its underlying securities, i.e., buying the security with a relatively lower price and short selling the one with a relatively higher price (Ben-David et al., 2018).

3.2.2 The effect of ETF ownership on the underlying securities

With the growth and the increasing popularity of ETFs, there has been a lot of academic debate about the effect of ETF ownership on the underlying securities over recent years (see, e.g., Ben-David et al., 2018; Glosten et al., 2021; Israeli et al., 2017).

On the dark side, there is a negative effect of ETFs on the underlying securities. On a theoretical level, Bhattacharya and O'Hara (2018) suggest that ETFs impair informational efficiency of underlying assets by propagating demand shock unrelated to the fundamental component of their constituents. This, in turn, results in persistent price dislocations, potentially increasing the market fragility of certain illiquid asset classes.

The negative effect of ETFs on their constituent securities is also confirmed by several empirical studies. For instance, due to the arbitrage activity, ETFs affect the underlying securities by increasing securities' intraday and daily volatility, especially for stocks with lower bid-ask spread and lending fees (Ben-David et al., 2018). Similarly, Da and Shive (2017) find that there is a positive relationship between ETF trading activity and return comovement at both the fund and the stock level, and this positive relationship is more pronounced among small and illiquid stocks. Other studies also find that high ETF ownership exerts negative influences on the pricing efficiency (DeLisle et al., 2017; Israeli et al., 2017) and the liquidity (Hamm, 2014) of the underlying stocks. In particular, Israeli et al. (2017) document that firms with higher levels of ETF ownership experience a decrease in analyst coverage and an increase in stock return synchronicity. Additionally, Dannhauser and Hoseinzade (2021) document that the in-kind creation and redemption mechanism of corporate bond ETFs minimize the incentive to maintain liquidity buffers and further exacerbates the liquidity mismatch between ETFs and underlying assets, which in turn, might lead to corporate bond market fragility. This means that ETFs amplify the impact of negative fundamental shocks.

Furthermore, because of the passive investment feature, individual investors tend to migrate from individual stocks to ETFs, which in turn, leads to a reduced incentive to monitor underlying securities among investors. Several studies report the potential consequences. For instance, Schmidt and Fahlenbrach (2017) document that an increase in passive ownership, i.e., index mutual funds and ETFs, is associated with an increase in CEO power, the appointment of fewer independent directors, and the lower quality of mergers and acquisitions. In other words, these changes related to higher passive ownership are not beneficial for shareholders, generating a higher level of agency costs. Heath et al (2022) find a similar result, arguing that passive investment are less likely to vote against firm management, such as director election, and lead to less board independence compared with active investment. Similarly, Evans et al. (2019) explain that the short-selling of ETFs leads to “phantom” ETF shares which are backed by collateral and do not enforce the voting rights. In addition, Dobmeier et al. (2019) find evidence of a negative relationship between ETF ownership and takeover success, which consequently reduces the efficiency of the market for corporate control and weakens the influence of shareholders. Taken together, these studies highlight the negative impact of ETF ownership on corporate governance of the constituent firms.

On the bright side, a number of studies also advocate a positive impact of ETFs on the underlying securities. Theoretically, Cong and Xu (2016) argue that stock prices reflect more systematic information than firm-specific information with the advent of composite securities, such as ETFs. This would reduce the incentive of firm-specific speculators to trade on their informational advantage, therefore facilitating systematic-information-based trading.

Empirically, Glosten et al. (2021) and Li et al. (2018) show that ETF ownership improves the systematic price efficiency of underlying securities. To be specific, Li et al. (2018) explain that since firm managers already have the firm-level information, they want to learn more from the system-specific information to improve their investment decisions. As higher ETF ownership is associated with a higher level of price informativeness about systematic shocks, this further improves firm's operating performance. Glosten et al. (2021) document that the increased informational efficiency of underlying stocks is attributed to the timely incorporation of systematic information during earnings announcements, and only for small stocks. Antoniou et al. (2022) also confirm that Higher ETF ownership facilitates the incorporation of earnings information into prices. Because investors are able to react to earnings information more quickly through ETFs, higher ETF ownership increases the liquidity of the underlying stocks and market liquidity (Boehmer and Boehmer, 2003; Saglam et al., 2019). This further improves the long-term valuation of underlying assets for corporate bond ETFs (Dannhauser, 2017). In addition, Hasbrouck (2003) and Ivanov et al. (2013) document that the arbitrage activity of ETFs contribute positively to the price recovery of their constituent securities.

Furthermore, because of the passive investment style, ETFs have a long-term investment horizon on and lower possibility to exist from the underlying securities. Taken this feature into account, several studies find positive impact of ETFs on corporate governance. For example, Appel et al. (2016) show that passive ownership enhances firm governance, in the form of more independent directors, more equal voting rights, and fewer takeover defenses. Boone and White (2015) find that higher ETF ownership results in better management disclosure and a higher level of analyst coverage, which consequently improves firm transparency and trading environment. Furthermore, Baig et al. (2018) suggest that passive ownership have a positive monitoring effect on the component firms, which reduces the misconduct of firm management. In addition, EL Kalak and Tosun (2022) also document a positive relationship between ETF ownership and firm's cash holding decisions, which in turn, generates a positive impact on firm value because of the increased cash holding.

Regardless of the positive or negative effects of ETFs, previous literature draws two main conclusions about the ETF and its underlying securities. First, noise traders in the market of individual securities tend to migrate toward the ETF market, as the composite securities provide uninformed investors with a more diversified investment vehicle at a lower cost. Israeli et al. (2017) argue that noise traders migrate to ETFs rather than other passive index products because they could satisfy their trading needs through buying/selling ETFs. Second, ETFs transmit a non-fundamental demand shock to the component securities. Because ETFs mimic different indexes, the creation/redemption mechanism of ETFs leads to simultaneous trading in the underlying securities. Furthermore, as additions to and deletions from the index are not related to the future performance of individual securities, these events could be regarded as exogenous to firm fundamentals. Thus, the migrations of noise traders to ETFs lead to a non-fundamental demand shock to all underlying securities in ETFs. ETFs may attract a new clientele of investors into the market, consequently leading to a larger investor base and increasing demand for securities held by ETFs (Ben-David et al., 2018).

Another strand of literature suggests a positive relationship between demand and stock price of the constituent securities in ETFs. For example, Shleifer (1986) finds that additions to the the Standard and Poor's 500 Index (S&P 500 index) resulted in approximately 3% abnormal return on the announcement dates over the period 1976-1983. Evidence that securities experience excess return after additions to the S&P 500 index is further confirmed over the period 1990-1995 by Lynch and Mendenhall (1997). Similarly, Kaul et al. (2000) report that the weight adjustment of Toronto Stock Exchange 300 Index leads to a 2.3% abnormal return of affected stocks within the following one week. Dhillon and Johnson (1991) also document a significant increase in the call option prices of stocks added to the S&P 500 index. As option values reflect the future stock prices, a call price increase indicates a permanent increase in the prices of these stocks. These findings suggest that as ETFs mechanically purchase stocks in proportion to their weights in the index that they replicate, the non-fundamental demand shock cause stock prices to deviate from their fundamental values.

The positive relationship between demand and stock price has commonly been attributed to the downward sloping demand curve (see, e.g., Lynch and Mendenhall, 1997; Shleifer, 1986). More specifically, since a firm is added to an index, a substantial number of its shares would be unavailable for circulation due to index-fund buying. As there is no perfect substitute for each stock, an increase in demand is associated with an increase in stock price (Shleifer, 1986). In a similar vein, Harris and Gurel (1986) argue that as additions to the index induce an immediate increase in the demand for the securities, a large scale of purchase would lead to upward price pressure. This upward pressure may be exacerbated by the liquidity suppliers, who would require compensation for their liquidity services. In other words, the price pressure hypothesis predicts that the costly information for non-fundamental demand shock causes the demand curve to be less elastic and stock prices to increase in the short-term.

With the presence of the unique creation and redemption mechanism in ETFs, the increasing demand for ETF shares can transmit to to the underlying securities (Zou, 2019). To be specific, on the primary market, when an ETF attracts new inflows, the AP sells the ETF shares to investors and purchase a basket of the underlying stocks, consequently resulting in a upward price pressure on the component stock. Furthermore, on the secondary market, arbitrageurs, such as hedge funds, can short sell overpriced stocks and buy the corresponding sector ETF to hedge the industry risk simultaneously. Thus, this arbitrage activity leads to a upward price pressure on the ETF price, which in turn, might further transfer to the component stocks.

To sum up, existing literature mainly investigates the effect of ETF ownership on the underlying securities from the asset pricing perspective (see, e.g., Ben-David et al., 2018; Israeli et al., 2017). By contrast, relatively fewer studies begin to investigate the role of ETFs in corporate decisions (see, e.g., Appel et al., 2016; EL Kalak and Tosun, 2022). In this study, we aim to extend the literature by examining whether ETF ownership affects a firm's decision to issue SEOs.

3.2.3 Seasoned equity offering motivation and post-issue underpricing

In the literature, previous studies have provided several reasons why a firm may issue SEOs. The pecking order theory suggests that companies tend to rely more heavily on internal finance or raising debt than equity issuance when they want to raise cash to meet their operating needs (Myers and Majluf, 1984). Thus, an equity issuance indicates that firms cannot raise sufficient funds through other tools. By contrast, the trade-off theory suggests that firms should have a target debt ratio to maintain optimal capital structure (Modigliani and Miller, 1958). Thus, according to this theory, firms should keep a balance between bankruptcy cost and tax saving benefits and issue SEOs to keep target debt ratios.

However, both the pecking order theory and trade-off theory have been heavily criticized. For instance, Fama and French (2005) find that more than 60% of their sample firms conduct equity issuance during 1973-2002, violating the prediction of the pecking order theory. In contrast to the trade-off theory, Fama and French (2002) also show that the annual mean-reverting rate for leverage is suspiciously slow (7-17%).

Because the above two theories are problematic, a novel alternative theory, namely the market timing hypothesis, has been the most popular explanation for SEOs motivation. The idea is that managers would exploit the "window of opportunity" to conduct equity issuance, when they believe the firms are overvalued (Baker and Wurgler, 2002). The rationale is that the information asymmetry between managers and investors enables managers to identify the time when their firm value exceeds its intrinsic value and to exploit the mispricing.

Advocators of the market timing hypothesis argue that firms tend to conduct equity issuance rather than debt issuance when their stocks have higher prices than their historical or book values (Hovakimian et al., 2001). Ikenberry et al. (1995) also find that firms tend to repurchase shares when their stock prices are undervalued. In addition, Alti and Sulaeman (2012) document that the market timing behavior of equity issuance only exists when institutional investor demand is high. More importantly, Graham and Harvey (2001) conduct a survey for 392 CFOs and find that stock price is the most important determinant of equity issuance decisions. More specifically, consistent with the market timing, Graham and Harvey show more than 60% of the CFOs agree they are more likely to conduct equity issuance following a recent increase in the price of their firms' shares.

The post-issue stock performance with respect to SEOs has also been extensively researched. Related research focuses either on the short-term market reaction to the SEO announcement and/or the long-run stock performance following the SEO. Prior studies generally document a negative return immediately after the SEO announcement. For example, Smith (1977) reports an average return from the close price (offer price) to the offer price (close price) of -0.54% (0.82%). Mola and Loughran (2004) find that the SEO discount has increased over time. Other studies, such as Asquith and Mullins (1986) and Masulis and Korwar (1996) document an average decline of 2-3% in firm value relative to the overall market after SEO announcement.

One plausible explanation for the negative market reaction to SEOs is provided by the adverse selection model of Myers and Majluf (1984). Specifically, the asymmetric information between firm managers and outside investors provides firm management the opportunity to time the market. When managers realize that their firms' shares are overvalued, they prefer to issue equity to maximize revenues. As a consequence, rational investors interpret equity issuance as an attempt to exploit the overvaluation to benefit existing shareholders. Thus, equity issuance is perceived as a negative signal by external investors, causing stock prices to decline. Consistent with the informational asymmetry implied by the adverse selection model, Lee and Masulis (2009) report that the SEO announcement effect is stronger for firms with lower quality accounting information. Similarly, Bowen et al. (2008) document that a higher level of analyst coverage reduces SEO underpricing. Furthermore, Rock (1986) argues that firms use a discounted price to induce uninformed investors to purchase new issues. He argues that since investors with superior information crowd their uninformed counterparts out of good issues and withdraw from bad issues, SEO discount would be required to motivate uninformed investors to participate in the issue.

The adverse selection model also predicts an SEO discount because of the potential agency issues. Specifically, SEOs will be heavily underpriced when the market believes that managers conduct SEOs to pursue their own interests rather than investors' interests (Ritter, 2003). Consistent with this view, Kim and Purnanandam (2014) document a stronger negative market reaction to the SEOs issued by firms with a previous record of poor governance.

The price pressure hypothesis provides a different explanation for the potential SEO underpricing. Shleifer (1986) suggests that the demand curve for stocks is downward sloping (i.e., there is no perfect substitute for each stock). Thus, since equity issuance increases the amount of shares in circulation, stock prices are expected to decline following SEOs. More specifically, when firms conduct SEOs, liquidity shocks lead to a temporary imbalance between demand and supply of the stocks in the market and, therefore, a price discount will be required to compensate investors for absorbing the newly issued shares (Corwin, 2003). In line with this view, empirical studies find that firms with relatively large issue size (i.e., proxy for price pressure) (Asquith and Mullins, 1986; Mikkelson and partch, 1985) and those with relatively inelastic demand (Corwin, 2003) experience higher level of SEO underpricing.

Several studies have also investigated the long-term performance of SEOs. For instance, Loughran and Ritter (1995) and Spiess and Affleck-Graves (1995) document that SEO-issuing firms underperform their non-issuing counterparts in the subsequent five-year period. The most promising explanation for the long-run SEO underperformance is attributed to asymmetric information and market timing. To be specific, Spiess and Affleck-Graves (1995) argue that as managers have an opportunity to take advantage of the stock overvaluation, the market might have an overly optimistic expectation about the future performance of SEO firms. As the market does not fully adjust the stock price in the short run, prices will keep moving in the same direction in the long run. Thus, the long-run underperformance could be regarded as an adjustment for initial overvaluation for SEO firms.

As the long-run underperformance violates the efficient market hypothesis, which implies that the stock price should be adjusted in the short run instead of the long run, several studies attribute the long-run underperformance to model misspecification. For instance, Fama (1998) criticizes the buy-and-hold return methodology, arguing that measures for long-term abnormal returns are especially vulnerable to the bad-model problem. Similarly, Brav et al. (2000) do not find evidence that SEO-issuers underperform in the long-run when using Fama and French 3-factor model. However, Alti and Sulaeman (2012) show that issuing firms exhibit negative abnormal return through a calendar-time approach based on 3-factor model. Thus, the explanation for long-term underperformance is still an unsettled question.

3.2.4 Hypothesis development

As mentioned previously, literature on ETFs does not address the potential impact of ETF ownership on corporate decision making. This study fills the void by investigating whether ETF ownership affects a firm's propensity to issue seasoned equity offerings and the post-issue performance of SEOs.

ETF ownership may influence a firm's propensity to SEO issuance in several ways. First, based on the existing models of information acquisition, informed investors acquire and exploit information and earn a return when trading with their uninformed counterparts (see, e.g., Hirshleifer et al. 1994; Israeli et al., 2017). However, since ETFs provide an attractive alternative for uninformed investors, who are interested in holding a well-diversified at lower costs, these investors may migrate to the ETF markets. As a consequence, the shares outstanding available for investors to trade reduces as a large proportion of shares outstanding are blocked in ETFs. Thus, the migration of uninformed traders decreases the firm-level liquidity of the underlying securities (Hamm, 2014), which implies a less opportunity for informed investors to trade on their information. Thus, the increased trading costs caused by the exodus of noise traders limit the profitability of information collection. In short, less opportunity and lower benefits reduce informed investors' incentives to collect firm-level information, causing firms with higher ETF ownership less informational efficient. In this case, under this migration hypothesis, the lower level of firm-level informational efficiency associated with higher ETF ownership allows firm managers to exploit their information and time the market to conduct SEOs.

Second, aside from the migration of noise traders to the ETF markets, ETFs might also attract a new clientele of investors who would not otherwise trade in the stock market (Ben-David et al., 2018). This, in turn, increases investor base and results in higher equity market participation. As a consequence, the increased transactions in the ETFs would trigger a simultaneous trading the ETF constituents, transmitting a non-fundamental demand shock to the underlying securities. The increased demand for underlying securities would further lead to upward price pressure on stock prices (Shleifer, 1986). To be specific, new inflows into ETFs lead the AP to sell the ETF shares to investors and purchase a basket of the underlying stocks, consequently resulting in a overvaluation on the component stocks. In short, an increase in ETF ownership leads to a liquidity demand shock that will transmit to the underlying securities and cause overvaluation of stocks. Such an overvaluation would provide a "window of opportunity" for firm managers to time the market. Therefore, this market participation hypothesis also predicts a positive relation between ETF ownership and SEO probability. Taken together, both the migration and the market participation views support the following hypothesis:

Hypothesis 2: *ETF ownership increases the firm's propensity of issuing SEOs.*

Furthermore, as it is well-documented that firms generally experience underperformance following SEOs, we are interested in examining whether ETF ownership affects the post-SEO performance over the short run. Under the migration view above, ETF ownership increase firm-level information asymmetry, which provides firm managers an opportunity to exploit their information advantage to conduct SEOs. However, the adverse selection model predicts, due to the asymmetry information, rational investors react negatively to SEOs as they perceive equity issuance as a signal of overvaluation (Myers and Majluf, 1984). Viewed collectively, the adverse selection model predicts that the overvaluation of stock prices is positively related to both the probability of equity issuance and SEO underpricing. In other words, the migration view suggests that higher ETF ownership increases information asymmetry, which in turn, leads these firms to experience a higher level of adverse reaction to SEO announcement. Thus, we conjecture that:

Hypothesis 3a: *Higher ETF ownership is positively associated with short-term SEO* *underpricing*.

On the other hand, existing literature documents that equity issuance generates a temporary liquidity shock from the supply side and investors require a discount to compensate them for absorbing the shock. However, under the market participation view, the increased investor base leads to higher and persistent demand for ETFs, and this non-fundamental shock is further transmitted to the underlying securities. In this way, the passive liquidity shock that ETFs provide for their constituents from the demand side can, at least partly, offset the downward pressure on SEOs. Thus, SEOs of the ETF constituents may experience lower levels of underpricing because of the benefit from the passive demand from ETFs. In addition, Rock (1986) interprets the discounted SEO price as a motivation or a compensation for noise traders to participate in the new issues. Nevertheless, the migration of noise traders to the ETFs reduces uninformed investors' demand for the new issues and increases the demand from ETFs which further transmit to the underlying stocks. This, in turn, reduces the costs of SEO issuance, allowing firms with higher ETF ownership to issue SEOs at a lower discount. Thus, according to the market participation view, we conjecture that:

Hypothesis 3b: *Higher ETF ownership is negatively associated with short-term SEO underpricing*.

Finally, we expect distinct long-term post-SEO performance patterns for firms with different levels of ETF ownership. While the question why SEO firms underperform in the long-run is still unsettled, the most predominant explanation has been the successful market timing. Specifically, because of their information advantage, managers issue new shares only when they believe that their firms are overvalued. While the efficient market theory suggests that the market should adjust the inflated stock price quickly, the market might be irrationally optimistic over the short-run and takes a long time to correct mispricing (Spiess and Affleck-Graves, 1995). Thus, the long-run post-issue underperformance may represent the mispricing corrections for the initial SEO overvaluation. On the one hand, under the market timing view based on migration hypothesis, firms with higher ETF ownership will experience a stronger adverse reaction during SEO issuance, which worsen their short-term performance. This implies that these firms may need a relatively longer time to correct the initial underpricing, consequently resulting in a poorer performance in the long-run. On the other hand, the market participation view suggests that firms with higher ETF ownership experience persistent demand from ETFs. Furthermore, the migration of noise traders from individual stock market to ETFs results in a relatively lower cost for firms with higher ETF ownership to conduct SEOs. Thus, if issuers can conduct SEOs with lower costs and pursue their investment opportunities under the persistent demand, higher ETF ownership may lead to a lower level of long-term underperformance. Taken together, we conjecture that:

Hypothesis 4a: *The firms with higher ETF ownership will experience lower long-term post-SEO underperformance*.

Hypothesis 4b: *The firms with higher ETF ownership will experience higher long-term post-SEO underperformance*.

