Two Essays on Mutual Funds

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Two Essays on Mutual Funds

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This dissertation consists of two essays on mutual funds. In the first essay, I hypothesize that mutual fund managers sell shares to induce price pressure in stocks owned by competitors in order to hurt competitors' performance, thereby improving their own funds' relative performance. I find that this predatory trading occurs primarily among top-ranked funds where the flow-performance relationship is highly convex and during the fourth quarter when incentives are the strongest. Predatory trading is not widespread, however, because managers anticipate and respond to the threat of predation. Specifically, smaller funds own fewer shares in illiquid stocks that are also held by larger competing funds ranked nearby. My paper is the first to provide evidence of strategic predatory trading by mutual funds and the resulting impact on the equilibrium allocation of assets within the mutual fund industry.

In the second essay, I use the setting of series trusts in mutual funds to examine the impact of board independence on mutual fund performance and further compare the board governance to the other primary governance mechanism, investors' right to redeem shares on any trading day. A series trust is a turnkey setup service provided by a third party to fund advisers where there is a weaker connection between boards and fund advisers. I find that funds with more independent boards perform better and that board governance is a complement rather than a substitute to the redemption right.

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Preface

I thank my dissertation committee members Professor David Denis, Professor Andrew Koch, Professor Frederik Schlingemann, Professor Ravi Shukla and Professor Chad Zutter for their guidance. I especially thank my dissertation co-chairs Professor Frederik Schlingemann and Professor Andrew Koch, for their support and encouragement. I am also grateful to other professors at the University of Pittsburgh who I had the opportunities to learn from. I thank fellow doctoral students in the finance department as well as in other disciplines for their friendship.

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1.0 Overview of the Literature on Mutual Funds

The primary source of revenue for mutual funds is the management fee charged based on the asset under management. If a fund wants to increase its revenue, it needs to charge a higher management fee or attract more investor flows to grow the assets under management (AUM).

A higher management fee is not a feasible choice in general. First, management fees usually fall between 0.5% and 2%, and a fund will adopt the fee level within a specific range based on its type (i.e., equity, fixed income, or mixed) as an industry norm. Second, mutual fund investors are sensitive to expense ratios, which include the management fee, the 12b-1 fee, and other operating expenses. For instance, Barber, Odean, and Zheng (2005) show that investors are more sensitive to salient, in-your-face fees, like front-end loads and commissions. Similarly, Ivković and Weisbenner (2009) find that individual investors pay attention to investment costs as redemption decisions are sensitive to both expense ratios and loads.

Increasing investor flows thus becomes the ultimate goal of mutual funds. Funds attract flows with superior performance. The performance of a fund is not evaluated in isolation but usually compared to a prespecified benchmark or a subset of funds with similar investment goals and strategies. Previous literature has shown that mutual funds take various strategies to achieve such a goal. Conventional strategies include increasing the riskiness of the portfolios, herding, and portfolio pumping. In this dissertation, I present an undocumented trading strategy, predatory trading, that serves the same goal of better relative performance.

1.1 Mutual fund Performance and Managerial Incentives

Research has shown that investors chase funds with better performance, and such performance-chasing is not restricted to specific groups or sub-segments of investors. Both retail and institutional clients have shown an inclination to chase performance (Goyal and Wahal, 2008; Bennyhoff and Francis, 2013). The underlying assumption is that the past high performance is likely to persist in the future. However, there is limited empirical evidence to support the persistence of past performance.

First, the performance of the lowest-performing funds is observed to be persistent (Hendricks et al., 1993; Brown and Goetzmann, 1995; Carhart, 1997). Second, there are mixed findings for performance persistence among highest-performing funds. Some researchers (Grinblatt and Titman, 1992; Goetzmann and Ibbotson, 1994) find evidence of persistence in winners, while others (Brown et al., 1992; Brown and Goetzmann, 1995) show that results are attributed to survivorship biases. Berk and Green (2004) indicate that the diminishing returns to scale can be used to reconcile the lack of average outperformance and performance persistence with the existence of managerial skills.

Empirical evidence has generally shown that the inflows and outflows of funds are related to lagged measures of returns. Ippolito (1992) concludes that mutual fund investors move cash into funds that had the best performance in the preceding year. Chevalier and Ellison (1997) and Sirri and Tufano (1998) further show that the relationship is asymmetric. Berk and Green (2004) develop a model that allows strong responses of flow to past performance even without the presence of persistence.

One explanation of the convex shape of the relationship is search costs (Sirri and Tufano,1998). The fund manager and the fund family will put more effort into advertising a fund performed well in the past, making the media coverage much higher for top funds. Fund families, in most cases, make family decisions on advertising, compensation, and promotions at the end of the year. For instance, Gallaher, Kaniel, and Starks (2006) report that advertising budgets are decided upon yearly. Given the desire to receive a favorable resource allocation within a family, fund managers are expected to enhance their year-end performance. If the funds are top-ranked in their subset of investment styles and compared to the rest of the funds in the family, the top-ranked funds could be advertised or supported by cross-fund subsidization, and the managers will possibly be promoted. Huang, Wei, and Yan (2007) introduce participation costs, which incorporates both information costs of collecting and analyzing information about a fund before investment and transaction cost involved with purchasing and redeeming fund shares. The paper shows that funds with lower participation costs have a higher flow sensitivity to median performance and a lower flow sensitivity to high performance than their higher-cost peers. Such discovery further supports the asymmetric flow-performance relationship.