3.2.5 Conclusion

The studies reviewed thus far provide evidence that ETFs provide both positive and negative effects on the component securities based on a series of reasons related to the ETF trading activity. However, existing studies mainly focus on the asset pricing perspective. Thus, in our second topic, we aim to fill the gap by providing new insight into the corporate finance perspective, examining whether ETF ownership affects a firm's decision on SEO issuance. Furthermore, studies related to SEOs highlight that SEO firms experience underperformance in the short- and long-run after SEO issuance. Thus, we also intend to shed light on the impacts of ETF ownership on post-SEO performance in both short- and long-term.

3.3 Research design

In this sub-section, the first section introduces the data source used and discusses the sample selection process. Next, we discuss how we construct our key variables in detail. Finally, descriptive statistics are presented.

3.3.1 Data source and sample selection

To examine the effect of ETF ownership on the probability of seasoned equity offerings, we obtain SEO data from Thomson One New Equity Issues Database and use the ETF holding data from CRSP Survivor-Bias-Free US Mutual Fund Database to construct the ETF ownership variable.[27] Other information on individual stocks is collected from CRSP stock database and Compustat Fundamentals Quarterly. Our sample covers the period from 2003 to 2018.[28]

Following Da and Shive (2016), we identify all ETFs from CRSP stock database with a share code of 73. To further confirm that these funds are ETFs, we only retain funds with etf_flag of "F" in the CRSP mutual fund database. Furthermore, our sample only includes ETFs investing in U.S. domestic equity stocks and excludes leveraged funds. Specifically, we select funds with Lipper asset code of EQ and the following Lipper Objective Codes: CA, EI, G, GI, MC, MR, SG, and SP (e.g., Ben-David et al., 2018). We also include domestic Sector Funds by selecting Lipper Objective Codes of BM, CG, CS, FS, H, ID, NR, RE, TK, TL, S, and UT. Our final sample contains 1,168 unique ETFs during the sample period. We further obtain holding information from the CRSP mutual funds holding database for these ETFs to construct our quarterly

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[27] Although empirical studies generally use Thomson Reuter Mutual Fund Ownership Database for ETF holding data, we follow Da and Shive (2016) to use the CRSP mutual fund holding dataset due to data availability, and they document that few ETFs are linked to Thomson Reuter holding database.

[28] ETF holding data is not available in the CRSP mutual fund holding database prior to 2003 because very few ETFs are traded previously (DeLisle et al., 2017).

ETF holding dataset.

Next, we construct our SEO sample following the previous literature (see, e.g., Chemmanur et al., 2009; Corwin, 2003). We only include the common share SEOs issued by U.S. firms that are listed on NYSE, AMEX or NASDAQ. We also exclude utility firms with a SIC code of 4000-4949[29], right issues, investment trusts, American depository receipts[30]. In addition, we only include SEOs that are either pure primary offerings or a combination of primary and secondary offerings. In total, we obtain an initial sample of 4,286 SEOs over our sample period. Finally, we exclude SEO firms with missing data on CRSP and Compustat database and match the remaining sample to the quarterly ETF holding dataset. Our final sample contains 120,737 firm-quarter observations and 2,267 SEOs for 5,122 firms.

3.3.2 Key variable construction

3.3.2.1 ETF ownership construction

To construct the ETF ownership, we employ two methods based on prior literature. Following Israeli et al. (2017, hereafter ILS), we define the ETF ownership of stock *i* in quarter *t* as follows:

$$ETF\ ownership\_ILS_{i,t} = \frac{Shares\ held\ by\ all\ ETFs_{i,t}}{Total\ share\ outstanding_{i,t}} \tag{8}$$

where $Shares\ held\ by\ all\ ETFs_{i,t}$ is the sum of number of stock i's shares held by all ETFs at the end of quarter *t* and $Total\ share\ outstanding_{i,t}$ is the total shares outstanding of stock *i* at the end of quarter *t*.

Consistent with Ben-David et al. (2018, hereafter BFM), we also use the following

[29] We exclude utility firms because the approval process limits their ability of time the market (Khan et al., 2012).

[30] Right issues and investment trusts are excluded because they are different from common offerings. More specifically, right issues are only available for existing shareholders. Also, American depository receipts are often issued by foreign companies, thus we exclude them.

measure:

$$ETF\ ownership\_BFM_{i,t} = \frac{\sum_{j=1}^{J} w_{i,j,t} AUM_{j,t}}{MktCap_{i,t}} \quad (9)$$

where J is the set of ETFs holding stock i; $w_{i,j,t}$ is the weight of stock i in the portfolio of ETF j at the end of the quarter t; $AUM_{j,t}$ is the assets under management by ETF j at the end of the quarter t. $MktCap_{i,t}$ is the market capitalization of stock i at the end of the quarter t. We also construct an ownership variable for index and active mutual funds based on above two measures.[31] Finally, we winsorize ownership variables at the 1% and 99% level to reduce the potential effects of outliers.

3.3.2.2 SEO issue date correction

Lease et al. (1991) document that the stated issue date is unsuitable for the price effect analysis, as firms conduct equity issuance when trading is closed. For these offers, the offer date should be corrected to the next day. Following Corwin (2003), we employ a volume-based method to correct the issue date. More specifically, if the trading volume on the next day is not only more than twice the trading volume on the reported issue date, but also more than twice the average trading volume in the prior 250 days, we correct the issue date to the day after the reported issue date. In our original sample of 4,286 SEOs, we correct the issue date for 1,389 SEOs (32.4%).[32]

3.3.3 Summary statistics

Panel A of Table 3-1 provides the descriptive statistics for our ETF sample at the fund level at the end of each year. The number of ETFs increased steadily from 94 in 2003 to 838 in 2018. We observe a steady increase in the average asset under management

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[31] To identify index mutual funds, we first use CRSP index fund identifier. Further, we manually select other index funds by identifying fund names including: Index, Idx, Indx, Ind, Russel, Nasdaq, Dow, Jones, DJ, NYSE, MSCI, S and P, SandP, SP, S&P, FTSE, Wilshire, Morningstar, STOXX, KBW, 100, 400, 500, 600, 900, 1000, 1500, 2000, 3000, 5000 (Busse and Tong, 2012). All other mutual funds are classified as active.

[32] This is comparable to the study of Corwin (2003), the author corrected the offer date for 35.1% of the sample.

(AUM) from 1,416.73 million to 2,341.67 million over the sample period, with fluctuations around 1,000 million from 2006 to 2012. The average ETF ownership has also experienced a significantly increase over time. The average BFM (ILS) ETF ownership has increased from less than 1% in 2003 to 6.13% (9.89%) in 2018. Also, the level of average ETF ownership in our sample is similar to Glosten et al. (2021) from 2004 to 2013, during which the ETF ownership increased from 1.22% to 4.93%. Panel B also shows that SEOs become increasing popular during our sample period. Specifically, the number of SEOs increased from around 80 in the first few years to approximately 200 in the last 10 years of the sample period, except for a dramatic decrease in 2008. The average (median) amount of shares offered is relatively steady at a level of 6 (5) million.

Table 3-2 shows the summary statistics for our firm-quarter sample from 2003 to 2018. The ETF ownership BFM and ETF ownership ILS have a mean (median) of 2.7% (1.4%) and 4.6% (2.9%),[33] respectively, which are almost the same as the index fund ownership. These numbers are relatively lower than active fund ownership, with a mean (median) of 7.2% (5.5%) and 12.3% (9.4%) for the measures of BFM and ILS, respectively. On average, our sample firms have a quarterly return of 4%, book-to-market ratio of 71.2%, and an age of 7.3 years.

[33] This is comparable to the study of Ben-David et al. (2018) and Glosten et al. (2021).

Table 3-1 Descriptive statistics

This table reports descriptive statistics. Panel A describes our ETF data at the fund-level and Panel B shows our SEO sample by year during the sample period of 2003-2018.

Panel A Fund level descriptive statistics by year (end of the year)

Year	Number of ETFs	Average ETF AUM ($million)	Average ETF ownership in firm (%)	
			BFM	ILS
2003	94	1,416.73	0.76	0.60
2004	110	1,684.78	1.00	0.53
2005	155	1,411.01	1.06	0.55
2006	287	965.33	1.12	1.05
2007	399	923.74	0.11	1.55
2008	420	755.80	0.21	1.93
2009	437	886.25	0.38	2.36
2010	485	1,001.36	2.93	5.05
2011	561	926.51	2.97	5.38
2012	534	1,228.66	3.37	6.04
2013	560	1,751.47	4.08	6.60
2014	579	2,098.79	4.22	6.88
2015	649	1,923.99	4.60	7.55
2016	722	2,131.68	5.36	8.69
2017	789	2,538.96	5.82	9.42
2018	838	2,341.67	6.13	9.89

Panel B Descriptive statistics for SEO sample by year

Year	Number of SEOs	Amount of shares offered (million)	
		Mean	Median
2003	67	6.12	5.00
2004	91	4.91	4.00
2005	74	5.55	4.59
2006	92	5.90	5.00
2007	91	5.72	4.61
2008	17	7.12	5.00
2009	181	11.15	5.80
2010	175	7.99	5.19
2011	152	10.14	5.00
2012	149	6.96	5.56
2013	177	6.55	4.48
2014	190	6.67	4.31
2015	203	6.71	4.00
2016	161	7.35	5.00
2017	238	6.76	4.64
2018	209	7.02	5.00

Table 3-2 Summary statistics

This table reports the summary statistics at the firm level. BFM ownership variables measures the ratio of the dollar value of stocks held by different types of funds to firm's market capitalization. ILS ownership variables measures the proportion of shares held by different types of funds in the firm's total number of shares outstanding. Return is the stock return over one quarter. ROA is the operating income before depreciation over total assets. Cash is cash and short-term investments over total assets. Size is the natural logarithm of total assets. BTM is book value of shareholders' equity over market value of equity. Leverage is long-term debt and long-term debt in current liabilities over total assets. Dividend is dividend per share divided by stock price. Volatility is standard deviation of daily stock returns over one quarter. Age is the firm's age.

	Obs.	Mean	Stdev	0.25	Median	0.75
ETF ownership BFM	120,737	0.027	0.033	0.002	0.014	0.041
ETF ownership ILS	120,737	0.046	0.047	0.009	0.029	0.074
Return	120,737	0.040	0.119	-0.085	0.023	0.138
ROA	120,737	0.009	0.279	0.004	0.018	0.037
Cash	120,737	0.223	0.247	0.038	0.116	0.334
Size	120,737	6.766	2.009	5.372	6.698	8.000
BTM	120,737	0.712	31.804	0.262	0.497	0.814
Leverage	120,737	0.201	0.247	0.016	0.134	0.302
Dividend	120,737	0.003	0.022	0.000	0.000	0.004
Volatility	120,737	0.028	0.020	0.016	0.023	0.034
Age	120,737	7.313	4.429	3.000	7.000	11.000
Active fund ownership BFM	120,737	0.072	0.067	0.014	0.055	0.115
Index fund ownership BFM	120,737	0.019	0.022	0.002	0.009	0.030
Active fund ownership ILS	120,737	0.123	0.111	0.029	0.094	0.193
Index fund ownership ILS	120,737	0.045	0.043	0.008	0.027	0.077

3.4 Findings and discussions

3.4.1 The effects of ETF ownership on firms' propensity of SEOs

In this section, we first investigate the impact of ETF ownership on the probability that a firm will conduct SEOs. To do so, we estimate the following logit model:[34]

$$SEO\ probability_{i,t} = \alpha + \beta ETF\ ownership_{i,\,t-1} + \gamma\ Control_{i,t} + e_{i,t} \quad (10)$$

where $SEO\ probability_{i,\,t}$ equals one if firm i has a SEO in quarter t, and zero otherwise; $ETF\ ownership_{i,\,t-1}$ is the ownership of firm i held by ETFs in quarter t-1, which is defined previously based on the measures of BFM and ILS; $Control_{i,\,t}$ is a vector of control variables, including ROA, cash, stock return, size, book-to-market ratio, leverage, dividend yield, stock volatility in the previous quarter, and the natural logarithm of firm age.[35] We also include industry and year-quarter fixed effects in the model and cluster standard errors at the firm level.

Regression results are reported in Table 3-3. Columns (1) and (2) report the results for the BFM and ILS measures of ETF ownership, respectively. The coefficients on both BFM and ILS measures are positive (4.460 and 4.446, respectively) and significant at 1% level, suggesting that, ceteris paribus, firms with higher ETF ownerships are more likely to conduct SEO in the following quarter.

While the above evidence is consistent with the prediction of the market-timing hypothesis, there is a concern that a firm's propensity to conduct an SEO might also be influenced by other institutional investors, such as active and index mutual funds. To address this concern, we further control for the one-quarter-lagged active and index mutual-fund ownership in columns (3) and (4). The results show that both active and index mutual fund ownership exert a significant effect on the SEO

[34] Similar to Khan et al. (2012), who regress SEO probability on inflow-driven buying pressure, we regress SEO probability against ETF ownership.

[35] Details for variable definition are shown in Appendix.

probability, the former is positive and the latter is negative. Importantly, ETF ownership remains significantly and positively related to SEO probability after controlling for the influences of other institutions; and the economic magnitude of ETF ownership is larger than that of active mutual funds.

Overall, our evidence suggests that there is a significantly positive relationship between ETF ownership and firm's propensity to conduct SEOs. Our finding implies that higher ETF ownership generates an opportunity for firm managers to issue equity to raise capital, consistent with the predictions of the market timing hypothesis (Baker and Wurgler, 2002). Furthermore, consistent with previous studies, the positive coefficient on *Return* and negative coefficient on *BTM* confirm that firms conduct SEOs after an increase in their stock prices, which also supports the market timing view.

Table 3-3 Logit analysis of the effect of ETF ownership on SEO probability

This table reports the logit regression results of the relationship between ETF ownership and SEO probability. The dependent variable equals one if the firm conducts a SEO in the quarter and zero otherwise. The main independent variables are the ETF ownership measured by BFM and ILS methods in the previous quarter. Other independent variables include firm's ROA, cash, return, size, book-to-market ratio, leverage, dividend, volatility, active and index fund ownership in the previous quarter and the natural logarithm of age. Quarter and industry fixed effects are included. T-statistics based on firm-clustered standard errors are reported in parentheses. The sample period is from 2003 to 2018. ***, ** and * denote the statistical significance at the level of 1%, 5% and 10%, respectively.

	SEO probability			
	(1)	(2)	(3)	(4)
$ETF\ ownership\ BFM_{t-1}$	4.460***		8.534***	
	(3.97)		(5.86)	
$ETF\ ownership\ ILS_{t-1}$		4.446***		10.984***
		(4.93)		(6.73)
ROA_{t-1}	-0.920*	-0.901*	-2.122***	-2.114***
	(-1.75)	(-1.73)	(-3.19)	(-3.16)
$Cash_{t-1}$	0.692***	0.662***	0.308*	0.325**
	(4.83)	(4.60)	(1.92)	(2.02)
$Return_{t-1}$	0.358***	0.356***	0.475***	0.476***
	(4.51)	(4.51)	(5.10)	(5.09)
$Size_{t-1}$	-0.327***	-0.347***	-0.355***	-0.371***
	(-9.75)	(-10.09)	(-10.06)	(-10.34)
BTM_{t-1}	-0.041***	-0.041***	-0.048***	-0.048***
	(-3.45)	(-3.46)	(-2.73)	(-2.89)
$Leverage_{t-1}$	0.350***	0.347***	0.261**	0.273**
	(3.27)	(3.27)	(2.00)	(2.09)
$Dividend_{t-1}$	-85.785***	-85.405***	-81.407***	-82.267***
	(-5.16)	(-5.13)	(-4.99)	(-5.03)
$Volatility_{t-1}$	2.709**	2.824**	3.533**	3.685**
	(2.30)	(2.43)	(2.42)	(2.52)
$Ln\ Age$	-0.225***	-0.248***	-0.210***	-0.209***
	(-3.87)	(-4.23)	(-3.41)	(-3.31)
$Active\ fund\ ownership\ BFM_{t-1}$			2.980***	
			(6.17)	
$Index\ fund\ ownership\ BFM_{t-1}$			-17.984***	
			(-5.43)	
$Active\ fund\ ownership\ ILS_{t-1}$				1.771***
				(5.30)
$Index\ fund\ ownership\ ILS_{t-1}$				-13.544***
				(-5.83)
Industry FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Obs.	108,788	108,788	101,088	101,089

3.4.2 Robustness tests

3.4.2.1 Robustness on alternative specifications

For robustness purposes, we conduct several additional analyses, the results are shown in the Table 3-4. To save space, we only report the estimates for the variable of interest, i.e., ETF ownership. First, we amend our regression by including industry and year-quarter fixed effects and find consistent results. Second, following Khan et al. (2012), we allow more time for issuing SEOs by extending managers' response window to four quarters and defining the SEO probability variables as one if firm *i* has a SEO in quarter *t to quarter t+3*, and zero otherwise. As a further check, we also construct SEO probability using two and three quarter window for managerial response. The regression results confirm the positive effect of ETF ownership on SEO probability. Interestingly, the coefficients of ETF ownership decreases with the increase in the length of managerial response window, suggesting that firm managers may react quickly to the impact of higher ETF ownership in their effort to time market. Finally, we re-estimate the regression after excluding crisis period, i.e., from the third quarter in 2008 to the fourth quarter in 2009, and the results still hold, implying that the effect of ETF ownership on the SEO probability works during normal time.

Overall, our evidence suggests that there is a significantly positive relationship between ETF ownership and firm's propensity to conduct SEOs, consistent with the predictions of the market timing hypothesis. In other words, higher ETF ownership implies a higher demand from ETFs, leading to an upward price pressure and providing managers with the opportunity to time the market.

Table 3-4 Robustness tests

This table reports the results of robustness tests for the relationship between ETF ownership and SEO probability. The dependent variable equals one if the firm conducts a SEO in the quarter and zero otherwise. In rows (1) and (2), the regressions employ 2-digit industry and year-quarter fixed effects. In rows (3) to (8), the dependent variable equals one if the firm conducts a SEO in quarter t to quarter t+1; in quarter t to quarter t+2; and in quarter t to quarter t+3, respectively, and zero otherwise. In rows (9) and (10), we exclude crisis period from the third quarter in 2008 to the fourth quarter in 2009. T-statistics based on firm-clustered standard errors are reported in parentheses. ***, ** and * denote the statistical significance at the level of 1%, 5% and 10%, respectively.

	ETF ownership_BFM		Obs.	*ETF ownership_ILS*		Obs.
	Coef.	t-statistics		Coef.	t-statistics	
(1) 2-digit industry and year-quarter fixed effects	4.413	(4.09)	111,939	4.350	(5.03)	111,939
(2) control for active and index mutual funds in (1)	9.284	(6.77)	107,195	12.751	(8.46)	107,196
(3) SEO probability for 2-quarter response window	3.984	(3.54)	104,721	3.849	(4.29)	104,721
(4) control for active and index mutual funds in (3)	8.302	(5.71)	98,077	10.747	(6.38)	98,078
(5) SEO probability for 3-quarter response window	3.582	(3.19)	101,070	3.559	(4.01)	101,070
(6) control for active and index mutual funds in (5)	8.289	(5.59)	95,169	11.030	(6.52)	95,170
(7) SEO probability for 4-quarter response window	2.826	(2.53)	97,778	3.049	(3.43)	97,778
(8) control for active and index mutual funds in (7)	7.371	(5.06)	92,256	10.350	(6.15)	92,257
(9) Exclude crisis period	5.286	(4.58)	99,252	4.948	(5.32)	99,252
(10) control for active and index mutual funds in (9)	9.034	(6.10)	92,907	11.301	(6.76)	92,908

3.4.2.2 Identification using S&P 500 index inclusion and deletion

So far, we find a significant relationship between ETF ownership and firm's propensity to issue SEOs. Since ETFs passively track well-defined stock indexes and aims to replicate index returns, they should be exogenous to firm characteristics affecting SEO decisions. However, the baseline results may fail to reflect a causal relation between ETF ownership and SEO probability because both passive investors and financing decisions may be correlated with some omitted variables, such as firm's investment opportunity. Therefore, to address these concerns, index revision is a common identification strategy as ETFs are forced to track index changes due to their passive strategy, which offers plausibly exogenous variation in ETF ownership.

There have been numerous studies apply Russel index reconstitution to exploit exogenous variation in ownership that takes place around the cutoff between Russel 1000 and 2000 indexes (see, e.g., Appel et al., 2016; Ben-David et al., 2018). However, there might be several issues for using the Russel 1000/2000 reconstitution as a source of exogenous variation in institutional ownership. First, Appel et al. (2020) argue that the reconstitution method of the Russel indexes has changed from 2007, which limits the analysis to pre-2007 period. Although several studies use various estimated methods to construct the Russel 1000/2000 cutoff after 2007, such as using end-of-May market capitalization as an instrument in a fuzzy regression discontinuity, they often lead to competing findings about the validity of Russel reconstitution as exogenous variation in institutional ownership. Second, Wei and Young (2019) suggest that the implementation of the Russel index reconstitution setting may lead to selection bias rather than a treatment effect. To be specific, the Russel June ranking are not suitable for regression discontinuity analysis because the Russel 1000/2000 Index assignment are measured at the end of May rather than June. The authors also document that the discontinuities at the Russel 1000/2000 cutoff before and after the reconstitution are almost identical, leading "control" firms to represent a poor counterfactual for "treatment" firms. Third, Ben-David et al. (2018) document that both ETF ownership and index fund ownership move in the same direction following the Russel index reconstitution, implying that this strategy may not be able to isolate the effect of ETFs.