Fund flow, following Sirri and Tufano (1998), is defined as:

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

where $TNA_{i,t}$ stands for the total net assets under management for fund i in year t, and $R_{i,t}$ stands for the fund's return in year t. Sirri and Tufano (1998) use several performance measures, including historical returns, return rankings relative to other funds with a similar objective, and market-adjusted returns.

[Figure 1 Here]

Figure 1 reports graphically the 20 groups of funds based on their relative performance. Funds are ordered within one of three objective categories (aggressive growth, growth and income, and long-term growth) and divided into 20 groups based on their total returns.

Similarly, Kempf and Ruenzi (2004) adopt the piecewise linear regression methodology as in Sirri and Tufano (1998) and estimate the regression for the three quintiles separately to show the convex relationship.

Mutual fund ranking is considered a repeated game that resets annually. The first reason is that the return in the most recent calendar year is generally more available to consumers. Listings of mutual funds, accompanied by calendar year returns, are published on an annual basis in news, business, and financial publications. The annual return is also used in the annual fund listings produced by Morningstar and other mutual fund rating agencies. Second, the flow-performance relationship relies on short-term performance rather than a more extended period. Ivković and Weisbenner (2009) find that fund inflows are related only to funds' relative performance measures, including funds' one-year performance relative to other funds with similar investment objectives. Similarly, outflows are related only to funds' one-year absolute returns. Thirdly, year-end performance is what the fund managers have shown to care about. Koski and Pontiff (1999) show that the change in portfolio riskiness is closely related to the prior interim performance within one calendar year. Brown et al. (1996) and Chevalier and Ellison (1997) also show that the incentives of altering portfolio riskiness strengthen toward the end of the year.

1.2 Trading Strategies and Their Impact on Stock Performance

Changing portfolio riskiness is a strategy with high outcome uncertainty. As a comparison, portfolio pumping is a strategy that enables managers to control the outcomes. Carhart et al. (2002)

show that top-ranked funds, compared to the rest, push up the stock price of their major holdings in the last trading day of the year. A recent working paper, Wang (2018), extends the portfolio pumping strategy to the group strategy of fund families.

Portfolio pumping is implemented by buying more shares of stocks, while predatory trading is the opposite. However, the two strategies differ more than the direction of trading. The appeal of the portfolio pumping strategy is that funds have perfect information about their holdings, but the portfolio holdings of competing funds are not perfectly observable. The best public information on a fund's holding is the quarterly report filed to SEC within a time frame of 60 days from the quarter-end. Further, there are concerns about window dressing that could undermine the accuracy of holding filings. First, Lakonishok et al. (1991) have examined whether institutional asset managers engage in window dressing, selling off poor performing assets from their portfolios before issuing year-end holdings reports. Their sample of managers undertakes very little window dressing. Second, the predatory trading strategy in my paper is based on holding information at the end of the third quarter, while window dressing is most likely to happen at the end of the year.

Market volatility has shown to be closely related to mutual fund flows (Coval and Stafford, 2007; Cao et al., 2008). On the one hand, inflows or outflows of funds create buying or selling pressure on stocks and increase the volatility of equity markets. Cao et al. (2008) use a structural VAR impulse response analysis that suggests that the shock in mutual fund flows has a negative impact on market volatility. This effect is particularly significant over the next ten days, and an inflow shock induces low market volatility, while an outflow induces high market volatility. On the other hand, market volatility also affects mutual fund performance and flows. Busse (1999) sheds light on the question of whether mutual funds time market volatility. The paper shows that funds decrease market exposure when market volatility is high. Further, Cao et al. (2008) find that flow is negatively related to the previous day's market volatility. Rakowski (2010) looks at how volatile fund flow affects fund performance and shows that increased daily flow volatility hurts risk-adjusted fund performance. Increased market volatility is related to predatory trading in that it triggers outflows of funds as well as the sale of stocks when funds are timing the volatility. Funds could be more likely to sell their holdings for providing liquidity to increased investor redemption or for implementing the strategy to time market volatility.

Several studies show that mutual fund trading could lead to price pressure on stocks and make trading prices deviate from the fundamentals and capture the effect of mutual fund flows on market returns and individual stocks (Warther, 1995; Wermers, 1999; Edelen and Warner, 2001). Edelen and Warner (2001) document a positive relationship between large fund flows and returns on the stocks held by the fund, and they find that daily mutual fund total inflows lead to higher market returns. Coval and Stafford (2007) show that mutual funds cause price pressure in securities held in common by distressed funds as those funds tend to decrease existing positions when facing large outflows. Similar to liquidating positions for massive outflows caused by investor redemption, mutual funds could purposefully cause price pressure and affect fund rankings, depending on portfolio weights of the stocks and their own returns and those of other funds holding the same stocks. Research on hedge funds shows such findings. Ahoniemi and Jylhä (2014) observe flow-induced price pressure and evidence that the reversal of the initial price impact occurs slowly; on average, it takes 24 months. This result could be explained by the persistence in price pressure, or by hedge funds being viewed as "informed" investors, so their trading sends a positive or negative signal to the market. In general, empirical evidence suggests short-lived price pressure in equity (Kraus and Stoll, 1972; Harris and Gurel, 1986; Shleifer, 1986; Mitchell et al., 2004), while slightly longer-lived price pressure, up to a few weeks, is presented in Greenwood (2005).

Mutual funds are regulated by the Securities and Exchange Commission under the provisions of the Investment Company Act of 1940. Unlike lightly regulated hedge funds, mutual funds are usually prohibited from engaging in high-risk transactions like selling stocks short. However, long-short funds that comply with special SEC requirements are allowed to short stocks. Funds do not have to own the stock at the moment of short sale and are allowed to make the delivery to the buyer within the standard three-day settlement period. Chen, Desai, and Krishnamurthy (2013) take a look at the use of short sales in mutual funds and show that the proportion of domestic equity mutual funds that allow short selling increased considerably from 24% in 1994 to 63% in 2009. The percentage of mutual funds that use short sales in a given year also increased from 2% in 1994 to 7% in 2009. Further, while both large and small funds use short sales, the short-selling funds are younger, have higher expense ratios, higher portfolio turnover, and higher management fees.

In the context of predatory trading, if the predator is allowed to short sell, then the predator does not need to hold the stock in its portfolio before selling, and it broadens the range of funds that could become predatory. With the three-day delay to deliver the stock, the predator could short sell the stock and buy back later at a lower price for delivery. Such short-selling behavior, however, is unlikely to be observed with quarterly holdings because the predator could have exited the short position during the impact of adverse price pressure to benefit from previous selling. However, it is also important to notice that funds taking such a strategy should be aware of the circumstances where short selling may cross the line from a legitimate trading strategy to stock price manipulation.

1.3 Players in the Mutual Fund Ranking Game

This section discusses the benefit and cost of predatory trading to involved parties, funds, investors, regulators, and performance ranking agencies.

1.3.1 Mutual Funds and Fund Families

Both fund managers and fund families have the incentive to trade predatorily because of the flow benefit of moving up in relative ranking. Individual fund managers benefit directly from net inflows through the compensation structure. Since 2006, mutual funds are required to disclose their compensation structure annually. Ma, Tang, and Gómez (2019) analyze the compensation structure of funds and find that 79% of fund managers' compensation is related to performance relative to the benchmark, and other funds have similar investment objectives. In addition to the cash benefit, fund managers will receive an advantageous resource allocation if they outperform. For example, Gallaher et al. (2006) report that advertising budgets are decided yearly.

In addition to increased fund flows to a top-ranked fund, the fund family benefits from a spillover effect of having a star fund. Nanda, Wang, and Zheng (2004) find that star performance results in higher cash inflow to the fund and the other funds in its family. Because families' profits are a direct function of fees charged and assets, and the relationship between inflows and past performance is convex, fund families have the incentive to transfer performance to their most money-making funds through cross-subsidization. Cross-subsidization refers to a family strategy that transfers performance from member funds to favored funds (i.e. high fee funds or good past performers). Guedj and Papastaikoudi (2003) construct a portfolio of funds that long the previous year's best-performing funds and short the previous year's worst-performing funds in large fund families. Such a portfolio generates a consistent monthly alpha of 58 basis points. Gaspar, Massa, and Matos (2006) show that high family-value funds outperform at the expense of low family-value funds.

Given the differences in the abilities and resources of the funds in the family, the size of the family also affects the behavior of the funds. Nanda, Wang, and Zheng (2004) discover that small or low-ability fund families are more likely to involve a star-making process, which increases the differentiation in risks across the funds. Huang, Wei, and Yan (2007) find that funds in smaller families have a more convex flow-performance relationship. Huang, Sialm, and Zhang (2011) show that funds with worse prior performance, smaller-family funds, and higher-expense funds experience more severe performance consequences when they increase risk.

1.3.2 Mutual Fund Investors

By mid-2017, an estimated 100 million individual investors owned mutual funds, and at the end of 2017, these investors held 90 percent of total mutual fund assets[1], directly or through retirement accounts. Empirical evidence mostly focuses on individual investors and separate inflows and outflows from the overall net flows that are used in the flow-performance relationship. There are several exciting observations associated with the buying and selling motivations of mutual fund investors. Fund inflows relate to performance different from fund outflows. While shareholder inflows correlate with performance, Johnson (2007) shows that shareholder outflow is unrelated to fund returns. Ivković and Weisbenner (2009) show that inflows are related only to

[1] 2018 Investment Company Fact Book, 58th edition.

relative performance, suggesting that new money chases the best performers in a fund category. Outflows are only related to absolute fund performance, the relevant benchmark for taxes. Taxation is also among the considerations that affect individuals' decisions. There is a negative relationship between the likelihood of a sale and past performance for mutual funds held in taxable accounts. That is, investors holding mutual funds in taxable accounts are reluctant to sell funds that appreciated and willing to sell funds that have fallen in price. Further, mutual fund investors are more sensitive to front-end-load fees compared with operating expenses (Barber et al., 2005).