Instead, we use the S&P 500 inclusion and deletion to address the potential endogeneity concern in this section following Aghion et al. (2013). A valid instrument should be significantly correlated with ETF flows and uncorrelated with SEO propensity except through its influence on ETF flows (Adams and Ferreira, 2009). As many ETFs track the S&P 500 index, when a firm is included (excluded) in (from) the index, the demand for shares by ETFs increases (decreases). Furthermore, since stocks are added to the index because of their sector representation rather than future expected performance, the SEO propensity following S&P 500 addition are unlikely to reflect the index selection criteria (Aghion et al., 2013). Thus, the relevance condition and exclusion restriction is likely satisfied in the setting using S&P 500 index as our instrument.

Our empirical analysis contains a two-stage estimation. In the first stage, we regress the ETF ownership on an instrument variable for additions to and deletions from the S&P 500 index. The second stage involves regressing the SEO probability on fitted value of the ETF ownership from the first stage regression. Specifically, the regression design is defined as follows:

$$ETF\ ownership_{i,\,t} = \alpha + \beta S\&P\ member_{i,\,t} + \gamma\ Control_{i,t} + e_{i,t} \quad (11)$$

$$SEO\ probability_{i,\,t} = \beta\ ETF\ \widehat{ownership}_{i,\,t-1} + \gamma\ Control_{i,t} + e_{i,t} \quad (12)$$

where $S\&P\ member_{i,\,t}$ is our instrument variable (IV), which equals positive one if firm *i* is added in S&P 500 index in quarter *t*, a negative one if firm *i* is deleted from S&P 500 index in quarter *t,* and zero otherwise. We collect the Index constituent data from the Compustat database.[36] We further convert the exact inclusion and deletion

[36] The S&P constituent data was removed from the database as of July 2020, however this does not

date into the quarterly frequency and match them to our SEO data. All other variables remain the same as before. Industry and quarter fixed effects are included in our regression and standard errors are clustered at the firm level.

Table 3-5 reports the results for our two-stage regression based on identification strategy of the S&P 500 additions and deletions. Columns (1) and (3) present the first stage in which we regress BFM and ILS ETF ownership, respectively, on our IVs. As what is expected, the coefficients for IVs are significantly positive in both columns, consistent with prior literature (see, e.g., Aghion et al., 2013; Ben-David et al., 2018). To be specific, additions to the S&P 500 index results in a 0.6% (1.1%) increase in BFM (ILS) ETF ownership, which is approximately 22% (24%) increase relative to the average BFM (ILS) ETF ownership. Columns (2) and (4) report the results for the second stage regression. The estimated coefficients on the fitted ETF ownership BFM and ILS are both positive and statistically significant. We notice that the magnitudes of the IV estimates are larger than our baseline results in Table 4-9, a finding that might be attributed to the possibility that the IVs' coefficients reflect a weighted average treatment effect. In other words, the effect of IV is tilted towards stocks that are added to or deleted from the S&P 500 index, consequently resulting in a much stronger impact of ETF ownership on the SEO probability. Overall, the regression results based on IV corroborate our findings that higher ETF ownership increases firm's SEO probability.[37]

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influence our analysis as our sample period is from 2003 to 2018.

[37] As a robust check, we also use the change in ETF ownership as the dependent variable in our first stage regression and its fitted value as the main independent variable in second stage regression, the results are consistent.

Table 3-5 S&P 500 index inclusion and deletion: ETF ownership and SEO propensity

This table reports the estimates from instrument variable model based on S&P 500 index inclusion and deletion. Columns (1) and (3) presents the first stage results, where the dependent variables are the ETF ownership based on BFM and ILS measures. The independent variable is our instrument variable, $S\&P\ member_{i,\,t}$, which equals positive one if firm *i* is included in the S&P 500 index in quarter *t*. In contrast, $S\&P\ member_{i,\,t}$ equals negative one if firm *i* is deleted from the S&P 500 index in quarter *t.* Otherwise, $S\&P\ member_{i,\,t}$ equals zero. Control variables are the same as those presented in table 3. Columns (2) and (4) presents the second stage results, where the dependent variable is SEO probability and the main independent variable is the fitted value of ETF ownership from first stage regression. Quarter and industry fixed effects are included. T-statistics based on firm-clustered standard errors are reported in parentheses. The sample period is from 2003 to 2018. ***, ** and * denote the statistical significance at the level of 1%, 5% and 10%, respectively.

Dependent Variable	*BFM ETF ownership*	*SEO probability*	*ILS ETF ownership*	*SEO probability*
	(1)	(2)	(3)	(4)
	1st stage	2nd stage	1st stage	2nd stage
$S\&P\ member_{t-1}$	0.006**		0.011***	
	(2.27)		(2.97)	
$ETF\ ownership_{t-1}$		198.912*		107.665*
		(1.92)		(1.92)
ROA_{t-1}	0.008***	-2.604***	0.011***	-2.185***
	(3.15)	(-2.59)	(3.36)	(-2.64)
$Cash_{t-1}$	0.009***	-1.046	0.015***	-0.829
	(19.64)	(-1.12)	(24.21)	(-1.01)
$Return_{t-1}$	0.001**	0.228**	0.002***	0.176
	(2.22)	(2.18)	(4.31)	(1.42)
$Size_{t-1}$	0.005***	-1.374**	0.008***	-1.153**
	(99.78)	(-2.42)	(104.50)	(-2.54)
BTM_{t-1}	0.000***	-0.043***	0.000***	-0.043***
	(8.09)	(-3.56)	(6.32)	(-3.50)
$Leverage_{t-1}$	-0.001	0.461***	0.000	0.297***
	(-1.54)	(3.67)	(0.87)	(2.70)
$Dividend_{t-1}$	0.002	-85.423***	-0.011**	-83.872***
	(0.38)	(-5.24)	(-2.28)	(-5.14)
$Volatility_{t-1}$	-0.100***	22.420**	-0.165***	20.342**
	(-17.66)	(2.15)	(-20.86)	(2.18)
$Ln\ Age$	0.001***	-2.004**	0.013***	-1.590**
	(46.96)	(-2.11)	(48.71)	(-2.17)
Industry FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Obs.	108,788	108,788	108,788	108,788

3.4.3 Cross-sectional effects of ETF ownership on SEO probability

In the previous section, we find that the ETF ownership has a significantly positive impact on firms' propensity to issue SEOs. In this section, we further explore whether firm characteristics that are related to mispricing and financial constraints affect the relation between ETF ownership and the probability of SEO. Baker and Wurgler (2006) argue that uninformed demand shock can cause severe mispricing in the presence of arbitrage constraints, particularly in newer, smaller, unprofitable, and non-dividend paying firms. Small and young firms are also generally more financially constrained and suffer from severe information asymmetry problems than their large and mature counterparts (see, e.g., Beck and Demirguc-Kunt, 2006; Schneider and Veugelers, 2010). Furthermore, unprofitable firms and dividend paying firms may rely more heavily on external financing (Khan et al., 2012).

To examine the cross-sectional effects, we add an interaction term between ETF ownership and a dummy, which classifies our sample firms into two groups based on a number of characteristics that are related to mispricing and financial constraints, in the regression:

$$SEO\ probability_{i,t} = \alpha + \beta_1 ETF\ ownership_{i,\,t-1} + \beta_2 ETF\ ownership_{i,\,t-1} \times D(Firm)_{i,\,t} + \beta_3 D(Firm)_{i,\,t} + \gamma\ Control_{i,t} + e_{i,t} \quad (13)$$

Where $D(Firm)_{i,\,t}$ is a dummy variable that classifies firms based on their mispricing- and constraints-related characteristics. More specifically, $D(Size)_{i,\,t}$ equals one if the firm size is below the median in a given quarter, and zero otherwise; $D(Age)_{i,\,t}$equals one if the firm size is below the 25^{th} quantile in a given quarter, and zero otherwise; $D(Profitability)_{i,\,t}$ equals one if the firm's ROA is negative, and zero otherwise; and $D(Dividend)_{i,\,t}$ equals one if the firm's dividend is 0, and zero otherwise. All other variables are as defined previously. The interaction term $ETF\ ownership_{i,\,t-1} \times D(Firm)_{i,\,t}$ is our main variable of interest. A positive (negative) β_2 indicates that the effect of ETF ownership on SEO probability is more (less) pronounced for firms whose stocks are more likely to be mispriced and face more capital constraints. Industry and quarter fixed effects are included and standard errors are clustered at the firm level.

The regression results are presented in Table 3-6. In columns (1) and (5), the coefficients on the interaction term between ETF ownership and firm size dummy are positive and statistically significant, indicating that smaller firms are more likely to conduct SEO when their ETF ownership is high. In columns (2) and (6), we also find a similar pattern for young firms, even though the positive coefficient on the interaction term between *ETF ownership ILS* and age dummy is insignificant. This is consistent with Brown et al. (2009) who suggest that young and growth firms rely more on equity financing for their investment. Furthermore, columns (3) and (7) show that unprofitable firms are more likely to issue SEOs with a high level of ETF ownership. In particular, a 1% increase in *ETF ownership BFM* (*ETF ownership ILS*) would result in 9.341% (8.242%) increase in the probability that unprofitable firms conducting SEOs.[38] Columns (4) and (8) also show that non-dividend paying firms are more likely to issue SEOs when their ETF ownerships are high. These results are consistent with Brown et al. (2009), with the authors documenting that equity capital can materially affect the investment and growth for financial constraint firms. The coefficient on ETF ownership is insignificant in five out of the eight columns in Table 3-6, implying that the effect of ETF ownership on the probability SEO issuance is driven mainly by mispriced and financially constrained firms. This further supports the market timing hypothesis. Specifically, as higher ETF ownership is regarded as a "window of opportunity" for firm management to time the market, firms with more capital constraints should have more incentive to exploit this opportunity for their capital needs. Thus, these firms should be more likely issue SEOs when ETF ownership is higher.

[38] -0.419 + 9.760 = 9.341; 0.996 + 7.246 = 8.242.

Table 3-6 Logit analysis of the effect of ETF ownership on SEO probability with interaction effects

This table reports the logit regression results of cross-sectional effects on the ETF ownership-SEO probability relationship. The dependent variable equals one if the firm conducts a SEO in the quarter and zero otherwise. The main independent variables are the interaction term between ETF ownership measured and a series of dummy variables. These dummy variables are created based on firm characteristics including firm's size, age, ROA, and dividend. Other independent variables include firm's ROA, cash, return, size, book-to-market ratio, leverage, dividend, volatility in the previous quarter and the natural logarithm of age. Quarter and industry fixed effects are included. T-statistics based on firm-clustered standard errors are reported in parentheses. The sample period is from 2003 to 2018. ***, ** and * denote the statistical significance at the level of 1%, 5% and 10%, respectively.

	SEO probability							
	ETF ownership BFM				*ETF ownership ILS*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ETF\ ownership_{t-1}$	0.097	3.242**	-0.419	-1.454	2.593*	3.808***	0.996	2.339
	(0.05)	(2.42)	(-0.26)	(-0.60)	(1.84)	(3.67)	(0.85)	(1.56)
$ETF\ ownership_{t-1}$ × *D(Size)*	5.691***				2.452*			
	(2.63)				(1.76)			
D(Size)	0.025				0.077			
	(0.20)				(0.59)			
$ETF\ ownership_{t-1}$ × *D(Age)*		3.406*				1.548		
		(1.87)				(1.12)		
D(Age)		0.243**				0.246**		
		(2.17)				(2.05)		
$ETF\ ownership_{t-1}$ × *D(Profitability)*			9.760***				7.246***	
			(5.61)				(5.83)	
D(Profitability)			0.797***				0.723***	
			(9.20)				(7.83)	
$ETF\ ownership_{t-1}$ × *D(Dividend)*				6.973***				2.608*
				(2.85)				(1.75)

D(Dividend)				0.396**				0.474***
				(2.52)				(2.98)
ROA_{t-1}	-1.010*	-0.933*	-0.460*	-0.974*	-0.991*	-0.911*	-0.451*	-0.948*
	(-1.79)	(-1.76)	(-1.66)	(-1.80)	(-1.77)	(-1.74)	(-1.70)	(-1.78)
$Cash_{t-1}$	0.655***	0.678***	0.059	0.672***	0.628***	0.651***	0.020	0.640***
	(4.53)	(4.73)	(0.43)	(4.67)	(4.34)	(4.52)	(0.15)	(4.44)
$Return_{t-1}$	0.358***	0.359***	0.426***	0.365***	0.355***	0.357***	0.420***	0.361***
	(4.52)	(4.53)	(5.20)	(4.57)	(4.51)	(4.53)	(5.16)	(4.56)
$Size_{t-1}$	-0.299***	-0.324***	-0.280***	-0.313***	-0.316***	-0.344***	-0.300***	-0.333***
	(-7.05)	(-9.62)	(-9.69)	(-9.17)	(-7.30)	(-9.95)	(-10.17)	(-9.53)
BTM_{t-1}	-0.041***	-0.041***	-0.046***	-0.043***	-0.041***	-0.041***	-0.046***	-0.042***
	(-3.46)	(-3.41)	(-3.88)	(-3.46)	(-3.50)	(-3.40)	(-3.93)	(-3.47)
$Leverage_{t-1}$	0.347***	0.354***	0.308***	0.334***	0.345***	0.351***	0.304***	0.333***
	(3.27)	(3.28)	(3.20)	(3.14)	(3.27)	(3.29)	(3.17)	(3.14)
$Dividend_{t-1}$	-83.109***	-83.933***	-69.335***	-37.668**	-83.441***	-83.819***	-69.066***	-35.249**
	(-5.13)	(-5.12)	(-4.45)	(-2.18)	(-5.10)	(-5.10)	(-4.43)	(-2.07)
$Volatility_{t-1}$	2.814**	2.814**	0.716	2.534**	2.939**	2.918**	0.844	2.629**
	(2.40)	(2.39)	(0.59)	(2.14)	(2.53)	(2.50)	(0.71)	(2.24)
Ln Age	-0.235***	-0.088	-0.223***	-0.224***	-0.256***	-0.111	-0.252***	-0.246***
	(-4.05)	(-1.30)	(-3.88)	(-3.87)	(-4.38)	(-1.62)	(-4.35)	(-4.21)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	108,788	108,788	108,788	108,788	108,788	108,788	108,788	108,788

3.4.4 ETF ownership and SEO underpricing

3.4.4.1 Univariate analysis

In the previous section, we show that there is a positive relationship between ETF ownership and SEO probability. This implies that higher ETF ownership results in a higher non-fundamental demand shock and an increase in stock price, thereby providing an "opportunity window" for manager to time the market. Next, we further examine the relationship between post-issue performance and ETF ownership for SEO firms.

In this subsection, we first provide univariate analysis to test the hypothesis that stock performance around SEOs is related to the ETF ownership of the SEO firms. To this end, we divide our sample into three portfolios based on the most recent level of firm's ETF ownership and calculate the average SEO underpricing for each portfolio. When a firm issue SEOs, the offer price is set after the end of the day prior to the offer date. Thus, if the offer price is lower than the pre-offer share price of the SEO firms, it would result in SEO underpricing. In this study, we measure SEO underpricing[39] as the ratio of prior closing price to the offer price, minus one.

Table 3-7 reports the mean SEO underpricing for each equally-weighted and value-weighted portfolio based on the firms' ETF ownership. Overall, the results show that underpricing is prevailing among SEO firms, consistent with prior studies. More importantly, we find that SEO underpricing for firms with higher ETF ownership is lower than those with lower ETF ownership. Specifically, the mean SEO underpricing of firms with higher ETF ownership BFM (4.994%) is 2.702% smaller than that of firms with lower ETF ownership BFM (7.695%) and this difference is statistically significant. For value-weighted portfolios, the mean difference in SEO

[39] To deal with outlier, we remove observations of SEO underpricing outside the range of [-0.50, 0.50] following Bowen et al. (2018).

underpricing between firms with high and low ETF ownership BFM (3.326%) is still significant. Although the level of SEO underpricing is a bit larger than the literature, the average SEO underpricing for our sample is similar to Chan and Chan (2014) prior to 2007 and SEO price discount is found to increase over time in literature (e.g., Mola and Loughran, 2004; Smith, 1997). We also find a similar pattern for ETF ownership ILS measures, confirming the negative relationship between ETF ownership and SEO underpricing.

To further investigate the whether ETF ownership affect the short-term market reaction to the SEO issuance, we also report the market-adjusted cumulative abnormal returns (CARs)[40] around SEOs with different event windows in Table 3-8. Overall, we find that firms with lower ETF ownership experience more negative risk-adjusted returns than their counterparts with higher ETF ownership. For example, firms with lower ETF ownership BFM, on average, lose 1.934%, 2.041%, 2.506% more than their counterparts with higher ETF ownership BFM during the event windows of (0,0), (-1,1), (-2,2), respectively. These results are robust to the use of ILS measures for ETF ownership and the value-weighted CARs. Furthermore, our finding that the most negative risk-adjusted returns typically occur on the issue date, i.e., event window of (0,0), confirms that SEOs are underpriced.

[40] For each SEO, we use the daily stock returns during the previous 60 trading days to estimate the expected return through capital asset pricing model (CAPM) and the abnormal return is calculated as the difference between realized stock returns and expected returns. Finally, the CAR for event window between q and s is to sum the mean abnormal returns for each ETF ownership-based portfolio.

Table 3-7 SEO underpricing for portfolios with different level of ETF ownership

This table reports the univariate analysis of SEO underpricing for portfolios of firms with different level of ETF ownership. Firms are sorted into three portfolios based on the most recent ETF ownership. SEO underpricing is the close-to-offer returns. The value-weighted SEO underpricing is calculated based on firm size which is the stock price times shares outstanding. The sample period is from 2003 to 2018. ***, ** and * denote the statistical significance at the level of 1%, 5% and 10%, respectively.

ETF ownership measures	SEO underpricing (%)							
	Equally-weighted portfolios				Value-weighted portfolios			
	Low	Mid	High	High - Low	Low	Mid	High	High - Low
BFM	7.695	5.823	4.994	-2.702***	5.873	4.347	2.547	-3.326***
ILS	6.346	6.456	5.502	-0.844	4.626	4.776	3.093	-2.235***

Table 3-8 Short-term market reaction after SEO issuance

This table reports the univariate analysis of short-term performance for portfolios of firms with different level of ETF ownership. Firms are sorted into three portfolios based on the most recent ETF ownership. Portfolio performance is cumulative abnormal returns (CAR) with different event windows. The value-weighted CAR is calculated based on firm size which is the stock price times shares outstanding. The sample period is from 2003 to 2018. ***, ** and * denote the statistical significance at the level of 1%, 5% and 10%, respectively.

Panel A Equally-weighted CAR (%)

Event widow (q, s)	ETF Ownership BFM				ETF Ownership ILS			
	Low	Mid	High	High - Low	Low	Mid	High	High - Low
(0,0)	-3.193	-1.867	-1.259	1.934***	-1.391	-3.182	-1.304	0.087
(-1,1)	-3.582	-2.401	-1.540	2.041**	-2.367	-3.335	-1.483	0.884
(0,1)	-3.243	-1.410	-1.255	1.988***	-1.260	-2.890	-1.259	0.001
(-2,2)	-4.262	-2.239	-1.755	2.506**	-2.682	-3.574	-1.552	1.130
(0,2)	-3.311	-1.138	-1.164	2.147***	-1.173	-2.798	-1.084	0.090

Panel B Value-weighted CAR (%)

Event widow (q, s)	ETF Ownership BFM				ETF Ownership ILS			
	Low	Mid	High	High - Low	Low	Mid	High	High - Low
(0,0)	-0.014	-0.002	-0.013	0.001	-0.003	-0.008	-0.010	-0.007
(-1,1)	-0.022	-0.003	-0.007	0.015	-0.012	-0.006	-0.007	0.005
(0,1)	-0.030	-0.000	-0.008	0.022*	-0.013	-0.000	-0.011	0.002
(-2,2)	-0.030	0.000	-0.006	0.024	-0.016	-0.008	-0.001	0.015
(0,2)	-0.033	0.002	-0.007	0.026*	-0.015	-0.001	-0.008	0.007

3.4.4.2 Multivariate analysis

Next, we further test our prediction that ETF ownership is related to SEO underpricing by controlling other possible determinants for underpricing. To do so, we estimate the following OLS regression:

$$SEO\ underpricing_{i,t} = \alpha + \beta_1 ETF\ ownership_{i,\,t-1} + \gamma\ Control_{i,t} + e_{i,t} \quad (14)$$

Where $SEO\ underpricing_{i,\,t}$ is the close-to-offer price return for each SEO i on the issue date *t*; $ETF\ ownership_{i,\,t-1}$ is the most recent ETF ownership for each SEO i based on the measures of BFM and ILS; $Control_{i,\,t}$ is a vector of control variables, including the natural logarithm of market capitalization and stock price, return volatility, relative offer size, CAR, IPO underpricing, a NYSE dummy and a tick size dummy.[41,42] Standard errors are clustered at the firm level. To support the negative relationship between EFT ownership and SEO underpricing in univariate analysis, we expect β_1 to be negative and significant.