1.3.3 Regulatory Authorities

Mutual funds and their advisers operate under both the Investment Company Act of 1940 and the Investment Advisers Act of 1940. The goal of regulatory authorities, such as SEC, lies in protecting investors and promoting fair trading. In May 2004, SEC set the final rule of mutual fund quarterly holding reports and required that the holdings needed to be filed within 60 days from the end of the quarter. While choosing the delay period with quarterly reports between 30 days to 60 days, SEC favors the 60-day delay due to the potential of expanding the opportunities for professional traders to exploit portfolio information by engaging in predatory trading practices that would harm fund shareholders. In addition to predatory trading, changing the riskiness of portfolios for better year-end performance is also considered harmful to fund shareholders. Ingersoll, Spiegel, Goetzmann, and Welch (2007) show that fund managers have an incentive to change risk levels to manipulate their performance.

1.3.4 Media and Rating Agencies

Individual investors, due to the lack of available data and analytical skills, rely on several sources to identify their ideal investments. As mentioned above, buying funds through brokers usually come with an advisory service. Brokers, on the other hand, get their data and information from rating services such as Morningstar, Lipper, Reuters, and Business Week, who are leading vendors of detailed information about past mutual fund returns, expenses, and turnover. The goal of such rating agencies is to produce investment services, including research and analysis.

Morningstar has been the undisputed market leader[2] of information intermediaries among mutual fund retail investors. The star ratings[3], which grade a fund from one to five stars, are one of the primary inputs to investor decisions. Investors, directly or indirectly, are affected by the rating practice of Morningstar (Guercio and Tkac, 2008). In addition to advisors and institutions, individual investors' investment choices are also influenced by media coverage. Publications used in the literature include major personal finance publications (*Money Magazine, Kiplinger's Personal Finance,* and *SmartMoney*), major business publications (*Barron's, Business Week, Forbes* and *Fortune*), and national news publications (*Wall Street Journal, U.S. News and World Report, USA Today,* and *Boston Globe*).

[2] Morningstar's platform for financial advisors is said to have up to an 80% market share among the 250,000 independent financial advisors and planners in the U.S (Jones and Smythe).

[3] Morningstar first offered its star ratings in 1986 by paid subscription to its print product Morningstar Mutual Funds. Funds with risk-adjusted ratings in the top 10% of their peer group are assigned five stars; the next 22.5% receive four stars, the next 35% receive three stars, the next 22.5% receive two stars, while the bottom 10% of funds in each peer group receive one star.

Reuter and Zitzewitz (2006) show that a single additional positive media mention for a fund is associated with inflows ranging from 7 to 15 percent of its assets over the following twelve months.

1.4 Predatory Trading

The best-known theory of predation is the long-purse theory, where firms with ample financial resources drive their financially-constrained competitors out of the market by reducing their rivals' cash flows. Past literature also focuses on theoretical models in predation. Fudenberg and Tirole (1986); Poitevin, (1989); Bolton and Scharfstein, (1990) investigate capital market imperfections that affect product market competition, which then creates the potential for predation. Other papers apply predatory pricing to the setting of mergers and acquisitions. For example, Saloner (1987) establishes a theoretical basis for predatory output expansions under circumstances where mergers are expected or not. Caves (1981) and Miller (1973) suggest that unrelated acquisitions may increase opportunities for predatory pricing and reciprocal buying and reduce intra-industry rivalry through the presence of several large firms facing each other in many markets. Bolton and Scharfstein (1990) analyze and develop a model of optimal contract for a poorly performing firm under the predatory threat from cash-rich firms.

However, the empirical evidence of predatory pricing has been limited to the case study of several industries. Burns (1996) uses data on the old American Tobacco Company between 1891 and 1906 and finds that predatory pricing significantly lowered the acquisition costs of the tobacco trust. Brady and Cunningham (2001) examine the evidence of predatory pricing in the airline industry and the effectiveness of the Department of Transportation's approach in addressing such issues.

Brunnermeier and Pedersen (2005) are the first to introduce the idea of predatory trading in the setting of traders. They refer to the trading that induces or exploits the needs of other investors to reduce their positions, and they show that a trader could benefit from triggering another trader's crisis by causing price overshooting and reducing liquidation value for the distressed trader. Carlin et al. (2007) model how illiquidity could arise from a breakdown in cooperation among market participants. However, there is little empirical evidence. Eisele et al. (2014) are the only other ones to discuss predatory trading in the mutual fund industry. They look at how funds that belong to the same fund family trade when another affiliated fund enters a distressing situation caused by severe investor redemption. In other words, predatory trading in their paper refers to when affiliated funds exploit the information on liquidity constraints of other funds by selling stock positions before the distressed fund does. Further, they only find predatory trading inside large fund families.

2.0 First Essay: Predatory Trading in Mutual Funds

2.1 Introduction

Every January of each year, the market leader in investment research service providers among mutual fund retail investors, Morningstar, announces the "Best 16 U.S. Fund Managers of the Year" awards while the *Wall Street Journal* releases the names of top 10 funds in each category as "Category Kings". Such rankings affect the investment decisions of investors and mutual fund managers have incentives to take actions that increase the fund inflow to maximize their fees. In this context, Chevalier and Ellison (1997) show that the flow-performance relationship is convex, and they provide empirical evidence that the rank of a fund is an important determinant for the inflows a fund receives in the next period. This convexity implies that the incremental inflow is positively associated with the fund's rank, that managerial incentives to improve their funds' rankings differ across ranks, and that fund managers have an incentive to trade strategically to improve their relative rankings.

In this paper, I consider a strategy available to mutual fund managers when they compete for higher rankings, which I refer to as predatory trading. I define predatory trading as the sale of a stock that is commonly held by the fund that initiates the strategy (the predator) and its higher-ranked competitor (the target), whereby the sale is meant to hurt the competitor's return more than the predator's return. Such definition is different from the traditional definition[4] of predatory

[4] In the traditional definition, predatory trading is referred to the front-running of other market participants that profit from the flow-induced trading of mutual funds (Dyakov and Verbeek, 2013; Shive and Yun, 2013).

trading in mutual funds. In my definition, I derive the necessary condition for successful predation, and I hypothesize that predators are more likely to sell common positions that have higher potential benefits of predation. I test this hypothesis empirically and find evidence of such predatory trading. The strongest evidence of predatory trading occurs in top-ranked funds that satisfy the necessary conditions of predatory trading in the last quarter of the year. Due to the strict, necessary conditions required for predatory trading, I do not expect such a strategy to happen commonly among funds. Further, the threat of predatory trading could incentivize funds to adopt strategies to avoid being targeted. Consistent with this, I show that the threat of predation affects the funds' portfolio choices. Specifically, my evidence suggests that funds would hold fewer common positions and fewer shares in common positions toward the end of the year when the threat is high.

The rationale for why predatory trading in mutual funds is effective is as follows: assume there are two funds, A and B, that belong to the same fund category so that these two funds compete for investment flows. Both funds hold stock S in their portfolios, but stock S has a higher portfolio weight in A than in B. Also, assume that A ranks one place above B, and B is relatively (to A) large and holds a large number of shares in stock S. Fund B can trade predatorily by selling its holding of stock S, whereby the negative price pressure in stock S will result in a relatively greater decrease in the portfolio value of A compared to that of B. For a significant enough negative price pressure, this could result in a higher ranking for B than for A. I formalize these arguments and illustrate the necessary conditions for such predatory trading. I show that the choice of stocks for predatory trading in a common position, $Decision_{Stock}$, is based on the stock's illiquidity and on differences in the portfolios' weights and the funds' returns. In practice, mutual funds report holdings quarterly and rely on the information for trading in the subsequent quarter. Funds make predatory trading decisions based on the relative return difference and the relative portfolio impact from selling one share in the stock.

Predatory trading could affect mutual fund portfolios and trading strategies both directly and indirectly (threat). In the direct channel, a lower-ranked fund could prey on common positions with its competitor(s). In my analysis, I define funds as competitors if they follow the same benchmarks reported in the funds' prospectus and create fund pairs with consecutive ranks (i.e., rank 1 & 2 or rank 2 & 3) based on their performance from the beginning of the year to the end of the third quarter. In each pair, I focus on commonly held stocks. The direct channel leads to the first three testable implications of predatory trading. First, all else equal, I predict that funds are more likely to trade predatorily when the fund return difference is lower and when the relative portfolio impact from selling the stock is higher or the lower value of the variable $Decision_{Stock}$[5]. Second, I predict that predatory trading is more likely to occur for higher-ranked funds because the convex flow-performance relationship implies that the marginal benefit of moving up one place and, consequently, the incentive for predatory trading, is higher for top-ranked funds (Chevalier and Ellison, 1997; Sirri and Tufano, 1998). Third, I predict that predatory trading is more likely to occur in the last quarter of the year because previous literature shows the managers' incentives to improve relative performance is the strongest in the last quarter of the year (Brown et al., 1996; Carhart et al., 2002; Kempf et al., 2009).