The results in Table 3-9 are striking. In columns (1) and (5), the coefficients on the ETF ownership BFM and ILS are negative (-0.247 and -0.141 respectively) and significant at the 5% level. This indicates that firms with higher ETF ownership experience lower discounts around the SEO issuance. We produce consistent results after controlling for the impact of underwriters' practice of rounding the offer price, which involves inclusions of a tick size dummy and its interaction with stock price in our model (see columns (2) and (6)). The results also remain robust when we incorporate year and industry dummy variables gradually in our model.

Overall, our results are consistent with the market participation hypothesis that higher ETF ownership reduces the level of SEO. One possible reason is that the

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[41] Details for variable definition are shown in Appendix.

[42] Another common used control variable is Rule 10b-21, which adopted on 25th August, 1988. This rule is implemented to restrict manipulative short selling before SEOs. Since our sample period is from 2003 to 2018, we do not include this control variable in our model.

non-fundamental demand shock from ETF offset parts of the supply shock associate with the immediate increase in firm shares following SEOs. Specifically, the price pressure view suggests that when a firm conducts SEOs, the amount of shares that becomes available to the public increase immediately (Corwin, 2003). However, to mimic the index, ETFs should also buy a relatively larger amount of shares of firms with higher ETF ownership. Consequently, this mitigates the effect of supply shock from the SEO issuance, thereby reducing the SEO underpricing. In addition, as noise trader migrate to ETFs, relatively less proportion of new issues will be held by noise trader. This, in turn, reduces the incentive of firms to offer larger discounts proposed by Corwin (2003), leading to lower underpricing for the SEOs of firms with higher ETF ownership.

Table 3-9 Multivariate analysis for the effect of ETF ownership on SEO underpricing

This table reports the multivariate regression results for the effect of ETF ownership on SEO underpricing. The dependent variable is the SEO underpricing for each SEO. The main independent variable is the ETF ownership measured by BFM and ILS methods. Other independent variables include the natural logarithm of firm market capitalization, volatility, relative offer size, CARs, the natural logarithm of stock price, a tick size dummy, IPO underpricing, and a NYSE dummy. The sample period is from 2003 to 2018. T-statistics based on firm-clustered standard errors are reported in parentheses. ***, ** and * denote the statistical significance at the level of 1%, 5% and 10%, respectively.

	SEO underpricing							
	ETF ownership BFM				*ETF ownership ILS*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ETF ownership	-0.247**	-0.241**	-0.364***	-0.397***	-0.141**	-0.137*	-0.312***	-0.323***
	(-2.52)	(-2.48)	(-2.96)	(-2.91)	(-1.98)	(-1.93)	(-3.13)	(-2.89)
Ln (Market cap)	0.003	0.003	0.004	0.004	0.003	0.003	0.005	0.004
	(0.86)	(0.78)	(0.98)	(0.75)	(0.73)	(0.65)	(1.20)	(0.91)
Volatility	0.281***	0.281***	0.281***	0.263**	0.286***	0.286***	0.284***	0.268**
	(2.62)	(2.64)	(2.73)	(2.47)	(2.64)	(2.66)	(2.72)	(2.50)
Rel offer size	0.031***	0.030***	0.030***	0.029***	0.031***	0.031***	0.030***	0.029***
	(4.27)	(4.13)	(3.77)	(3.97)	(4.31)	(4.18)	(3.87)	(4.07)
CAR positive	0.001	0.001	-0.008	-0.018	0.001	0.001	-0.008	-0.018
	(0.04)	(0.02)	(-0.28)	(-0.67)	(0.05)	(0.03)	(-0.31)	(-0.68)
CAR negative	-0.010	-0.008	-0.003	0.010	-0.011	-0.009	-0.004	0.010
	(-0.21)	(-0.17)	(-0.07)	(0.22)	(-0.23)	(-0.19)	(-0.09)	(0.21)
Ln(Price)	-0.001	-0.001	-0.004	-0.003	-0.001***	-0.005	-0.004	-0.002
	(-0.17)	(-1.07)	(-0.69)	(-0.40)	(-0.15)	(-1.07)	(-0.72)	(-0.39)
Tick < 1/4		-0.058***	-0.057***	-0.062***		-0.059***	-0.057***	-0.062***
		(-3.11)	(-3.08)	(-3.35)		(-3.12)	(-3.07)	(-3.36)
Ln(Price) × Tick < 1/4		0.017***	0.017**	0.019***		0.017***	0.016**	0.019***
		(2.59)	(2.52)	(2.82)		(2.60)	(2.51)	(2.83)
IPO underpricing	-0.047	-0.047	-0.020	-0.020	-0.048*	-0.048*	-0.022	-0.032
	(-1.62)	(-1.63)	(-0.67)	(-0.67)	(-1.66)	(-1.67)	(-0.72)	(-1.07)
NYSE dummy	-0.001	0.001	-0.004	-0.004	-0.001	0.001	-0.003	0.003
	(-0.04)	(-0.04)	(-0.15)	(-0.15)	(-0.06)	(0.02)	(-0.13)	(0.19)
Year dummy	No	No	Yes	Yes	No	No	Yes	Yes
Industry dummy	No	No	No	Yes	No	No	No	Yes

Obs.	2,143	2,143	2,143	2,143	2,143	2,143	2,143	2,143

3.4.4.3 Address the adverse selection concern

Previously, we document a negative relationship between ETF ownership and SEO underpricing. This finding is consistent with that the non-fundamental demand shock from ETFs reduces the supply shock of SEO issuance, but not with the adverse selection view, which suggests that market perceives SEO announcements as a negative signal, thus react negatively to the SEO issuance. However, the adverse selection view also predicts that investors may worry that firm managers raise capital from SEOs to serve their own interests rather than the investors' interests (Kim and Purnanandam, 2014).

To explore this alternative view of adverse selection, we examine the effect of ETF ownership on SEO underpricing across different offering types. In a SEO, the primary offering is to offer new shares to the public, therefore raising new capital for firms, whereas the secondary offering is to sell existing shares, benefiting existing shareholders, such as insider (e.g., firm directors) and blockholders.[43] Thus, when investors perceive that SEOs include secondary offering, they may think that firm managers raise capital for their own interest, and thus react more negatively. We expand our model in equation (15) as follows:

$$SEO\ underpricing_{i,t} = \alpha + \beta_1 ETF\ ownership_{i,\,t-1} + \beta_2 ETF\ ownership_{i,\,t-1} \times D(Secondary\ offering)_{i,\,t} + \beta_3 D(Secondary\ offering)_{i,t} + \gamma\ Control_{i,t} + e_{i,t}$$

(15)

where $D(Secondary\ offering)_{i,\,t-1}$ is a dummy variable which equals one if the SEO include secondary offering, and zero otherwise. All other variables are as previously defined and Standard errors are clustered at the firm level. The interaction term $ETF\ ownership_{i,\,t-1} \times D(Secondary\ offering)_{i,\,t}$ is our main variable of interest. A positive (negative) β_2 indicates that the effect of ETF ownership on SEO

[43] Similarly, Boehme et al. (2018) find that greater crash risk emerged after SEOs including secondary offerings.

underpricing is more (less) pronounced for SEO including secondary offering. If the adverse selection holds, we would expect a significantly positive coefficient on β_2.

Table 3-10 reports the results. In columns (1) and (4), the coefficients on the interaction term are insignificant (t-value are 0.71 and 0.75, respectively) for both the BFM and ILS measures of ETF ownership. This finding holds regardless whether we control for year dummy only or both the year and industry dummy. Overall, the results suggest that adverse selection does not play a role in the relationship between ETF ownership and SEO underpricing, which is inconsistent with the theory proposed by Myers and Majluf (1984). In order words, investors do not react more negatively when the funds raised by SEO are potentially used for agency spending.

Table 3-10 The effect of SEO offering type on SEO underpricing - ETF ownership relationship

This table reports the regression results for the effect of SEO offering type on the relationship between ETF ownership and SEO underpricing. The dependent variable is the SEO underpricing for each SEO. The main independent variable is the interaction term between ETF ownership and a dummy variable of SEO offering type, which equals one if the SEO includes secondary offering, and zero otherwise. Other independent variables include the natural logarithm of firm market capitalization, volatility, relative offer size, cumulative abnormal returns (CAR), the natural logarithm of stock price, a tick size dummy, IPO underpricing, and a NYSE dummy. The sample period is from 2003 to 2018. T-statistics based on firm-clustered standard errors are reported in parentheses. ***, ** and * denote the statistical significance at the level of 1%, 5% and 10%, respectively.

	SEO underpricing					
	ETF ownership BFM			*ETF ownership ILS*		
	(1)	(2)	(3)	(4)	(5)	(6)
ETF ownership	-0.310***	-0.400***	-0.415***	-0.199**	-0.345***	-0.337***
	(-2.95)	(-3.16)	(-3.01)	(-2.55)	(-3.39)	(-3.02)
ETF ownership × D (Secondary offering)	0.200	0.042	0.100	0.154	-0.010	-0.001
	(0.71)	(0.15)	(0.30)	(0.75)	(-0.05)	(-0.00)
D(Secondary)	-0.022**	-0.016	-0.009	-0.024**	-0.016	-0.009
	(-2.20)	(-1.49)	(-0.75)	(-2.26)	(-1.52)	(-0.72)
Ln(Market cap)	0.003	0.004	0.004	0.003	0.005	0.005
	(0.87)	(1.03)	(0.81)	(0.79)	(1.28)	(0.97)
Volatility	0.280***	0.283***	0.264**	0.287***	0.286***	0.268**
	(2.62)	(2.76)	(2.48)	(2.65)	(2.75)	(2.50)
Rel offer size	0.031***	0.030***	0.029***	0.031***	0.031***	0.030***
	(4.06)	(3.72)	(3.94)	(4.12)	(3.82)	(4.04)
CAR positive	-0.002	-0.009	-0.018	-0.001	-0.010	-0.019
	(-0.07)	(-0.34)	(-0.69)	(-0.05)	(-0.37)	(-0.71)
CAR negative	-0.007	-0.003	0.010	-0.008	-0.004	0.010
	(-0.14)	(-0.07)	(0.23)	(-0.18)	(-0.09)	(0.21)
Ln(Price)	-0.004	-0.003	-0.002	-0.004	-0.003	-0.002
	(-0.79)	(-0.52)	(-0.35)	(-0.79)	(-0.53)	(-0.33)
Tick < 1/4	-0.058***	-0.057***	-0.062***	-0.059***	-0.057***	-0.062***
	(-3.10)	(-3.08)	(-3.36)	(-3.11)	(-3.07)	(-3.36)
Ln(Price) × Tick < 1/4	0.017**	0.017**	0.019***	0.017***	0.016**	0.019***
	(2.57)	(2.52)	(2.83)	(2.58)	(2.50)	(2.84)
IPO underpricing	-0.045	-0.019	-0.030	-0.047	-0.021	-0.032

	(-1.57)	(-0.62)	(-0.98)	(-1.60)	(-0.68)	(-1.04)
NYSE dummy	-0.000	-0.005	0.002	-0.000	-0.004	0.003
	(-0.01)	(-0.19)	(0.14)	(-0.02)	(-0.17)	(0.16)
Year dummy	No	Yes	Yes	No	Yes	Yes
Industry dummy	No	No	Yes	No	No	Yes
Obs.	2,143	2,143	2,143	2,143	2,143	2,143

3.4.5 ETF ownership and long-term post-issue performance

In this section, we examine the long-run post-SEO performance for firms with different levels of ETF ownership. We measure the long-term performance using both event-time and calendar-time calculations in the 3 and 5 years following the offerings.

3.4.5.1 Event-time long-run performance

We first use the buy-and-hold returns (BHARs) to examine the event-time long-run performance, which are defined as follows:

$$BHAR_i = \prod_{t=1}^{T}(1 + R_{i,t}) - \prod_{t=1}^{T}(1 + Rm_t) \quad (16)$$

where $R_{i,t}$ is the firm i's stock return during month t; Rm_t is the market return[44] during month t, and T is the holding period after the SEO issuance. We create 3×3 portfolios of firms in bivariate sorts based on ETF ownership and market capitalization and calculate the mean BHARs for each portfolio over 3 and 5 years.[45] To adjust the size effect, we further compare long-term post-issue performance between groups of high and low ETF ownership by averaging the BHARs of three size-related sorts.

Panels A and B in Table 3-11 show that the equally-weighted BHARs of firms with lower ETF ownership are, on average, lower than those with higher ETF ownership and the difference between groups of high and low ETF ownership is significant. For example, the 3-year (5-year) equally-weighted BHARs of firms with high BFM and ILS are 8.629% (16.662%) and 41.263% (24.256%) higher than their counterparts with low ETF ownership, respectively. We also calculate the value-weighted BHARs over 3- and 5-year holding period in Panels C and D, and the results are consistent. Overall, we conclude from Table 3-11 that higher ETF ownership improves the firm's

[44] We use the CRSP value-weighted NYSE-Ames-Nasdaq index returns as the market return benchmark.

[45] We exclude those SEOs which do not have enough data for subsequent 3 or 5 years.

long-run performance following SEO issuance.

Table 3-11 event-time approach for long-term post-issue performance

This table reports the long-term post-issue performance through an event-time approach. The firms are sorted into 3×3 portfolios based on the most recent ETF ownership and market capitalization. The long-term post-issue performance are measured by buy-and-hold abnormal returns (BHAR) over 3 and 5 years. The value-weighted BHAR is calculated based on firm size which is the stock price times shares outstanding. The sample period is from 2003 to 2018. ***, ** and * denote the statistical significance at the level of 1%, 5% and 10%, respectively.

Panel A Equally-weighted BHAR - 3 years (%)

Size	ETF Ownership BFM				ETF Ownership ILS			
	Low	Mid	High	High - Low	Low	Mid	High	High - Low
Small	0.742	67.574	21.673	20.931	-1.505	16.136	78.593	80.098*
Mid	-13.870	-8.352	-24.058	-10.188	-20.600	-2.513	-21.272	-0.672
Big	-31.789	-27.784	-10.550	42.339***	-35.759	-20.117	8.603	44.363***
Average	-14.972	10.479	-4.317	8.629***	-19.288	-2.165	21.975	41.263***

Panel B Equally-weighted BHAR - 5 years (%)

Size	ETF Ownership BFM				ETF Ownership ILS			
	Low	Mid	High	High - Low	Low	Mid	High	High - Low
Small	-1.990	69.639	51.221	53.211	-16.920	33.807	69.296	86.216**
Mid	-10.881	-14.122	-29.613	-18.732	-6.954	-20.620	-28.283	-21.329
Big	-32.914	-25.098	-17.407	15.507	-34.641	-12.654	-26.761	7.880
Average	-15.262	10.140	1.400	16.662***	-19.505	0.018	4.751	24.256**

Panel C Value-weighted BHAR - 3 years (%)

Size	ETF Ownership BFM				ETF Ownership ILS			
	Low	Mid	High	High - Low	Low	Mid	High	High - Low
Small	-0.048	0.858	-0.045	0.003	0.012	0.090	0.721	0.709
Mid	-0.146	-0.029	-0.273	-0.127	-0.143	-0.000	-0.240	-0.097
Big	-1.097	-0.145	0.117	1.214**	-0.650	-0.082	0.106	0.756***
Average	-0.431	0.228	-0.067	0.364***	-0.260	0.003	0.196	0.456***

Panel C Value-weighted BHAR - 5 years (%)

Size	ETF Ownership BFM				ETF Ownership ILS			
	Low	Mid	High	High - Low	Low	Mid	High	High - Low
Small	-0.164	1.964	0.701	0.865	-0.535	0.443	1.377	1.912***

Mid	-0.058	-0.083	-0.451	-0.392	-0.010	-0.226	-0.385	-0.375
Big	-1.551	-0.127	0.674	2.225**	-0.725	-0.128	0.736	1.461*
Average	-0.591	0.584	0.308	0.899**	-0.423	0.030	0.576	0.999***

3.4.5.2 Calendar-time long-run performance

As the event-time approach for long-run post-issue performance is problematic (Brav et al., 2000; Fama, 1998), we further examine the long-term performance using the calendar-time approach. More specifically, we create three portfolios of firms according to their ETF ownership levels. For every calendar month, we reform our portfolios by including the firm-month return of the firms that conduct SEOs and dropping the observations of firms without SEOs during the past 3 or 5 years. We then estimate the abnormal returns of each portfolio using the Carhart four-factor model[46]:

$$R_{pt} - R_{ft} = \alpha + b(R_{mt} - R_{ft}) + sSMB_t + hHML_t + mMOM_t + e_t \qquad (17)$$

where R_{pt} is the portfolio return in month *t*; R_{ft} is the risk-free rate proxied by the 30-days Treasury bill rate in month *t*; R_{mt} is the market return proxied by value-weighted NYSE-AMEX-Nasdaq index return in month *t*; SMB_t is the return on small firms minus the return on large firms in month *t*; $hHML_t$ is the return on high book-to-market stocks minus the return on low book-to-market stocks in month *t*; MOM_t is the return of stocks with high prior return minus the return of stocks with low prior return in month *t*. The intercept, α, measures the long-run performance of our portfolios.

Table 3-12 reports the results for both equally-weighted and value-weighted portfolios. Consistent with prior studies (see, e.g., Alti and Sulaeman, 2012), all estimated alphas are negative, confirming the long-term underperformance following the equity issuance. Panels A and B show that the portfolio of firms with lower BFM (ILS) experience abnormal returns of -10.4% (-12.2%) and -9.7% (-11.4%) over 3 and 5 years, respectively. On the contrary, the portfolios with high BFM (ILS) perform better over the long-run, with the 3- and 5- years abnormal returns being -7.7%

[46]Following Billett et al. (2011), to avoid high idiosyncratic noise in portfolios with few firms, we employ the model using weighted least squares. The weight for each observation is the square root of the number of firms in each month.

(-3.5%) and -7.3% (-2.6%), respectively. Panels C and D show similar results for value-weighted portfolios.

Overall, the results of calendar-time approach are in line with results of event-time approach. Our finding confirms that SEO issuers experience a poor performance in the long-run. However, the negative long-term abnormal returns for these SEO issuers are attenuated by ETF ownership, rejecting the migration hypothesis in favor of the market participation hypothesis, suggesting that persistent demand from ETFs and lower costs for SEO issuance improve the long-run underperformance for SEO issuers with higher ETF ownership.

Table 3-12 Calendar-time approach for long-term post-issue performance

This table reports the long-term post-issue performance through a calendar-time approach. The firms are sorted into three portfolios based on the most recent ETF ownership. For every calendar month, each portfolio is reformed by including the firm-month return in the portfolio if the firm conduct SEOs and dropping the observations without an SEO during the past 3 or 5 years. For each portfolio, the long-term post-issue performance is the intercept estimated by the Carhart four-factor model. The regression is estimated through weighted least squares. The weight for each observation is the square root of the number of firms in each month. The value-weighted portfolio is constructed based on firm size which is the stock price times shares outstanding. The sample period is from 2003 to 2018. ***, ** and * denote the statistical significance at the level of 1%, 5% and 10%, respectively.