Predatory trading also indirectly affects portfolio choices of funds because of the threat of predatory trading. In a repeated game of fund rankings, mutual funds are expected to respond strategically to the threat of predatory trading. The target funds could react by selling commonly

[5] $\text{Decision}_{\text{Stock}} = \frac{\text{Return difference between the two funds}}{\text{Illiquidity of the stock}*\text{Weight difference of the stock}}$

held positions before predatory trading takes place, or target funds could reduce their holding size so that the impact is not significant enough to reverse ranking. The number of shares needed for predatory trading is usually very high compared to average mutual fund holdings, so the predators are most likely large funds that hold more shares, while the targets of predatory trading are more likely to be smaller funds as they have less ability to target others or to react to predatory trading. Consequently, I predict that small funds react to the threat of predatory trading by reducing or exiting illiquid and common positions shared with their larger competitors.

My results support the hypothesis that funds trade predatorily primarily in the last quarter of the year. For the most comprehensive sample, I find that funds are more likely to sell common positions that generate more substantial relative portfolio impact or with lower $Decision_{Stock}$. Specifically, the coefficient on $Decision_{Stock}$, which is negatively related to the predatory impact of a common position, decreases as I expand the sample to include lower quintiles of fund rankings[6]. However, the coefficient on $Decision_{Stock}$ is insignificant in the top 20% ranking of all fund pairs, which is inconsistent with my prediction. To address this issue, I further limit the sample to fund pairs where predatory trading is more plausible. In these fund pairs, the lower-ranked fund can target the higher-ranked fund by selling up to all the common positions. In this sample, I find that $Decision_{Stock}$ is negative and significant only in the top 20% ranked funds. Economically this effect is material as well, For example, a one standard deviation increase in $Decision_{Stock}$ reduces the likelihood of the sale of the stock by 57%. Overall, the evidence supports that top-ranked funds are more likely to target their higher-ranked peers when they satisfy

[6] I divide all fund pairs into quintiles based on their rankings in each benchmark.

the necessary condition of predatory trading. These funds trade predatorily by selling common positions that generate more significant relative portfolio impact.

The empirical evidence further suggests that the threat of predatory trading affects the portfolio choices of funds and the holding size of the stocks. First, I find evidence of funds reducing commonly held positions toward the end of the year. The number of fund pairs that satisfy the necessary condition decreases from 138 pairs at the end of the first quarter to 83 pairs at the end of the third quarter (Figure 2). Additionally, I find cyclical changes in the average number of overlapped stock positions in fund pairs (Figure 3). Second, I show that when funds cannot avoid holdings in common, they hold fewer shares when the threat of predatory trading is high. The prediction is that small funds, which are vulnerable targets of predatory trading, anticipate the threat of predation from large competitors and avoid common and illiquid holdings. I find that small funds hold fewer stocks in common with their large competitors when competitors rank closer. I also compare the average illiquidity ratio of holdings by small funds versus large funds. As shown in Figure 4, the small funds that rank in the top third in each benchmark improve the liquidity of their portfolios in the last quarter of the year, while the bottom third-ranked small funds do not change much in liquidity. In contrast, I find no difference in the changes in liquidity across the fund ranks for larger funds.

I conduct several robustness tests. First, funds may sell the commonly held stocks for reasons other than predatory trading. If funds sell the stocks because of the changes in fundamentals or portfolio strategies, then they will try to minimize the price impact to reduce trading costs. On the contrary, I find that common stocks sold through predation, on average, underperform other common holdings by 9.72 basis points on the last trading day. Second, by assessing non-competing funds, I examine how reliable the reported benchmark is in grouping competitors. I find no evidence of predatory trading when I do not follow the same benchmark and group fund pairs with consecutive ranks. Third, I repeat similar regressions on the sample of commonly held stocks with negative weight differences (higher weights in the lower-ranked funds) and find no evidence of predatory trading. Lastly, I use the alternative measure of fund return, net return, and stock illiquidity, estimated by dollar volume as in the Amihud illiquidity ratio, and my main results are robust.

My paper is related to the literature on flow-performance relationship and its effect on funds' trading strategies. The convex flow-performance relationship (Chevalier and Ellison, 1997; Sirri and Tufano, 1998) generates incentives for mutual funds to make strategic portfolio decisions to increase the funds' relative rankings. Such actions include changing the portfolio's riskiness (K. C. Brown et al.; Kempf et al.) and portfolio pumping (Carhart et al., 2002; Wang, 2018). My findings suggest that mutual fund managers indeed engage in such strategic portfolio decisions.

My paper also contributes to the broader literature on predatory trading and predatory pricing. Previous literature on this topic mostly focuses on theory and model development, while only a few papers look at the empirical evidence of predatory behavior. My paper contributes to the literature by presenting novel empirical evidence of predatory trading in mutual funds. I define predatory trading as the interaction among mutual funds rather than between funds and other market participants, which differs from the traditional definition of front running. The findings exploit institutional rigidities in composing mutual fund performance rankings and sheds light on funds' choice of stocks in their portfolios.

Lastly, my findings could have important policy implications. From the regulator's perspective, predatory trading could hurt short-term investors and be considered unfair competition. When compared to semi-annual reporting, quarterly reporting increases the risk of predatory trading because of the frequency of updating holdings information. One way to solve this issue while preserving the timely reporting of funds' holdings could be to change the year-end performance calculation. Instead of using the value of the portfolio from the last trading day, we could require the use of a 10-day average value. Then, the price pressure is short-lived, so the impact from price manipulation could be significantly reduced by averaging fund performance within a longer time window.