Panel A Equally-weighted portfolios - 3 years

Portfolio	ETF Ownership BFM			ETF Ownership ILS		
	Intercept	t-statistics	Obs.	Intercept	t-statistics	Obs.
Low	-0.104	-10.01	199	-0.122	-11.26	203
Mid	-0.093	-9.48	204	-0.080	-8.60	204
High	-0.077	-7.97	199	-0.035	-5.89	133

Panel B Equally-weighted portfolios - 5 years

Portfolio	ETF Ownership BFM			ETF Ownership ILS		
	Intercept	t-statistics	Obs.	Intercept	t-statistics	Obs.
Low	-0.097	-9.44	199	-0.114	-10.85	202
Mid	-0.095	-9.83	204	-0.082	-8.74	204
High	-0.073	-7.58	198	-0.026	-4.62	132

Panel C Value-weighted portfolios - 3 years

Portfolio	ETF Ownership BFM			ETF Ownership ILS		
	Intercept	t-statistics	Obs.	Intercept	t-statistics	Obs.
Low	-0.103	-10.25	199	-0.121	-11.49	203
Mid	-0.095	-9.94	204	-0.082	-9.22	204
High	-0.080	-9.13	199	-0.035	-6.44	133

Panel D Value-weighted portfolios - 5 years

Portfolio	ETF Ownership BFM			ETF Ownership ILS		
	Intercept	t-statistics	Obs.	Intercept	t-statistics	Obs.
Low	-0.098	-9.89	199	-0.115	-11.03	202
Mid	-0.095	-9.88	204	-0.084	-9.28	204
High	-0.077	-8.69	198	-0.027	-5.59	132

3.5 Conclusion

It is widely documented that managers time the market and issue SEOs when their firms' stocks are overpriced. Since ETFs transmit non-fundamental demand shocks to their constituents, high ETF ownership may inflate stock prices and create more opportunities for managers to time the market. Consistent with this argument, we document evidence of a strong positive association between ETF ownership and the firm's propensity to issue SEOs. This evidence remains robust after controlling for the confounding effects of other institutions and to alternative definitions of the managerial response window. We also show that the effect of ETF ownership on SEO probability is stronger for younger, smaller, unprofitable, and non-dividend paying firms. This further confirms the market timing view, as these types of firms tend to more financially constrained and are, therefore, more likely to time the market.

We further examine the relation between ETF ownership and the post-SEO performance. We find that firms with higher ETF ownership experience lower levels of underpricing around the SEO issuance. This evidence is consistent with the market participation view, which suggests that ETFs provide persistent demand for the underlying securities, which offsets the supply shock of equity offerings and, therefore, reduces the SEO underpricing. We also show that investors do not react more negatively to SEOs with secondary offerings, inconsistent with the competing migration view. Finally, our evidence that high ETF ownership reduces the long-run post-SEO underperformance suggests that if issuers can conduct SEOs with lower costs and pursue their investment opportunities under the persistent demand, which can reduce the long-term post-SEO underperformance .

Chapter 4 Portfolio pumping activity among multi-fund managers

4.1 Introduction

Our third essay examines whether portfolio pumping activity is prevalent among fund managers who manage multiple funds simultaneously. Portfolio pumping is a well-documented illegal fund trading activity in the literature. Through portfolio pumping, fund managers tend to purchase a significant amount of the securities they already held at the year- or quarter-ends, to artificially inflate the fund value. This illegal trading behavior results in a return reversal on the following trading day.

In the early 21st Century, portfolio pumping has attracted increasing attention from regulators and practitioners. As regulatory scrutiny increased, the portfolio pumping behavior has become increasingly evasive. For instance, some studies document that fund managers can inflate their fund value at the month-end rather than year- or quarter-ends (Kim, 2020) and through depressed selling strategy rather than excessive buying (Hu et al., 2014).

In the mutual fund industry, the assets under management captured by multi-fund managers has increased significantly since 2000 (Fu, 2020), which is coincident with the time period when regulators began to focus more attention on portfolio pumping. Since Wang (2019) documents that fund family tend to inflate the performance of star funds at the cost of the performance of non-star funds after the increasing regulator attention on portfolio pumping. We link the multiple fund management structure to the portfolio pumping activity, because multi-fund managers have more direct source to use cross-subsidization mechanism to improve fund performance with a lower coordination cost. Thus, our third essay aims to shed light on the unsettled topic of whether portfolio pumping activity exists among multi-fund managers.

The most intuitive rationale for portfolio pumping among multi-fund managers is that multi-fund managers have more resources to inflate the performance of one fund at the cost of the performance of another fund managed by them. Furthermore, the coordination costs between two funds for this cross-fund subsidization behavior is lower for multi-fund managers and such a behavior is less likely to be detected by the regulators. Furthermore, because of the spillover effect, when better-performing funds attract a significant amount of inflows as a result of portfolio pumping behavior, the surplus inflows are more likely to shift to other funds managed by the same manager. The spillover effects across funds managed by multi-fund managers could be pronounced because investment expertise is directly related to fund managers themselves (Choi et al., 2016). Thus, portfolio pumping might be a prevalent phenomenon among multi-fund managers.

By contrast, the career concern view argues that fund managers are more inclined to participate in deceptive activities in the early stages of their careers in order to stand out from the crowd (Chevalier and Ellison, 1999). However, multi-fund managers are generally those who have more experience and superior investment skills. As a result, multi-fund managers may be more concerned with their reputation rather than the short-term performance, which, in turn, avoids this illegal portfolio pumping activity.

To investigate whether the portfolio pumping activity is prevalent among multi-fund managers, we construct a sample of U.S. domestic actively managed equity funds from 2001 to 2021 using the CRSP Survivor-Bias-Free US Mutual Fund Database and MorningStar Direct database. We only include funds that are managed by multi-fund managers. Our final sample contains a total of 4194 unique funds with 12,145,080 daily observations.

Our first empirical test examines whether portfolio pumping activity exists at the year-, quarter-, and month-ends. Our finding shows that multi-fund managers inflate fund value at both the year-ends and quarter-ends, whereas experience a return reversal on the following trading days, providing evidence supporting the existence of portfolio pumping.

We next examine the portfolio pumping activity among multi-fund managers across different investment objectives. The results for the effects of investment objectives show that multi-fund managers are more likely to pumping aggressive growth funds. This is not surprising because these funds generally invest in small and less liquid stocks, which could maximizes the cost effectiveness of portfolio pumping, consistent with Carhart et al. (2002).

Another cross-sectional heterogeneity we test for portfolio pumping activity among multi-fund managers is the effect of managerial structure. In a team-based organization, peer monitoring improves individual accountability among team members, putting a pressure on team members to adhere to the right behavior, and joint monetary incentives reduces the possibility of cheating to team members. However, we find no evidence for the effects of team size on the portfolio pumping activity among multi-fund managers.

A potential concern for prior results is that portfolio pumping may not be attributed to the benefits of managing multiple funds for fund managers, but related to fund managers themselves or other potential reasons. To address such concern, we examine whether there is a difference between portfolio pumping activity before and after fund manager's ascension to manage more funds. Our results show that a shift from single-fund managers to multi-fund managers leads to an incremental fund performance of 23bps at the quarter-ends. More importantly, these multi-fund managers do not have portfolio pumping behavior when they only manage one fund.

Furthermore, we examine the potential explanations for portfolio pumping activity among multi-fund managers. Due to the convex flow-to-performance relationship, fund managers are more likely to engage in portfolio pumping. This is because increasing inflows will be reward for the better performing funds they inflated, whereas the “sacrificed” fund will not be penalized by a large amount of outflows. Our results indicate that the flow-to-performance relation is more convex after these managers manage more than one funds, implying multi-fund managers are more likely to be motivated to inflate fund performance.

Another possible explanation for portfolio pumping activity is the spillover effect. To be specific, when the star funds of multi-fund managers attract inflows due to their inflated fund performance, the excessive inflows will move to other poor-performing funds managed by the same fund manager. Our results suggest that when these multi-fund managers manage at least one star funds, they would receive a significant increase in inflows, which confirms the role of spillover effect in the portfolio pumping activity among multi-fund managers.

Our third essay primarily contributes to the literature on portfolio pumping activity in the mutual fund industry (see, e.g., Carhart et al., 2002; Duong et al., 2020; Wang, 2019). Prior studies have found a decline in portfolio pumping activity as a result of increased regulatory monitoring (Duong et al., 2020). In response to this, several studies provide evidence that portfolio pumping has become more evasive. For instance, portfolio pumping experience a shift from fund level to fund family level (Wang, 2019), from year- and quarter-ends to month-ends (Kim, 2020). To the best of our knowledge, this study is the first relating portfolio pumping to multi-fund managers. Our third essay complements the literature by documenting that portfolio pumping activity among fund managers who operate multiple funds simultaneously is another type of portfolio pumping activity that regulators may not be aware of.

This essay is also related to the literature on cross-fund subsidization and agency conflicts. Agarwal et al. (2018) show that multitasking leads to an improved fund performance for newly assigned funds at the sacrifice of the performance of incumbent funds. Gaspar et al. (2016) confirm the agency problem of cross-subsidization, documenting that fund families transfer the performance of less profitable funds to those more profitable funds. Del Guercio et al. (2018) find that fund managers tend to maximize the hedge funds rather than mutual funds, because their compensation is more directly and heavily related to hedge funds. Our study adds to this area of research by suggesting that multi-fund managers exploit the cross-fund subsidization mechanism to inflate their fund performance through portfolio pumping.

The remainder of this essay is organized as follows. Section 2 reviews the literature and develops the hypotheses. Section 3 describes the sample and key variable construction. Section 4 reports the empirical results and Section 5 makes a conclusion.

4.2 Literature review and hypothesis development

In this sub-section, we first introduce some possible explanations for fund return seasonality. Following that, we review the research that has been done on portfolio pumping in the mutual fund industry. Finally, we develop our hypotheses about whether multi-fund managers engage in portfolio pumping behavior.

4.2.1 Seasonality of returns

Because relevant information is incorporated and reflected in the current stock price, the efficient market hypothesis (EMH) assumes that stocks are always traded at their fair value, making it impossible for investors to beat the market (Fama, 1970). Another school of thought, on the other hand, questions the EMH, providing empirical evidence of market anomalies (see, e.g., Collins and Hribar, 2000; Keim, 1983). Among them, calendar anomaly, such as the January effect, is an important fact with a long history, which has been well-researched in the finance literature (see, e.g., Ritter, 1988; Sias and Starks, 1997).

Some evidence of the turn-of-the-year seasonality attracts increasing attention from the popular press (Zweig, 1997). Zweig (1997) reminds investors that the year-end mutual fund outperformance is a flimflam because fund managers artificially inflate their fund performance on the last day of the year. More importantly, this superior performance only lasts a limited time span, with the following trading day witnessing immediate underperformance. The statement of Zweig (1997) is as follows:

“If, like many people, you use calendar-year returns to help you pick funds, you’re using a flawed tool that may well prevent you from getting the solid performance you seek”.

To explain the turn-of-the-year seasonality in the stock market, two hypotheses have been proposed in the literature. One strand of literature proposes the tax-loss hypothesis, which states that individual investors are more likely to sell stocks with a fall in price at the end of the year (see, e.g., Keim, 1983; Sias and Starks, 1997). The rationale is that this generates capital losses to avoid tax on capital gains. Keim (1983) confirms the tax-loss theory based on the finding that a significantly higher proportion of trades driven by seller takes place in December and experience a reverse trend in January. Furthermore, Sias and Starks (1997) document that tax-lossing selling is only pronounced among stocks with higher individual ownership. Similarly, Ritter (1988) proposes a parking-the-proceeds hypothesis, suggesting that investors do not reinvest their sale proceeds in late December immediately, but instead wait until January to do so.

Another strand of literature focuses on the trading behavior of institutional investors, proposing the window dressing hypothesis (e.g., Lakonishok et al., 1991; Musto, 1997). According to the window dressing explanation argument, institutional investors sell poor-performing stocks and purchase good-performing stocks at the end of the year to improve the appearance of their fund performance. Pension fund managers, for example, are more inclined to sell losers in the last quarter of the year (Lakonishok et al., 1991). Similarly, Ng and Wang (2004) find that small stocks with the most extreme losses are more likely to be sold by institutional investors at the end of the year, especially among fund managers with poor performance. In a similar vein, Musto (1999) documents that fund managers might tweak their holdings prior to disclosure to investors because they would like to present a different risk profile for the investors.

However, both tax-loss and window dressing explanations are less convincing because they fail to explain why this turn-of-the-year effect takes place on the day before the end of the year. Also, window dressing is most common among poorly performing funds, which is also inconsistent with the finding of Zweig (1997).

More recently, Carhart et al. (2002) propose the portfolio pumping explanation, suggesting that fund managers would purchase the holdings they already held to push the stock price up artificially. Through this manipulative behavior, the closing prices of stocks they held would increase temporarily, which, in turn, inflates the portfolio value. More specifically, Carhart et al. (2002) find that 80% (62%) of the funds outperformed the S&P 500 Index on the last trading day of the year (each quarter), whereas the outperformance does not persist on the following day for 37% (40%) of the funds. Moreover, the authors mention that this manipulative trading behavior is more prominent among small-cap funds because the assets they trade are relatively less liquid. To support the portfolio pumping explanation, Carhart et al. (2002) also provide strong evidence for excessive trading value during the last half hour at the year- and quarter-ends, indicating that fund managers tend to implement this activity at the last minute of the trading day.

4.2.2 Portfolio pumping activity

According to Brown et al. (1996), mutual fund incentives to "paint the tape" are driven by the tournament-like investment behavior in the industry. In other words, because managers are competitors in a tournament in which their fund performance are constantly evaluated and compared with each other, a direct link between fund performance and managers' compensation leads to a natural incentive for managers to engage in portfolio pumping (Bhattacharyya and Nanda, 2013). Since the frequency of abnormal patterns in fund returns is coincident with the portfolio disclosure frequency for mutual funds, Carhart et al. (2002) attribute the motivation of portfolio pumping to the convex flow-to-performance relationship. To be specific, Sirri and Tufano (1998) document that the sensitivity of fund inflow to good performance is stronger than that of fund outflow to poor performance. In other words, high-performing managers receive a disproportionate amount of fund inflows, whereas poor-performing managers do not experience an equivalent outflow. Therefore, the strong relation between managers' compensation and the asset under management (AUM) provides fund managers a great incentive to artificially inflate their fund performance in order to maximize their personal benefits. In a more extreme case, the portfolio pumping is more prevalent among funds that are near the top of the distribution because the majority of inflows go to the highest performing funds with the occurrence of significant search costs (Carhart et al., 2002). As an illustration, fund managers would benefit more through improving their performance rank from 2nd to 1st than from 101st to 100th.

Subsequent studies provide theoretical evidence supporting the existence of portfolio pumping. For example, Bhattacharyya and Nanda (2013) develop an equilibrium model in which fund managers' compensation is related to the fund's NAV. They document that the concern of short-term fund performance creates the incentive of fund managers to alter the closing price of their portfolio holdings, which, in turn, hurts the long-term performance due to the excessive transaction costs. Focusing on the model of investment decision around the quarter-ends, Bernhardt and Davies (2009) confirm the fund managers' incentive to manipulate the stock price of existing holdings. They also show that portfolio pumping not only obtains the rewards of greater inflows but also results in subsequent a return deficit that is unable to be overcome. In other words, such manipulative behavior results in short-term performance persistence and long-term return reversal, implying that fund managers involved in portfolio pumping activity are more likely to do it again in the future.

Apart from the theoretical literature, several studies provide empirical evidence on the NAV inflation in the fund industry. For example, Argrwal et al. (2011) find that this opportunistic fashion of performance inflation is also prevalent among hedge fund managers to maximize their performance-related incentive fees at the end of the year. Similarly, Ben-David et al. (2013) confirm a higher incentive of portfolio pumping among hedge fund managers, as fund manager compensation is directly linked with fund performance for hedge funds. Moreover, Ben-David et al. (2013) show that NAV inflation leads to significant monthly price distortion. In addition, manipulation activity is not only pronounced among past winners due to convexity in the relationship between fund flow and fund performance but also significant among top performers who experienced poor performance in the past (Ben-David et al., 2013). This is because these fund managers are especially eager to be reassessed as a winner rather than a loser, refreshing investors' impressions of them. Even if fund managers are not directly rewarded by compensation, they may implement portfolio pumping to avoid a bad reputation caused by poor performance (Agarwal et al., 2001).

Following the publication of Carhart et al.'s work in 2002, portfolio pumping draw increasing attention from regulators and practitioners. The first regulatory action was taken by the Ontario Securities Commission (OSC), who accuses the RT Capital of repeated and intentional portfolio pumping activities at month-, quarter-, and year-ends (OSC, 2000). Ultimately, the Royal Bank of Canada paid a $3 million penalty and public an apology in newspapers. Similarly, the SEC also strengthens its regulation against portfolio pumping, with a senior SEC office announcing that the SEC is examining the possibility of portfolio pumping among dozens of mutual funds (Burns, 2001). A few months later, the commission fined Oechsle International Advisor and ABN AMRO because of market manipulation (SEC, 2001).

Duong and Meschke (2020) provide further empirical support for the increased regulatory scrutiny of portfolio pumping. They document that the aggregate level of portfolio pumping declined substantially from late 2000 to 2011, compared with the period from 1993 to 2000; attributing this to the increasing regulatory attention, which raises the risk and cost of market manipulation. Furthermore, Kim (2020) find similar results supporting the decreasing trend of portfolio pumping due to the heightened regulatory scrutiny in the 21st century. In addition, several studies provide evidence to support that the increasing attention from regulators or public reduces portfolio pumping activities. For instance, Gallagher et al. (2009) find a decreasing trend of portfolio pumping activity on the Australian Securities Exchange after introducing the closing auction session mechanism in 1997 and after introducing a different algorithm to measure the closing price in 2002. In addition, Xiao et al. (2005) suggest that a published article named "Fund Inside Story of a Plot" reduce the portfolio pumping activity in China, implying the impact of media coverage on portfolio pumping activity.

However, while regulatory scrutiny has mitigated the portfolio pumping, the phenomenon has not completely disappeared. For example, Hu et al. (2014) document that despite the excessive buying, institutional investors could also inflate their fund performance through depressed selling. In general, institutional investors inflate fund value and performance through placing a large amount of buying order on stocks they already held. However, Hu et al. (2014) find that these investors hold the buying amount constant whereas reduce the selling amount to increase the buying proportion, which consequently inflates the stock price. The rationale for the depressed selling strategy is similar to the traditional methods, which create an imbalance between buying order and selling order (Ben-David et al. 2013). Furthermore, Kim (2020) shows that fund managers tend to inflate their month-end NAV and, therefore, improve their Morningstar ratings when their fund performance is just below a rating threshold. With the heightened regulatory scrutiny in late 2000, fund managers may migrate their portfolio pumping behavior from quarter- and year-ends to month ends, which are less prominent (Kim, 2020). This is because quarter- and year-ends are common dates for reporting, whereas star ratings are assessed every month, which is also helpful to attract inflows. In addition, Wang (2019) find a migration of portfolio pumping activity from individual fund level to fund family level. More specifically, within a fund family, non-star fund managers tend to buy securities held by star funds in the same fund family to inflate the value of star funds. Subsequently, those star funds with pumping activities also experience a significant return reversal. He also finds that the performance of pumping funds declines substantially due to the unnecessary transaction costs associated with buying stocks held by star funds.

The above literature suggests that increased regulatory attention motives fund managers to adopt different portfolio pumping strategies that are less likely to be detected. More importantly, the study of Wang (2019) indicates that transform from the individual fund manager behavior to the cooperation behavior among different fund managers. In the case of family level pumping, the convexity in the flow-to-performance relationship generates a disproportionately high amount of inflows into star fund, which increase the family size and the excess cash would flow to other funds in the same fund family. This spillover effect creates the incentive within fund families to inflate star fund performance through collaboration strategy. Similarly, Nanda et al. (2004) document that fund families with relatively poor performance are more likely to create star funds and enjoy the spillover effects of collaborative pumping. This is confirmed by Wang (2019) who shows that fund families with fewer star funds are more likely to engage in family level portfolio pumping. In addition, Wang (2019) reveals that among non-star funds, pumping funds are more likely to attract spillover inflows than non-pumping funds and fund families exert more effort to redirect inflows to the former.

4.2.3 Multi-fund management

The management structure in the mutual fund industry can take two distinct forms. First, fund manager is only responsible for one singular fund. By contrast, another form of management structure is that fund managers manage multiple funds simultaneously. One possible motivation for multiple fund management structure is to increase fund performance. Naturally, portfolio managers begin their careers as single-fund managers and earn promotion in the competition against other fund managers within the same fund family. Chevalier and Ellison (1999) suggest that when fund managers are acknowledged by fund families as star talent, they are more likely to be rewarded with higher compensation and more funds for management.

A concern about the multi-fund management is the conflicts of interest between these fund managers and investors. To be specific, although the positive fund performance is persistent following the the ascension of single-fund managers to the multi-fund managers, they may focus on the performance of funds which create value to increase their remuneration at the cost of the performance of other funds they managed (Abdesaken, 2019). Because multi-fund managers share many of the same career concern as their single counterparts, it is feasible that multi-fund managers cross-subsidize better-performing to increase their performance-based compensation.

Several studies provide evidence confirming the existence of collaboration strategy across different funds. For instance, Agarwal et al. (2018) show that mutual fund families tend to arrange well-performing fund managers to manage poorly performing funds or new funds. They also indicate that the performance of newly assigned funds improves, whereas the performance of incumbent funds deteriorates following multitasking. They argue that the multitasking arrangement hurts the interest of investors of incumbent funds by transferring their wealth to shareholders of the newly assigned funds. Similarly, several other studies provide evidence that fund families or fund managers may chase superior fund performance at the sacrifice of the performance of other funds. Gaspar et al. (2016) confirm the agency problem of cross-subsidization, documenting that fund families transfer the performance of less profitable funds to those more profitable funds (i.e. higher fund fees or past winners). Furthermore, Del Guercio et al. (2018) reveal that when mutual fund managers simultaneously manage hedge funds, their mutual fund performance experience relatively lower return than peer mutual funds. This is because managers have a higher incentive to maximize the performance of the hedge fund rather than that of the mutual fund, as their compensation is more directly and heavily related to the former. Similarly, Fu (2020) documents that when simultaneously managing multiple mutual funds, managers tend to bet on gaining from at least one fund and hope that such gain will spill over to the remaining funds.

Furthermore, Bryant and Liu (2010) argue that when fund managers operate multiple funds simultaneously, there is a significant increase in the risk of one of the managed funds. In turn, the increased risk minimizes the inherit benefits of stock diversification for mutual funds, which consequently results in fund misclassification. In addition, Choi et al. (2016) document that under the multi-fund management structure, fund flows into a fund of multi-fund managers are positively related to the past performance of another fund managed by the same fund manager, because of the performance-chasing behavior of investors, suggesting a spillover effect among funds under the multi-fund management structure.

According to Agarwal et al. (2018) and Fu (2020), the early 21st Century has witnessed a steady increase in the market share managed by multi-fund managers.

This is coincident with the time when portfolio pumping has drawn the attention of the regulators (Duong and Meschke, 2020). As a consequence of heightened regulation, portfolio pumping has become more evasive in the mutual fund industry, such as the emergence of family level manipulative behavior across different funds (Wang, 2019). Therefore, in this study, we raise an unsettled question that whether portfolio pumping activity exists among multi-fund managers who manage multiple mutual funds simultaneously.

4.2.4 Hypotheses development

Intuitively, in the case of that increased regulatory attention increasing the risk of portfolio pumping, multi-fund managers would have the opportunity and incentive to manipulate fund performance in a subtler way. First, since multi-fund managers manage different funds simultaneously, they have the resources to utilize one fund to purchase the holdings of another fund they managed, which, in turn, generates inflation of the portfolio value. Furthermore, cross-fund subsidization should be more pronounced between funds managed by the same manager as they can avoid coordination costs occurred in the cross subsidization between two single-fund managers. In addition, as the portfolio pumping activity is implemented across two or more funds for multi-fund managers, this illegal trading behavior is less likely to be detected. As a consequence, the funds with artificially inflated value will be rewarded with a large amount of new inflows, while the funds which implement pumping activities will not be penalized. Similarly, previous studies provide evidence for effort diversion among multi-fund managers, such as those who manage both mutual and hedge funds (Del Guercio et al., 2018) and those who are assigned a new fund (Agarwal et al., 2018). Second, when better-performing funds attract a large proportion of inflows because of the portfolio pumping activities, the excessive inflows are more likely to move to other funds managed by the same manager due to the spillover effect. The spillover effects across funds managed by multi-fund managers could be pronounced because investment skill is directly linked to fund managers themselves (Choi et al., 2016). Thus, investors are more likely to expect that all funds managed by star fund managers have the potential to generate superior performance. In this respect, poorly performing funds managed by multi-fund managers would also be rewarded by spillover inflows of the star funds, rather than being penalized. Third, multi-fund managers are usually those who are skilled in the fund family, as Agarwal et al. (2018) document that fund families tend to assign newly launched funds or poorly performing funds to their skilled managers. Also, Massa et al. (2010) show that fund managers with superior performance have more bargaining power to extract rents from the fund family. In this case, we assume multi-fund managers are assigned to manage different funds because they have superior performance or are more experienced professionals. Thus, multi-fund managers may have more bargaining power to implement the portfolio pumping activities.

Hypothesis 5a: *portfolio pumping activity is prevalent among multi-fund managers*.

On the other hand, multi-fund managers may also have no incentive to engage in portfolio pumping. More specifically, according to the career concern view, fund managers are more likely to engage in deceptive activities to stand out from the crowd at the beginning of their careers (Chevalier and Ellison, 1999). As we assumed previously, multi-fund managers are relatively more experienced. Thus, multi-fund managers may care more about their reputation rather than their short-term performance. Moreover, Luo and Qiao (2020) find that the flow-to-performance sensitivity is relatively weaker among non-committed funds in which managers manage another fund simultaneously, implying inertia among investors in these funds. In this case, the less convexity in the flow-to-performance relationship may also result in less incentive to engage in portfolio pumping among multi-fund managers. Taken together, multi-fund managers may have no attempt to implement illegal trading activities, such as portfolio pumping.

Hypothesis 5b: *portfolio pumping activity is not prevalent among multi-fund managers*.

With the portfolio pumping activity under the multi-fund management structure may differ depending on the characteristics of funds or management structure, we add the following research hypotheses considering Cross-Sectional Heterogeneity.

First, aggressive growth funds and growth funds are more likely to be the portfolio pumping candidates for multi-fund managers. To be specific, these two types of funds generally invest in small-cap and less liquid stocks, which implies that trades on these funds are less costly to execute for fund managers. In other words, for the same cost, a relatively large change in NAV can be expected for small funds than their larger counterparts, which consequently leads to a better performance. This maximizes the cost effectiveness of portfolio pumping. Several studies confirm this portfolio pumping preference. For instance, Ben-David et al. (2013) and Carhart et al. (2012) find that smaller-size funds are more prone to portfolio pumping because they are less diversified in nature.

Second, managerial structure may also have an impact on the portfolio pumping activity among multi-fund managers. Becker (1968) suggests that the propensity of an organization to engage in illegal activity relies on the benefits and costs. Kandel and Lazear (1992) show that when peer monitoring and joint monetary incentive reduce the agency costs for taking risks. To be specific, peer monitoring improves individual accountability among team members, putting a pressure on team members to adhere to the right behavior, whereas joint monetary incentives reduces the possibility of cheating to team members. In this study, fund managers who operate multiple funds alone (i.e., single multi-fund managers) may have more incentive to mark up their portfolio value when they anticipate a poor performance for their funds, compared with fund managers who operate multiple funds with other fund managers (i.e., team multi-fund managers). This is because that the cost of cheating (e.g., probability of being caught) is relatively lower and the benefit of pumping (e.g., better fund performance and associated inflows) is much greater for single multi-fund managers than their team-managed counterparts. Thus, we conjecture that:

Hypothesis 6a: *multi-fund managers are more likely to pump the portfolio for funds investing in small and illiquid stocks*.

Hypothesis 6b: *multi-fund managers in a team management structure are less likely to implement portfolio pumping activity*.

4.2.5 Conclusion

Overall, the studies reviewed in this sub-section provide evidence that mutual fund managers artificially inflate their quarter- and year-end fund performance through an illegal trading activity - portfolio pumping. This is motivated by the convex relationship between fund flow and fund performance. Furthermore, with the heightened regulation, fund managers and fund managers implement the portfolio pumping activity in a relatively subtler way since the early 21st Century. In the meantime, the asset under management by multi-fund managers has experienced a steady increase, which implies the growing research potential of investigating multi-fund managers' investment behaviors. Therefore, in this study, we raise an unsettled question that whether portfolio pumping activity exists among multi-fund managers.

4.3 Research design

In this sub-section, the first section introduces the data source used and discusses the sample selection process. Next, we discuss how we construct our key variables in detail. Finally, descriptive statistics are presented.

4.3.1 Data source and sample selection

Our primary data sources for examining the portfolio pumping behavior among multi-fund managers are the CRSP Survivor-Bias-Free US Mutual Fund Database and MorningStar Direct database. Our sample period is from 2001 to 2021.

First, we use CRSP Survivor-Bias-Free US Mutual Fund Database to collect basic fund characteristics, such as the information on fund return, total net asset. To remove incubation bias (Evans, 2010), we also exclude funds with a NAV less than $10 million. Second, we collect information on fund managers from Morningstar Direct as it is more accurate than CRSP and Moningstar Principia databases (Patel and Sarkissian, 2017). We then combine the data collected from two databases. Following Patel and Sarkissian (2021), we restrict our sample by including four types of funds with different investment objectives, namely aggressive growth funds, growth funds, growth and income funds, equity income funds. Also, we focus on U.S. domestic equity funds that are actively managed, excluding all sector, balanced, international and index funds. We also remove observations with missing value in fund manager information. Finally, we only include observations of funds that are managed by multi-fund managers, all these funds should have the same fund manager information with another fund. Our final sample contains a total of 4194 unique funds with 12,145,080 daily observations.[47]

4.3.2 Key variable construction

4.3.2.1 Multi-fund definition

We define multi-fund when they are managed by the same manager or teams that have the managers in common and restrict our sample by only including these multi-funds.

[47] This is similar to the sample employed by Patel and Sarkissian (2021) which contains 3,929 unique funds with around 8,600,000 daily observations during the period from 1992 to 2015.

4.3.2.2 Mutual fund flows

Similar to section 3.2.1.1, we calculate the mutual fund flows as the percentage change in the fund's TNA minus the percentage change in TNA due to fund return in a given year. Specifically, the net flow of a corporate bond fund *i* in year *t* is defined as:

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1+R_{i,t})}{TNA_{i,t-1}} \tag{18}$$

where $R_{i,t}$ is the return of fund *i* over year *t* and $TNA_{i,t}$ is the TNA of fund *i* at the end of year *t*. To reduce the potential effect of outliers, fund flows are winsorized at the 1% and 99% levels.

4.3.3 Summary statistics

Table 4-1 provides summary statistics for our portfolio pumping sample during the period from January 2001 to December 2021. The average and median daily return for multi-funds is 0.053% and 0.086% respectively. On average, multi-funds have a fund size of 974.2 millions, a turnover ratio of 62%, an expense ratio of 1.2%, and an age of 9.1 years. In addition, the average yearly fund flow is -7.3%.

Table 4-1 Summary statistics

This table reports the summary statistics. Return (%) is the daily net return in percent. Fund size is fund total net asset (TNA). Turnover ratio is the minimum of aggregated sales or purchases of securities in a year divided by the average 12-month total net assets of the fund. Fund fees are the annual total expense ratio of the fund. Fund age is the fund age in years. Fund flows are the percentage fund flow in percent in a given year.

	Obs.	Mean	Stdev	0.25	Median	0.75
Return (%)	12,145,080	0.053	1.269	-0.448	0.086	0.623
Fund size	12,145,080	974.2	4,131	14.2	93.5	501.4
Turnover ratio	12,145,080	0.620	0.545	0.270	0.470	0.800
Fund fees	12,145,080	0.012	0.005	0.008	0.011	0.014
Fund age	12,145,080	9.1	5.6	4.0	8.0	13.0
Fund Flows	46,270	-0.073	0.385	-0.199	-0.067	0.104

4.4 Findings and discussions

4.4.1 Portfolio pumping among multi-fund managers

In this section, we first examine whether portfolio pumping activity exists among multi-fund managers. To do so, we estimate the following regression following the study of Patel and Sarkissian (2021):

$$r_{i,t} = b_0 + b_1 Yend_t + b_2 Ybeg_t + b_3 Qend_t + b_4 Qbeg_t + b_5 Mend_t + b_6 Mbeg_t + \delta Controls_{i,t} + \varepsilon_{i,t} \qquad (19)$$

Where $r_{i,t}$ is the fund *i*'s return on day *t* in excess of the daily S&P 500 index return. $Yend_t$ is the dummy variable that equals one if day *t* is the last trading day in a given year, and zero otherwise. $Qend_t$ is the dummy variable that equals one if day *t* is the last trading day in a given quarter that is not the year-end, and zero otherwise. Specifically, $Qend_t$ takes the value of one on the last trading day of March, June, and September. Similarly, $Mend_t$ is the dummy variable that equals one if day *t* is the last trading day in a given month that is not the quarter-end, and zero otherwise. Furthermore, $Ybeg_t$, $Qbeg_t$, $Mbeg_t$ are the dummy variables for the first trading day of the year, quarter and month, respectively, and are defined analogously. $Controls_{i,t}$ is a vector of control variables, including fund size, fund age, turnover ratio, fund past performance and fund fees. Year fixed effects are included and standard errors are double clustered by fund and year.

Table 4-2 shows the results for the portfolio pumping activity among multi-fund managers. In column (1), we run the regression in equation (19) without fund-level controls. Our results provide strong evidence supporting portfolio pumping activity among multi-fund managers at both the year-ends and quarter-ends, with coefficients being statistically significant. This is consistent with prior literature (e.g. Carhart et al., 2002). Not surprisingly, these multi-funds also experience a return reversal at the beginning of the next year or quarter. In particular, it seems that multi-fund managers inflate the fund performance more heavily at the quarter-ends than at the year-ends, with the magnitude of the coefficient on quarter-ends being about twice as strong as the coefficient on year-ends. Furthermore, return reversal is stronger at the beginning of the year compared with that of the quarter. In addition, although we find month-end return significantly is significantly higher than the rest of the year, there is no return reversal at the beginning of the next month. Column (2) reports the results for the regression including fund controls and the results are consistent. It should be noted here that the data frequency of our return variable and other controls are measured daily and yearly, respectively. This may not result in a substantial change in our coefficients compared with Column (1).

Furthermore, to test whether portfolio pumping activity is more intense at the quarter-ends compared with other month-ends, we amend equation (1) as follows:

$$r_{i,t} = b_0 + b_1(Yend_t + Qend_t) + b_2(Ybeg_t + Qbeg_t) + b_3(Yend_t + Qend_t + Mend_t) + b_4(Ybeg_t + Qbeg_t + Mbeg_t) + \delta Controls_{i,t} + \varepsilon_{i,t} \qquad (20)$$

Where $r_{i,t}$ is the fund *i*'s return on day *t* in excess of the daily S&P 500 index return. $Yend_t$ $(Ybeg_t)$, $Qend_t$ $(Qbeg_t)$, $Mend_t$ $(Mbeg_t)$ are the dummy variables that take the value of one on the last (first) trading day for a year, quarter, and month, respectively. $Controls_{i,t}$ is a vector of control variables, including fund size, fund age, turnover ratio, fund past performance and fund fees. Year fixed effects are included and standard errors are double clustered by fund and year.

Columns (3) and (4) in Table 4-2 report the results for our regression without fund controls and with fund controls, respectively. It is clear that the inflated value at the quarter-ends is significantly higher than other month-ends. Moreover, our results suggest that pumping funds experience a significant larger return reversal on the first trading day of the next quarter.

Overall, our results show that multi-fund managers tend to artificially inflate their fund performance at both the year- and quarter-ends, especially at the quarter-ends, with a return reversal on the following trading day, which provides evidence for the portfolio pumping activity among multi-fund managers. This is consistent with our hypothesis *5a.* The rationale is that multi-fund managers have more resources to utilize the portfolio pumping activity to inflate their portfolio value because the coordination costs for the cross subsidization are smaller for them compared with their single-fund counterparts.

Table 4-2 Portfolio pumping among multi-fund managers

This table reports the regression results for portfolio pumping activity among multi-fund managers. The dependent variable is the daily return in excess of the S&P 500 index return. Main independent variable are the six dummy variable: Yend (last trading day of the year), Ybeg (first trading day of the year), Qend (last trading day of the quarter), Qbeg (first trading day of the quarter), Mend (last trading day of the month), Mbeg (first trading day of the month). Other control variables include fund size, fund age, turnover ratio, fund past performance, fund expense ratio. Year fixed effects are included. T-statistics based on fund-year-clustered standard errors are reported in parentheses. The sample period is from January 2001 to December 2021. ***, ** and * denote the statistical significance at the level of 1%, 5% and 10%, respectively.

	Fund excess return			
	(1)	(2)	(3)	(4)
Yend	0.0003***	0.0002***		
	(21.10)	(16.24)		
Ybeg	-0.0008***	-0.0008***		
	(-33.62)	(-37.06)		
Qend	0.0007***	0.0007***		
	(60.32)	(61.33)		
Qbeg	-0.0005***	-0.0005***		
	(-38.71)	(-36.50)		
Mend	0.0001***	0.0001***		
	(13.09)	(13.94)		
Mbeg	0.0001***	0.0001***		
	(12.90)	(8.47)		
Yend + Qend			0.00005***	0.0004***
			(40.32)	(36.38)
Ybeg + Qbeg			-0.00007***	-0.0006***
			(-50.03)	(-46.27)
Yend + Qend + Mend			0.00001***	0.0001***
			(12.90)	(13.94)
Ybeg + Qbeg + Mbeg			0.00001***	0.0001***
			(13.09)	(8.48)
Size		0.0000**		0.0000***
		(2.06)		(4.81)
Age		-0.0000*		-0.0000***
		(-1.83)		(-3.85)
Turnover		-0.0000**		-0.0000*
		(-2.37)		(-1.92)
Past performance		0.0001***		0.0001***
		(4.98)		(4.87)
Fees		-0.0022***		-0.0013***
		(-5.71)		(-2.84)
Year FE	Yes	Yes	Yes	Yes

Obs.	12,039,420	9,482,273	12,039,420	9,482,273

4.4.2 Portfolio pumping among multi-fund managers across different investment objectives

In the previous section, we find that portfolio pumping is prevalent among multi-fund managers. In this section, we further explore whether multi-fund managers have a preference in funds they are willing to inflate the value across different fund investment categories. To do so, based on fund investment objectives, we classify our sample into three categories, namely aggressive growth funds, growth funds, growth and income funds which contains growth and income funds and equity income funds. Next, we run the regression in equation (19) to examine the portfolio pumping activity across these three fund categories.

The results are presented in Table 4-3. Across the three fund categories, we find that aggressive growth funds reveal the largest magnitude of outperformance at the end of each period, followed by growth funds, except that the fund return of aggressive growth funds is negative at the year-end. This pattern is more pronounced at the end of the quarter, with the coefficient on $Qend_t$ for aggressive growth funds being 1.5 times and 6 times as strong as that of growth funds and growth and income funds, respectively. The results are consistent with our hypothesis *6a*. It is not surprising that multi-fund managers are more likely to inflate the value of aggressive funds because these funds generally invest in small and less liquid stocks, which are more likely to be influenced. In other words, purchasing the securities of these funds is more likely to create an upward price pressure than stocks held by other fund categories, which would, in turn, inflate the fund value. This is consistent with Carhart et al. (2002) who find that small-cap funds have the most dramatic increase in stock returns at the year- and quarter-ends, providing further support for the portfolio pumping activity among multi-fund managers.

Table 4-3 Portfolio pumping among multi-fund managers across different investment objectives

This table reports the regression results for portfolio pumping activity among multi-fund managers across different investment objectives. The three fund categories are aggressive growth (AG) fund, growth (G) fund, and growth and income (GI) fund. The dependent variable is the daily return in excess of the S&P 500 index return. Main independent variable are the six dummy variable: Yend (last trading day of the year), Ybeg (first trading day of the year), Qend (last trading day of the quarter), Qbeg (first trading day of the quarter), Mend (last trading day of the month), Mbeg (first trading day of the month). Other control variables include fund size, fund age, turnover ratio, fund past performance, fund expense ratio. Year fixed effects are included. T-statistics based on fund-year-clustered standard errors are reported in parentheses. The sample period is from January 2001 to December 2021. ***, ** and * denote the statistical significance at the level of 1%, 5% and 10%, respectively.