2.2 Hypothesis Development

Each year in January, the investment research and investment management company Morningstar announces the "Best 16 U.S. Fund Managers of the Year" awards and fund (star) rankings while *Wall Street Journal* regularly releases the names of top 10 funds in each category as "Category Kings". Morningstar and other similar companies, such as Lipper and Standard and Poor's, base such fund rankings on past performance, the fund manager's skill, risk- and cost-adjusted returns, and performance consistency of the fund. Such rankings affect the investment decisions of investors. Mutual fund companies and fund managers, in particular, have incentives to take actions that increase the inflow of investments. In this context, Chevalier and Ellison (1997) show that the flow-performance relationship is convex, and they provide empirical evidence that the rank of a fund is an essential determinant for the inflows a fund receives in the next period. This convexity implies that the incremental inflow is positively associated with the fund's rank, that managerial incentives to improve their funds' rankings differ across rank quintiles, and that fund managers have an incentive to trade strategically to improve their relative rankings.

I illustrate the necessary conditions of predatory trading with an example. First, I assume there are two funds, A and B, in the same fund category where they compete for flows. At the end of the third quarter, fund A ranks one place above fund B. Both funds hold stock i, but stock i has a higher portfolio weight for A than for B. R_A and R_B denote the funds' cumulative return from the beginning of the year to the end of the third quarter, and W_{Ai} and W_{Bi} denotes the portfolio weights of stock i for fund A and B, respectively. N_{Bi} denotes the number of shares of stock i held by fund B, and Ill_i[7] measures price pressure based on the monthly average value of the illiquidity ratio.

The impact on relative portfolio value (absolute value) from selling one share of stock i is $\mathrm{Ill}_i * (\mathrm{W}_{\mathrm{Ai}} - \mathrm{W}_{\mathrm{Bi}})$. The illiquidity ratio is based on the definition in Amihud (2002) with a modification.

$$\mathrm{Ill}_i = \frac{1}{T} * \sum_{t=1}^{T} \frac{|R_{i,t}|}{Vol_{i,t}}$$

$R_{i,t}$ is the daily return for stock i in day t, and $Vol_{i,t}$ is the respective daily trading volume on that day. I use the number of shares traded to simplify the calculation of portfolio impact, which differs from the dollar trading volume used in Amihud (2002). Because the timing of predatory trading is unobservable and using the dollar trading volume would require estimating the stock

[7] Illiquidity ratio is calculated as the absolute value of daily return over daily trading volume, and it is non-negative.

price on the day when the stock is sold to calculate the portfolio impact[8], using the trading volume with number of shares would avoid estimating the timing of predatory trading.

The necessary condition of predatory trading for fund B is:

$$\sum_i^n N_{Bi} * \mathrm{Ill}_i * (\mathrm{W_{Ai}} - \mathrm{W_{Bi}}) > R_A - R_B, \tag{1}$$

The left-hand side of Equation (1) is the sum of relative portfolio impact if fund B sells all common positions with positive weight differences. The right-hand side is the actual return difference between the two funds when holdings are reported. We can infer that in order to trade predatorily, the total relative portfolio impact from selling all common positions should be higher than the actual return difference between the two funds. Further, it is important to note that predatory trading only works with common positions with $\mathrm{W_{Ai}} - \mathrm{W_{Bi}} > 0$; otherwise, fund B will experience a larger decline in portfolio value relative to A. In addition, funds are more likely to trade predatorily when the return difference is small.

When fund B chooses to sell a stock or several stocks from the common positions with predatory potential, or where $\mathrm{W_{Ai}} - \mathrm{W_{Bi}} > 0$, each common position will create a different relative portfolio impact calculated by Equation (2):

$$\mathrm{Decision}_{\mathrm{Stock\ i}} = \frac{\Delta \mathrm{R}}{\mathrm{Ill}_i * \Delta \mathrm{W}_i}, \tag{2}$$

where $\Delta\mathrm{R} = \mathrm{R_A} - \mathrm{R_B}, and\ \Delta\mathrm{W}_i = \mathrm{W_{Ai}} - \mathrm{W_{Bi}}$

8 Then the equation (1) would become $\sum_i^n Price_{i,t} * N_{Bi} * \mathrm{Ill}_{i(dollor\ vol)} * (\mathrm{W_{Ai}} - \mathrm{W_{Bi}}) > R_A - R_B$, where t refers to the day of predatory trading. In Appendix B, I replicate my main results using dollar trading volume and estimate the selling price using the average stock price in December.

Because in the same fund pair the fund return difference is the same for each stock, Equation (2) shows that funds are more likely to sell the stock that creates higher relative impact per share, or a higher $Ill * \Delta W$. Thus $Decision_{Stock}$ is expected to be negatively related to the likelihood of selling the stock.