	Fund excess return					
	AG		*G*		*GI*	
	(1)	(2)	(3)	(4)	(5)	(6)
Yend	-0.0004***	-0.0002	0.0002***	0.0002***	0.0006***	0.0004***
	(-3.19)	(-1.53)	(11.37)	(10.42)	(30.03)	(18.73)
Ybeg	-0.0003	0.0006***	-0.0009***	-0.0008***	-0.0005***	-0.0009***
	(-0.77)	(2.66)	(-31.69)	(31.12)	(-13.03)	(-23.09)
Qend	0.0012***	0.0010***	0.0008***	0.0008***	0.0002***	0.0003***
	(10.68)	(9.50)	(60.63)	(59.96)	(10.16)	(15.63)
Qbeg	-0.0004***	-0.0001	-0.0005***	-0.0005***	-0.0004***	-0.0004***
	(-3.29)	(-0.78)	(-33.90)	(-32.91)	(-19.30)	(-16.71)
Mend	0.0002***	0.0000	0.0001***	0.0001***	0.0000**	0.0001***
	(2.71)	(0.94)	(12.66)	(10.81)	(2.56)	(10.23)
Mbeg	0.0001	0.0002**	0.0001***	0.0001***	0.0000	0.0000
	(1.48)	(2.17)	(13.71)	(8.89)	(0.97)	(0.15)
Size		0.0000*		0.0000***		-0.0000
		(1.91)		(5.13)		(-0.32)
Age		-0.0000*		-0.0000***		-0.0000

		(-1.93)		(-3.26)		(-1.15)
Turnover		0.0000		-0.0000***		-0.0000
		(0.14)		(-2.70)		(-0.27)
Past performance		0.0004		0.0001***		0.0001***
		(1.16)		(4.91)		(2.52)
Fees		0.0026		-0.0018***		-0.0028***
		(0.70)		(-2.84)		(-4.63)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	169,161	136,814	9,013,185	7,101,684	2,857,074	2,243,775

4.4.3 Portfolio pumping among multi-funds managed by single- and team-managers

Thus far, we find significant evidence of multi-fund managers engaging in portfolio pumping at the quarter-ends, especially in aggressive growth funds. Despite the fund investment objectives, the managerial structure is another potential reason that may affect the portfolio pumping activity. To be specific, in a team-based organization, peer monitoring improves individual accountability among team members, putting a pressure on team members to adhere to the right behavior, whereas joint monetary incentives reduces the possibility of cheating to team members. For instance, Patel and Sarkissian (2021) document that portfolio pumping activity declines with the increase in team size because team managers have a relatively higher cost of cheating than their single counterparts. To examine the potential effects of managerial structure on portfolio pumping activity among multi-fund managers, we divide our sample into single managers and team managers. Among team managers who handle multiple funds simultaneously, we further split them into team managers consisting of two managers, three managers, and four or more managers following prior studies. We then run the regression in equation (19) for each group with a different managerial size.

As shown in Columns (1), (3),(5) and (7) of Table 4-4, the coefficients on $Yend_t$ ($Ybeg_t$), $Qend_t$ ($Qbeg_t$) and $Mend_t$ ($Mbeg_t$) does not reveal significant differences among different team sizes. All columns indicate that regardless of the team size, multi-fund managers have the strongest incentive to implement portfolio pumping activity at the quarter-ends, which reveals a similar pattern to Table 4-2. The results are robust after controlling fund characteristics in Columns (2), (4), (6) and (8).

Overall, we find no evidence that managerial structure would affect the portfolio pumping activity, which is inconsistent with the results of Patel and Sarkissian (2021).

A possible explanation is that in our setting, multi-funds share the same management irrespective of the number of fund managers. In this case, the costs and benefits are equal for all members in the team as they jointly manage multiple funds, and thus these team multi-fund managers could be also regarded as individual multi-fund managers.

Table 4-4 The effect of managerial structure on portfolio pumping among multi-fund managers

This table reports the regression results for the effect of managerial structure on portfolio pumping activity among multi-fund managers. The dependent variable is the daily return in excess of the S&P 500 index return. Main independent variable are the six dummy variable: Yend (last trading day of the year), Ybeg (first trading day of the year), Qend (last trading day of the quarter), Qbeg (first trading day of the quarter), Mend (last trading day of the month), Mbeg (first trading day of the month). Other control variables include fund size, fund age, turnover ratio, fund past performance, fund expense ratio. Year fixed effects are included. T-statistics based on fund-year-clustered standard errors are reported in parentheses. The sample period is from January 2001 to December 2021. ***, ** and * denote the statistical significance at the level of 1%, 5% and 10%, respectively.

	Fund excess return							
	n = 1		*n = 2*		*n = 3*		*n >= 4*	
	(1)	(2)	(3)	(4)	(5)	(6)	(5)	(6)
Yend	0.0003***	0.0002***	0.0004***	0.0003***	0.0003***	0.0003***	0.0002***	0.0001***
	(8.18)	(7.00)	(15.50)	(11.59)	(11.08)	(9.62)	(6.60)	(4.18)
Ybeg	-0.0006***	-0.0005***	-0.0008***	-0.0007***	-0.0008***	-0.0009***	-0.0009***	-0.0010***
	(-10.91)	(-10.09)	(-19.33)	(-19.26)	(-17.84)	(-20.88)	(-18.60)	(-23.59)
Qend	0.0007***	0.0006***	0.0007***	0.0007***	0.0006***	0.0006***	0.0007***	0.0007***
	(24.24)	(23.10)	(37.98)	（40.52）	(26.17)	(26.13)	(30.51)	(30.70)
Qbeg	-0.0004***	-0.0004***	-0.0005***	-0.0005***	-0.0004***	-0.0005***	-0.0005***	-0.0005***
	(-13.90)	(-13.19)	(-24.50)	(-22.21)	(-17.21)	（-17.80）	(-20.47)	(-18.90)
Mend	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***	0.0002***	0.0002***
	(3.10)	(5.13)	(8.47)	(7.74)	(3.35)	(3.83)	(9.87)	(10.67)
Mbeg	0.0001***	0.0000*	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***	0.0000***
	(3.36)	(1.87)	(10.27)	(7.00)	(6.60)	(4.34)	(5.12)	(3.12)
Size		0.0000		0.0000***		0.0000**		0.0000***
		(1.00)		(4.79)		(2.36)		(4.13)
Age		-0.0000		-0.0000***		-0.0000***		-0.0000**
		(-1.18)		(-2.93)		(-2.64)		(-2.46)

Turnover		-0.0000*		-0.0000*		-0.0000		0.0000**
		(-1.90)		(-1.73)		(-1.33)		(2.43)
Past performance		0.0002***		0.0001***		0.0001		0.0001
		(3.31)		(3.04)		(1.38)		(1.54)
Fees		-0.0025		-0.0021***		-0.0009		-0.0005
		(-1.15)		(-3.42)		(-1.33)		(-0.68)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	2,138,812	1,658,561	4,165,789	3,309,359	2,671,710	2,068,015	3,063,082	2,446,308

4.4.4 The effect of switch from single-fund manager to multi-fund manager on portfolio pumping activity

Our previous results show that multi-fund managers have the behavior of inflating the value of funds they managed at the year- and quarter-ends, implying a portfolio pumping activity among them. However, a potential concern is that the portfolio pumping activity is not attributed to the benefits of managing multiple funds for fund managers, but related to fund managers themselves or other potential reasons. In this case, our previous results might be biased. In other words, we could not draw a conclusion that managing multiple funds provide a subtler way for fund managers to implement portfolio pumping activity.

To address this concern, we examine whether the portfolio pumping magnitude experiences a change when fund managers switch from single-fund managers to multi-fund managers. To perform this test, we amend our baseline regression as follows:

$$r_{i,t} = b_0 + b_1 Yend_t \times \Delta Multi_{i,t} + b_2 Ybeg_t \times \Delta Multi_{i,t} + b_3 Qend_t \times \Delta Multi_{i,t} + b_4 Qbeg_t \times \Delta Multi_{i,t} + b_5 Mend_t \times \Delta Multi_{i,t} + b_6 Mbeg_t \times \Delta Multi_{i,t} + b_7 Yend_t + b_8 Ybeg_t + b_9 Qend_t + b_{10} Qbeg_t + b_{11} Mend_t + b_{12} Mbeg_t + b_{13} \Delta Multi_{i,t} + \delta Controls_t + \varepsilon_{i,t} \quad (21)$$

Where $\Delta Multi_{i,t-1}$ is a dummy equals one if the fund managers no longer manage only one fund at time *t*, i.e. the fund *i* is newly assigned to the fund manager at time *t,* and zero otherwise. Other variables are defined as previously. The interaction term between $\Delta Multi_{i,t}$ and $Yend_t$, $Ybeg_t$, $Qend_t$, $Qbeg_t$, $Mend_t$ and $Mbeg_t$ are the main variable of interest. Year fixed effects are included and standard errors are double clustered by fund and year.

Results are presented in Table 4-5. As shown in Column (1), the coefficients on the interaction term between $\Delta Multi_{i,t}$ and $Yend_t$, $Qend_t$, $Mend_t$ are all positive and statistically significant at the 1% level. Among them, the largest extent of portfolio pumping takes place at the end of the quarter, which is similar to the findings in prior sections. More specifically, a shift from single-fund managers to multi-fund managers leads to an incremental fund performance of 23bps at the quarter-ends. Also, the significant negative coefficients on the interaction term between $\Delta Multi_{i,t}$ and $Ybeg_t$, $Qbeg_t$, $Mbeg_t$ provide evidence for the significant return reversals on the following trading days. Moreover, our results are robust after controlling for fund characteristics as shown in Column (2).

Furthermore, to reinforce our results, we also construct a sub-sample in which fund managers are assigned to manage multiple funds from the beginning of their careers. As shown in Columns (3) and (4), the results indicate that these multi-fund managers also exhibit portfolio pumping behavior.

Table 4-5 The effect of switch from single-fund manager to multi-fund manager on portfolio pumping activity

This table reports the regression results for the effect of switch from single-fund manager to multi-fund manager on portfolio pumping activity. The dependent variable is the daily return in excess of the S&P 500 index return. Main independent variable are the six dummy variable: Yend (last trading day of the year), Ybeg (first trading day of the year), Qend (last trading day of the quarter), Qbeg (first trading day of the quarter), Mend (last trading day of the month), Mbeg (first trading day of the month). The switch from single-fund manager to multi-fund manager is defined as a dummy variable, $\Delta Multi_{i,t-1}$ which equals one if the fund managers no longer manage only one fund at time *t.* Other control variables include fund size, fund age, turnover ratio, fund past performance, fund expense ratio. Year fixed effects are included. T-statistics based on fund-year-clustered standard errors are reported in parentheses. The sample period is from January 2001 to December 2021. ***, ** and * denote the statistical significance at the level of 1%, 5% and 10%, respectively.

	Fund excess return			
	(1)	(2)	(3)	(4)
Yend	-0.0003***	-0.0003***	0.0001	0.0001
	(-8.52)	(-6.69)	(1.20)	(1.40)
Yend × Δ(multi)	0.0006***	0.0005***		
	(15.50)	(11.99)		
Ybeg	0.0013***	0.0009***	-0.0010***	-0.0011***
	(14.02)	(14.15)	(-9.02)	(-11.57)
Ybeg × Δ(multi)	-0.0019***	-0.0015***		
	(-20.46)	(-25.52)		
Qend	-0.0009***	-0.0007***	0.0006***	0.0006***
	(-25.04)	(-21.16)	(13.54)	(13.15)
Qend× Δ(multi)	0.0014***	0.0012***		
	(43.23)	(39.27)		
Qbeg	0.0010***	0.0005***	-0.0004***	-0.0005***
	(24.65)	(12.34)	(-7.67)	(-10.05)
Qbeg× Δ(multi)	-0.0013***	-0.0009***		
	(-34.63)	(-23.80)		
Mend	-0.0006***	-0.0005***	0.0000	0.0000
	(-27.96)	(-21.59)	(1.48)	(1.43)

Mend× Δ(multi)	0.0006***	0.0005***		
	(30.67)	(25.05)		
Mbeg	0.0002***	-0.0003	0.0001***	0.0000
	(8.49)	(-1.47)	(2.83)	(1.10)
Mbeg× Δ(multi)	-0.0001***	0.0001***		
	(-2.70)	(4.55)		
Δ(multi)	-0.0000	-0.0000		
	(-1.43)	(-1.04)		
Size		0.0000***		0.0000***
		(3.58)		(3.74)
Age		-0.0000***		-0.0000***
		(-2.82)		(-4.68)
Turnover		-0.0000		-0.0000
		(-1.45)		(-1.10)
Past performance		0.0001***		-0.0001
		(4.99)		(-0.66)
Fees		-0.0017***		-0.0007
		(-3.15)		(-0.42)
Year FE	Yes	Yes	Yes	Yes
Obs.	11,073,420	8,740,484	880,270	671,543

4.4.5 Possible explanations for portfolio pumping activity among multi-fund managers

Thus far, our results indicate that portfolio pumping activity is prevalent among fund managers who manage multiple funds simultaneously, especially at the end of the quarter. We also provide evidence that with the heightened regulation, managing multiple funds provides fund managers a subtler way to pump their funds, as there is no evidence suggesting that these multi-fund managers have the portfolio pumping behavior when they are single-fund managers. In this section, we aim at exploring the possible explanations for portfolio pumping activity among multi-fund managers.

4.4.5.1 Convex relationship between fund flow and fund performance

First, existing studies have documented a convex relationship between fund flow and fund performance in equity funds (see, e.g., Chevalier and Ellison, 1997; Sirri and Tufano, 1998). To be specific, the convex flow-to-performance relation implies better performed funds will be rewarded by a disproportionate amount of inflows, whereas poorly performed funds will not be penalized with significant outflows. Thus, as fund managers' compensation is highly related to the fund's asset under management, the convex flow-to-performance relationship has the potential to motivate fund managers to implement portfolio pumping activity.

To examine whether the convex flow-to-performance relationship plays a role in portfolio pumping activity among multi-fund managers, we perform the following test:

$$Flows_{i,t} = b_0 + b_1 Performance_{i,t-1} \times \Delta Multi_{i,t} + b_2 Performance_{i,t-1} + b_3 Star\ Manager + \delta Controls_t + \varepsilon_{i,t} \quad (22)$$

Where $Flows_{i,t}$ is the net flow of fund i in year t, estimated by equation (18). $Performance_{i,t-1}$ is constructed by two measures, the first is the return from the first trading day to the second-to-last trading day of the year following Patel and Sarkissian (2021), and the second one is the risk-adjusted performance of fund i is estimated using a rolling regression of the past 12-month data on Carhart (1997) four-factor model. $\Delta Multi_{i,t}$ are defined as previously. Despite the control variables defined previously, we further include fund return volatility as controls. Year fixed effects are included and standard errors are clustered at the fund level. The interaction term is the main variable of interest.

Table 4-6 provides the results for this test. Both Columns (1) and (2) show significantly positive coefficients (0.066 and 1.278) on the interaction term between fund performance and the dummy variable $\Delta Multi_{i,t}$, which represents the time when managers start to manage multiple funds. This finding suggests that the fund flow is more sensitivity to fund performance among multi-fund managers, implying that funds managed by multi-fund managers have a more convex relationship between fund flow and fund performance. This supports the explanation of convex flow-to-performance relation for the portfolio pumping activity, which is consistent with prior research (see, e.g., Argrwal et al., 2011; Ben-David et al., 2013).

Furthermore, the explanation of convexity in flow-to-performance relation implies portfolio pumping activity is more likely to take place among better performed funds rather than their poorly performed counterparts. To strengthen our results, we further examine the portfolio pumping activity across funds with different past performances. To perform this test, we create three sub-samples based on past fund performance and conduct the regression in equation (19). The results are documented in Table 4-7. More specifically, the largest extent to inflate fund value at the quarter-ends occurs among the funds with top 25% past performance, which is consistent with our expectations that better performed funds are more likely to be motivated to artificially inflate the fund performance to attract new fund inflows due to the convex flow-to-performance relationship.

Table 4-6 The convex flow-to-performance relationship among multi-fund managers

This table reports the regression results for the convex flow-to-performance relation among multi-fund managers. The dependent variable is yearly net fund flows. The main independent is the fund performance, measured as past fund return in column (1) and past fund alpha in column (2), and a dummy variable $\Delta Multi_{i,t-1}$ which equals one if the fund managers no longer manage only one fund at time *t*. Other control variables include fund size, fund age, turnover ratio, fund volatility, fund expense ratio. Year fixed effects are included. T-statistics based on fund-year-clustered standard errors are reported in parentheses. The sample period is from January 2001 to December 2021. ***, ** and * denote the statistical significance at the level of 1%, 5% and 10%, respectively.

	Fund flows	
	(1)	(2)
Performance	0.873***	6.831***
	(22.17)	(8.95)
Performance× Δ(multi)	0.066**	1.278*
	(1.98)	(1.71)
Δ(multi)	-0.018**	-0.012*
	(-2.52)	(-1.81)
Size	0.029***	0.033***
	(18.73)	(20.17)
Age	-0.197***	-0.136***
	(-34.55)	(-18.43)
Turnover	-0.049***	-0.037***
	(-8.50)	(-6.67)
Fees	-0.934	-0.563
	(-1.50)	(-0.85)
Volatility	-0.580***	-0.520***
	(-6.40)	(-8.30)
Year FE	Yes	Yes
Obs.	42,198	42,198

Table 4-7 Past performance ranking and portfolio pumping

This table reports the regression results for the effect of past performance ranking on portfolio pumping activity among multi-fund managers. Funds are divided into three groups based on their past performance: the top quartile, the mid two quartile, and the bottom quartile. The dependent variable is the daily return in excess of the S&P 500 index return. Main independent variable are the six dummy variable: Yend (last trading day of the year), Ybeg (first trading day of the year), Qend (last trading day of the quarter), Qbeg (first trading day of the quarter), Mend (last trading day of the month), Mbeg (first trading day of the month). Other control variables include fund size, fund age, turnover ratio, fund past performance, fund expense ratio. Year fixed effects are included. T-statistics based on fund-year-clustered standard errors are reported in parentheses. The sample period is from January 2001 to December 2021. ***, ** and * denote the statistical significance at the level of 1%, 5% and 10%, respectively.

	Fund excess return					
	Bottom25%		*Mid 50%*		*Top 25%*	
	(1)	(2)	(3)	(4)	(5)	(6)
Yend	0.0005***	0.0003***	0.0003***	0.0003***	-0.0001***	0.0001**
	(17.66)	(10.43)	(21.01)	(17.10)	(-2.69)	(2.08)
Ybeg	-0.0004***	-0.0005***	-0.0009***	-0.0009***	-0.0007***	-0.0008***
	(-10.15)	(-11.85)	(-35.67)	(-36.12)	(-16.24)	(-15.69)
Qend	0.0004***	0.0007***	0.0005***	0.0006***	0.0012***	0.0009***
	(16.69)	(31.79)	(34.87)	(39.17)	(43.92)	(36.20)
Qbeg	-0.0008***	-0.0009***	-0.0003***	-0.0005***	0.0001***	-0.0001*
	(-33.21)	(-35.15)	(-21.72)	(-28.55)	(3.29)	(-1.77)
Mend	-0.0002***	-0.0000**	-0.0000	0.0000***	0.0005***	0.0005***
	(-14.19)	(-2.41)	(-0.06)	(3.67)	(28.81)	(24.95)
Mbeg	0.0001***	-0.0000*	0.0001***	0.0001***	0.0002***	0.0001***
	(4.78)	(-1.84)	(14.45)	(7.46)	(10.00)	(8.21)
Size		0.0000***		0.0000		0.0000***
		(4.07)		(0.23)		(3.78)
Age		-0.0000***		-0.0000		-0.0000***

		(-5.59)		(-0.80)		(-4.30)
Turnover		0.0000***		-0.0000		-0.0000***
		(3.41)		(-0.71)		(-3.33)
Past performance		-0.0003***		0.0001		0.0003***
		(-3.03)		(1.56)		(3.11)
Fees		-0.0012*		-0.0042***		0.0026***
		(-1.75)		(-5.25)		(3.09)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	2,885,579	2,433,585	5,432,550	4,645,717	2,936,114	2,479,987

4.4.5.2 Spillover effects of fund flows

Next, we examine another potential reason that may lead to portfolio pumping activity among multi-fund managers, derived from the convexity in flow-to-performance relation. Prior studies document that fund families with relatively poor performance are more likely to create star funds and enjoy the spillover effects of star funds to other non-star funds in the same mutual fund family (Nanda et al., 2004). Furthermore, the study of Fu (2020) indicates that the excess fund flows of star funds would spill over into non-star funds managed by the same fund managers. Thus, following prior studies, we examine the spillover effects among multi-fund managers through the following regression:

$$Flows_{i,t} = b_0 + b_1 Performance_{i,t-1} \times Star\ Manager_{i,t} + b_2 Performance_{i,t-1} + b_3 Star\ Manager_{i,t} + \delta Controls_t + \varepsilon_{i,t} \qquad (23)$$

Where $Star\ Manager_{i,t}$ is defined as a dummy variable that equals one if fund manager *i* have at least one fund that is at the top quartile in year *t*, and zero otherwise. Despite the control variables defined previously, we further include fund return volatility as controls. Year fixed effects are included and standard errors are clustered at the fund level. If the spillover effect exists, we would expect a positive coefficient of b_1.

Table 4-8 presents the results. The coefficients on the interaction term between fund performance and the dummy variable of star managers support the existence of spillover effects among multi-fund managers, which is consistent with Fu (2020). For instance, Column (1) shows that a 1% increase in a fund's past return would result in 0.955% (0.845 + 0.110) increase in fund flows for fund managers who own star funds. Furthermore, the incremental fund inflow for star fund managers is almost twice as large as that for non-star fund managers, with a 1% increase in a fund's alpha.

Table 4-8 Spillover effects among multi-fund managers

This table reports the regression results for the spillover effects among multi-fund managers. The dependent variable is yearly net fund flows. The main independent is the fund performance, measured as past fund return in column (1) and past fund alpha in column (2), and a dummy variable $Star\ Manager_{i,t}$ that equals one if fund manager *i* have at least one fund that is at the top quartile in year *t*. Other control variables include fund size, fund age, turnover ratio, fund volatility, fund expense ratio. Year fixed effects are included. T-statistics based on fund-year-clustered standard errors are reported in parentheses. The sample period is from January 2001 to December 2021. ***, ** and * denote the statistical significance at the level of 1%, 5% and 10%, respectively.

	Fund flows	
	(1)	(2)
Performance	0.845***	8.886***
	(17.53)	(12.40)
Performance× *Star manager*	0.110***	7.383***
	(3.33)	(7.11)
Star manager	-0.043***	-0.042***
	(-5.35)	(-5.72)
Size	0.030***	0.034***
	(19.56)	(20.57)
Age	-0.200***	-0.138***
	(-36.43)	(-19.02)
Turnover	-0.045***	-0.033
	(-7.85)	(-5.92)
Fees	-1.124*	-0.416
	(-1.86)	(-0.64)
Volatility	-0.592***	-0.477***
	(-5.65)	(-12.74)
Year FE	Yes	Yes
Obs.	46,270	46,270

4.4.5.3 Career concern

Previously, we find that portfolio pumping is prevalent among fund managers who manage multiple funds and document that the convexity in flow-to-performance relation and spillover effects of substantial inflows motives these managers to artificially inflate their fund performance at the end of the quarter to attract new inflows. However, the competing view from the career concern perspective proposes that younger managers may be more likely to engage in illegal investment practices to stand out from the crowd (Chevalier and Ellison, 1999). In this view, multi-fund managers who are generally more experienced might be less likely to engage in portfolio pumping as this may hurt their professional career and reputation. In this section, we test the effects of career concern on the portfolio pumping activity among multi-fund managers. To perform this test, we use fund manager tenure as the proxy for the level of career concern for fund managers. To do so, we run the following regression:

$$r_{i,t} = b_0 + b_1 Yend_t \times Tenure_{i,t} + b_2 Ybeg_t \times Tenure_{i,t} + b_3 Qend_t \times Tenure_{i,t} + b_4 Qbeg_t \times Tenure_{i,t} + b_5 Mend_t \times Tenure_{i,t} + b_6 Mbeg_t \times Tenure_{i,t} + b_7 Yend_t + b_8 Ybeg_t + b_9 Qend_t + b_{10} Qbeg_t + b_{11} Mend_t + b_{12} Mbeg_t + b_{13} \Delta Multi_{i,t} + \delta Controls_t + \varepsilon_{i,t} \quad (24)$$

Where $Tenure_{i,t}$ is a dummy equals one if the fund manager tenure is above the median, which is regarded as a high career concern, and zero otherwise. Other variables are defined as previously. The interaction term between $\Delta Multi_{i,t}$ and $Yend_t$, $Ybeg_t$, $Qend_t$, $Qbeg_t$, $Mend_t$ and $Mbeg_t$ are the main variable of interest. Year fixed effects are included and standard errors are double clustered by fund and year.

Table 4-9 reports the estimation results for portfolio pumping activity between multi-fund managers with high and low career concerns. We find that both experienced fund managers and young managers implement portfolio pumping activity at the end of year- and quarter-ends. However, our results show that more experienced fund managers with a relatively longer professional career are more likely to implement portfolio pumping activity than their younger counterparts, with the coefficients between the interaction terms being significantly positive. Thus, this additional test rules out the possibility of career concern.

Table 4-9 The effect of career concern on portfolio pumping

This table reports the regression results for the effect of career concern on portfolio pumping activity. The dependent variable is the daily return in excess of the S&P 500 index return. Main independent variable are the six dummy variable: Yend (last trading day of the year), Ybeg (first trading day of the year), Qend (last trading day of the quarter), Qbeg (first trading day of the quarter), Mend (last trading day of the month), Mbeg (first trading day of the month). Career concern is proxied by the tenure of fund managers. $Tenure_{i,t}$ is a dummy equals one if the fund manager tenure is above the median, which is regarded as high career concern, and zero otherwise. Other control variables include fund size, fund age, turnover ratio, fund past performance, fund expense ratio. Year fixed effects are included. T-statistics based on fund-year-clustered standard errors are reported in parentheses. The sample period is from January 2001 to December 2021. ***, ** and * denote the statistical significance at the level of 1%, 5% and 10%, respectively.

	Fund excess return	
	(1)	(2)
Yend	0.0003***	0.0002***
	(14.08)	(9.05)
Ybeg	-0.0008***	-0.0007***
	(-20.38)	(-21.15)
Qend	0.0006***	0.0006***
	(37.90)	(37.24)
Qbeg	-0.0004***	-0.0005***
	(-23.85)	(-23.48)
Mend	0.0001***	0.0001***
	(6.23)	(6.93)
Mbeg	0.0001***	0.0001***
	(10.56)	(6.66)
Yend × Tenure	0.0000	0.0001**
	(0.36)	(1.99)
Ybeg × Tenure	-0.0001	-0.0002***
	(-1.63)	(-3.75)
Qend× Tenure	0.0001***	0.0001**
	(2.91)	(2.30)
Qbeg× Tenure	-0.0001***	-0.0000
	(-2.01)	(-0.32)
Mend× Tenure	0.0000***	0.0000***
	(2.95)	(2.58)
Mbeg× Tenure	-0.0000**	-0.0000*
	(-2.75)	(-1.65)
Tenure	0.0000***	0.0000
	(2.72)	(0.92)
Size		0.0000***
		(4.93)

Age		-0.0000***
		(-3.89)
Turnover		-0.0000*
		(-1.70)
Past performance		0.0001***
		(4.86)
Fees		-0.0014***
		(-2.97)
Year FE	Yes	Yes
Obs.	12,039,467	9,482,326

4.5 Conclusion

This essay investigates the portfolio pumping behavior among multi-fund managers. First, we find evidence that multi-fund managers tend to implement portfolio pumping at the year- and quarter-ends, with the value of their funds being inflated experiencing a reversal on the first trading of the next year or quarter. Next, we further find that multi-fund managers are more likely to inflate the value of aggressive funds which hold small and less liquid securities. However, we do not find supporting evidence that managerial structure has an impact on the portfolio pumping activity among multi-fund managers. To reinforce our results, we further examine whether a swift from single-fund manager to multi-fund manager has an effect on portfolio pumping activity. Our results show that these fund managers only implement portfolio pumping after they start to manage multiple funds, which implies that managing multiple funds provide an advantage for fund managers to implement portfolio pumping. Finally, we explore possible explanations for portfolio pumping among multi-fund managers. Our results suggest that a convex relationship between fund flow and fund performance motivates the portfolio pumping behavior, because this activity allows multi-fund managers to attract more inflows. Furthermore, the excess inflows in better-performing funds would spill over to poor-performing funds managed by the same fund managers, suggesting that spillover effects also play a role in motivating the portfolio pumping activity.

Chapter 5 Conclusion

5.1 Thesis overview

This thesis investigates three topics related to the research area of mutual funds in the U.S. market. The first essay investigates the flow-to-performance relation in corporate bond mutual funds. Our analysis focuses mainly on the difference in the sensitivity of fund flows to performance between the direct-sold segment and the broker-sold segment and yields several interesting results. Firstly, we find the concave flow-to-performance relation in corporate bond funds is only evident in the broker-sold segment, with the sensitivity of outflows to poor performance being almost three times as strong as the inflow-to-good performance sensitivity. Secondly, we show that the redemption behavior subsequent to poor performance in the broker-sold segment is amplified by both market and fund illiquidity, suggesting a potential run behavior under unfavorable conditions. Finally, we investigate the possible explanations of the concave flow-to-performance relation in the broker-sold funds. We find that this concave relation only exists in broker-sold funds with high distribution fees, suggesting that broker advice may play a role in the concave relation between fund flow and fund performance due to the trust of investors and advisors' incentive to facilitate investor redemptions. We also find that investors of underperforming broker-sold funds are more likely to trust brokers and switch to other outperforming broker-sold funds during the non-crisis period and mistrust them and switch to direct-sold funds during the crisis period.

Our second essay investigates the relationship between ETF ownership and a firm's decision on SEO issuance. It is widely documented that managers time the market and issue SEOs when their firms' stocks are overpriced. Since ETFs transmit non-fundamental demand shocks to their constituents, high ETF ownership may inflate stock prices and create more opportunities for managers to time the market. Consistent with this argument, we document evidence of a strong positive association between ETF ownership and the firm's propensity to issue SEOs. This evidence remains robust after controlling for the confounding effects of other institutions and to alternative definitions of the managerial response window. We also show that the effect of ETF ownership on SEO probability is stronger for younger, smaller, unprofitable, and non-dividend-paying firms. This further confirms the market timing view, as these types of firms tend to more financially constrained and are, therefore, are more likely to time the market. We further examine the relation between ETF ownership and the post-SEO stock performance. We find that firms with higher ETF ownership experience lower levels of underpricing around the SEO issuance. This evidence is consistent with the price pressure view, which suggests that the demand shocks from ETFs offset the supply shock of equity offerings and, therefore, reduce the SEO underpricing. We also show that investors do not react more negatively to SEOs with secondary offerings, inconsistent with the competing view of adverse selection. Finally, we show that high ETF ownership reduces the long-run post-SEO underperformance, suggesting that ETFs cause permanent increases in the prices of their constituents.

The third essay investigates the portfolio pumping behavior among multi-fund managers. First, we find evidence that multi-fund managers tend to implement portfolio pumping at the year- and quarter-ends, with the value of their funds being inflated experiencing a reversal on the first trading of the next year or quarter. Next, we further find that multi-fund managers are more likely to inflate the value of aggressive funds which hold small and less liquid securities. However, we do not find supporting evidence that managerial structure has an impact on the portfolio pumping activity among multi-fund managers. To reinforce our results, we further examine whether a swift from single-fund manager to multi-fund manager has an effect on portfolio pumping activity. Our results show that these fund managers only implement portfolio pumping after they start to manage multiple funds, which implies that managing multiple funds provide an advantage for fund managers to implement portfolio pumping. Finally, we explore possible explanations for portfolio pumping among multi-fund managers. Our results suggest that a convex relationship between fund flow and fund performance motivates the portfolio pumping behavior, because this activity allows multi-fund managers to attract more inflows. Furthermore, the excess inflows in better-performing funds would spill over to poor-performing funds managed by the same fund managers, suggesting that spillover effects also play a role in motivating the portfolio pumping activity.

5.2 Contributions

Our first essay makes several contributions to the literature. First, it contributes to the growing body of literature on the fund flow dynamics of fixed income mutual funds (see, e.g., Zhao, 2005; Chen and Qin, 2016; Goldstein et al., 2017). Chen and Qin (2016) argue that there is no significant convexity in the flow-to-performance relation for corporate bond mutual funds. Goldstein et al. (2017) document a concave relation between investor flows and fund performance. To the best of our knowledge, we are the first to analyze the patterns of fund flows of corporate bond funds in different retail market segments and find that the concave relation is evident only in the broker-sold segment.

Furthermore, our first essay adds to the body of research on the link between mutual funds and stability. Chen et al. (2010) argue that strategic complementarities among fund investors is conducive to financial fragility. Others suggest that strategic complementarities play a key role in the run-like behaviors in money market mutual funds (Schmidt et al., 2016) and in corporate bond funds (Goldstein et al., 2017). Feroli et al. (2014) document a feedback loop between decreasing fund returns and large fund redemptions that threatens financial stability. Complementing the above studies, our study investigates whether fund and market illiquidity may amplify the potential run behaviors among two distribution channels, which in turn, destabilizes the market.

Our second essay makes several important contributions to the literature. First, our findings add to the growing body of research examining the effect of ETF ownership on the underlying securities (e.g., Ben-David et al., 2018; Israeli et al., 2017). Prior studies mainly focus on the asset pricing implications of ETS, showing that higher ETF ownership increases return volatilities (Ben-David et al., 2018), decreases pricing efficiency (Israeli et al., 2017), and impairs stock liquidity (Hamm, 2014) of the underlying securities. We complement the existing literature by providing evidence on the implications of ETFs to corporate decision making, such as SEO decisions.

Second, our study extends the literature on the motivation behind security issuance (e.g., Masulis and Korwar, 1986; Myers and Majluf, 1984). Previous studies suggest that firm managers time the market and conduct equity issuance when their stocks are overvalued (Baker and Wurgler, 2002, Loughran and Ritter, 1995). Our research suggests that ETF ownership leads to decreasing informational efficiency and persistent demand for underlying securities, thereby offering an opportunity for firms to time the market and increasing the SEO probability among those firms.

Finally, our study also relates to the literature on post-issue performance (see, e.g., Corwin 2003; Kim and Purnanandam, 2014). Prior work suggests that firms exhibit negative performance both in the short-run (Asquith and Mullins, 1986; Masulis and Korwar, 1996) and in the long-run (Loughran and Ritter, 1995). Our evidence advances this literature by documenting that although the underperformance exists, firms with higher ETF ownership outperform their counterparts with lower ETF ownership. This evidence implies that higher ETF ownership implies higher market participation, which generates persistent demand for the underlying stocks, and imporves the post-issuance performance.

Our third essay primarily contributes to the literature on portfolio pumping activity in the mutual fund industry (see, e.g., Carhart et al., 2002; Duong et al., 2020; Wang, 2019). Prior studies have found a decline in portfolio pumping activity as a result of increased regulatory monitoring (Duong et al., 2020). In response to this, several studies provide evidence that portfolio pumping has become more evasive. For instance, portfolio pumping experience a shift from fund level to fund family level (Wang, 2019), from year- and quarter-ends to month-ends (Kim, 2020). To the best of our knowledge, this study is the first relating portfolio pumping to multi-fund managers. Our third essay complements the literature by documenting that portfolio pumping activity among fund managers who operate multiple funds simultaneously.

The third essay is also related to the literature on cross-fund subsidization and agency conflicts. Agarwal et al. (2018) show that multitasking leads to an improved fund performance for newly assigned funds at the sacrifice of the performance of incumbent funds. Gaspar et al. (2016) confirm the agency problem of cross-subsidization, documenting that fund families transfer the performance of less profitable funds to those more profitable funds. Del Guercio et al. (2018) find that fund managers tend to maximize the hedge funds rather than mutual funds, because their compensation is more directly and heavily related to hedge funds. Our study adds to this area of research by suggesting that multi-fund managers exploit the cross-fund subsidization mechanism to inflate their fund performance through portfolio pumping.

Overall, our study employ a large sample in the U.S. market covering the most recent data, thus, our research findings can be applied to the whole U.S. mutual fund industry. These findings also provide several important practical implications. For instance, our findings imply that the compensation that brokers receive when investors switch funds serves as an incentive to encourage transactions. Regulators should therefore try to restrain such incentives, as it may destabilize the market. Furthermore, our findings suggest that ETF ownership improves the post-issuance performance. This may provide regulators an insight into that the popularity of ETFs may improve the market efficiency. Finally, our findings suggest that portfolio pumping is prevalent among multi-fund managers. This type of value inflation across various funds managed by the same fund managers tells the regulators another portfolio pumping activity that they may not be aware of.

5.3 Limitation and future work

It is acknowledged that this study has several limitations. First, due to data availability, we can not access to the Russel 1000/2000 reconstitution data, which is a common used method to test the endogenity issues related to the ETF ownership. If there are sufficient data, future study can complement our investigation about the impact of ETF ownership on seasoned equity offerings through this alternative regression discontinuity method. Second, there might be several missing variable, such as the equity issuance size that may affect the firm's seasoned equity offering decision and following performance, which is omitted in this study. Future research may improve the current version through including these control variables related to issuer's characteristics.

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Appendix

Variable definition in the first essay

Variable	Definition	Source
Log TNA	the natural logarithm of fund net assets	CRSP
Log Age	the natural logarithm of fund age in years	CRSP
Expense	Fund expense ratio	CRSP
Return	Fund monthly returns	CRSP
Net flow	the percentage change in fund TNA minus the change in TNA caused by fund return during a given period	CRSP
Alpha	the intercept from the rolling-window time-series regressions using the past 12 month of data based on 4-factor model	CRSP
STK	The excess return on the CRSP value-weighted stock index	CRSP
BOND	The excess return on the Barclays US aggregate bond index	Bloomberg
DEF	The return spread between the Barclays US high-yield bond index and the Barclays US intermediate government bond index	Bloomberg
OPTION	The return spread between the Barclays US mortgage-backed security index and the Barclays US intermediate government bond index.	Bloomberg
VIX	The Chicago Board Options Exchange (COBE)	Bloomberg
TED spreads	The difference between the 3-month London Interbank Offered Rate (LIBOR) and the interest rate of 3-month Treasury bill rate	Bloomberg
Crisis	Period from August 1998 to December 1998 and from August 2008 to December 2009	
Marketing fees	Annualized total loads (divided by 7) plus 12b-1 fees	CRSP
GDP	The growth rate of GDP	HIS
CPI	Log difference of CPI	FRED
BAA - AAA	The yield spread between Moody's BAA corporate bond and Moody's AAA corporate bond	FRED

Variable definition in the second essay

ETF ownership BFM	the sum of the dollar value of holdings by all ETFs investing in the stock divided by the stock's market capitalization	CRSP/Compustat
ETF ownership ILS	the proportion of shares owned by all ETFs in the total number of shares outstanding of stock	CRSP/Compustat
Size	Natural logarithm of total assets	Compustat
ROA	Operating income before depreciation over total assets	Compustat
Cash	Cash and short-term investments over total assets	Compustat
Return	Stock return over one quarter	CRSP
BTM	Book value of shareholders' equity over market value of equity	CRSP/Compustat
Leverage	Long-term debt plus long-term debt in current liabilities over total assets	Compustat
Dividend	Dividend per share divided by stock price	Compustat
Volatility	Standard deviation of daily stock returns over the quarter	CRSP
Ln Age	Natural logarithm of firm age	Compustat
Active fund ownership BFM	the sum of the dollar value of holdings by all active funds investing in the stock divided by the stock's market capitalization	CRSP/Compustat
Active fund ownership ILS	the proportion of shares owned by all active funds in the total number of shares outstanding of stock	CRSP/Compustat
Index fund ownership BFM	the sum of the dollar value of holdings by all index funds investing in the stock divided by the stock's market capitalization	CRSP/Compustat
Index fund ownership ILS	the proportion of shares owned by all index funds in the total number of shares outstanding of stock	CRSP/Compustat
SEO underpricing	Close-to-offer return: (prior closing price - offer price) / prior closing price	Thomson one/CRSP
Ln (Market cap)	Natural logarithm of market capitalization, which is defined as the number of shares outstanding multiplied by price on the day prior to the offer	CRSP
Volatility	Standard deviation of daily return over the 30 trading days ending 11 days prior to the issue date	CRSP
Rel offer size	Offer shares divided by total shares outstanding prior to the issue date	Thomson one/CRSP
CAR positive (negative)	CAR is the cumulative market-adjusted return over the 5 days prior to the issue date. CAR positive (negative) equals CAR if positive (negative) and zero otherwise	CRSP

Ln (Price)	Natural logarithm of stock price on the day prior to the issue date	CRSP
Tick < 1/4	Equals one if the decimal portion of the closing price on the day prior to the issue date is less than $0.25, and zero otherwise	CRSP
IPO underpricing	Average underpricing across IPOs during the same month as the SEO	http://bear.cba.ufl.edu/ritter
NYSE	Equals one if the firm was listed on the NYSE at the time of SEO and zero otherwise	CRSP
Variable definition in the third essay		
Excess return	Fund daily return in excess of S&P 500 index return	CRSP
Yend	Equals one if it is the last trading day of the year	
Ybeg	Equals one if it is the first trading day of the year	
Qend	Equals one if it is the last trading day of the quarter	
Qbeg	Equals one if it is the first trading day of the quarter	
Mend	Equals one if it is the last trading day of the month	
Mbeg	Equals one if it is the first trading day of the month	
Fund size	Fund total net assets	CRSP
Fund age	Fund age in years	CRSP
Fund fees	Fund expense ratio	CRSP
Fund turnover	minimum of aggregated sales or purchases of securities in a year divided by the average 12-month total net assets of the fund	CRSP
Past performance	the return from the first trading day to the second-to-last trading day of the year	CRSP
	the intercept from the rolling-window time-series regressions using the past 12 month of data based on 4-factor model	CRSP
Fund flow	the percentage change in fund TNA minus the change in TNA caused by fund return during a year	CRSP
Tenure	Fund managers tenure	Morningstar direct