According to Equations (1) and (2), the choice of stock in predatory trading relies on stock illiquidity, the weight difference in the stock, and the fund return difference between the predator and the target. Among all common holdings, the predator will first restrict the strategy to the positions where the stock weights are higher in the target's portfolio than in the predator's portfolio so that the negative impact on the target's portfolio is greater. For funds that are competing for flows, their portfolios often overlap in a handful of stocks. For example, the average percentage of common portfolio holdings, regardless of weight difference, is roughly a third in my sample. In this context, predators could trade predatorily by selling several commonly held stocks with the combined effect of reducing the return gap between two portfolios. It leads to several testable implications:

*H1: all else equal, I predict that funds are more likely to sell common positions when the portfolio return difference is lower and when the relative portfolio impact is higher. In other words, the likelihood of sale is **negatively** related to* $Decision_{Stock}$.

H1 Extension 1: I predict that predatory trading is more likely to occur in top-ranked funds.

H1 Extension 2: I predict that predatory trading is more likely to occur in the last quarter of the year.

Chevalier and Ellison (1997) show funds with superior performance, i.e., higher ranks, are rewarded through a convex flow-performance relationship. It implies that the marginal benefit of moving up one place is higher and, consequently, the incentives for predatory trading are higher for top-ranked funds. Further, the incentives for predatory trading are the strongest at the end of the year because of the year-end fund performance evaluation and the fund family resources allocation (Brown, Harlow and Starks, 1996; Gallaher, Kaniel, and Starks, 2006).

2.3 Sample and Empirical Design

2.3.1 Empirical Design

Ideally, the empirical evidence of predatory trading would be easier to detect if funds could observe each other's holdings more frequently, i.e., monthly or weekly. Unfortunately, the best information publicly available is quarterly holdings. I create pairs of predators and targets with consecutive rankings based on their cumulative return[9], i.e., rank 1 & 2 and rank 2 & 3. Such treatment allows me to simplify the predatory trading strategy to the most intuitive case because a predator is most likely targeting those ranked nearby and above. The choice of targets should be considered with a combination of three factors, including fund return difference, weight differences in those overlapped holdings, and stock liquidity. Thus, the range of targets cannot be readily determined with absolute values of rank distance or return difference.

[9] Cumulative return before all expenses, including management fees and 12b-fees, starting from the beginning of the year to the end of the third quarter. As a robustness check, I use the net return and replicate my main findings in Appendix C.

Further, it is crucial to notice that predatory trading only exists among funds that are competing for flows. For instance, a fund that uses the Russell 1000 index as its benchmark is unlikely to compete with funds trying to beat the Russell 2000 index. Such inference can also be applied to the reported compensation structure of fund managers in mutual funds' annual SEC filings. In the example of Eagle Small Cap Growth Fund, the prospectus states, "… benchmarks for evaluation purposes include Morningstar ranking for mutual fund performance and the Russell 2000 Index for separate accounts along with peer group rankings such as those from Callan Associates and Mercer Investment Consulting". I identify funds as competitors if they follow the same benchmark reported in the funds' prospectus (Cremers and Petajisto, 2009; Petajisto, 2013).

Third, based on the convex flow-performance relationship, the marginal benefit of moving up one place is higher for top-ranked funds. To distinguish funds that are ranked as top from those that are ranked bottom, I divide funds with the same benchmark into rank quintiles. The evidence of predatory trading is expected to be the strongest in the top quintile.

Fourth, the incentive of predatory trading is expected to be the strongest in the last quarter of the year. I focus my tests on the last quarter of the year as previous literature has documented that funds adopt strategies to improve their year-end rankings. Carhart et. al (2002) show that in the last trading day of a year, top-ranked funds create temporary positive pressure on their holdings, and the price pressure reverses in the first trading day of the following year. Further, the managerial incentives are the strongest at the end of the year. Fund families, in most of the cases, make family decisions on advertising, compensation, and promotions at the end of the year. For example, Gallaher, Kaniel, and Starks (2006) report that advertising budgets are decided annually. Therefore, fund managers would be expected to try to enhance their performance by year-end in order to earn a higher bonus and receive favorable resource allocations within their families.

Lastly, the prediction on which stocks the funds are more likely to sell is only related to common positions with positive weight differences (higher-ranked minus lower-ranked in each pair). Lower weights in the predator's portfolio guarantee that the target's portfolio will suffer a more significant portfolio value loss when the stocks are sold. I exclude the common holdings where the weights in the predator's portfolio are higher because I do not expect the funds to change these positions for a predatory purpose. On the one hand, it is unreasonable to sell the common positions if the predators will be hurt more from the price pressure than their competitors. On the other hand, if a fund is intended to create positive price pressure, it is unlikely to target common positions that will benefit its competitors. In the falsification tests, I show supportive evidence that there is no evidence of predatory trading in the common positions with negative weight differences and that if a fund chooses to boost the returns of its holdings, it will avoid the positions commonly held by its competitors.

2.3.2 Data and Summary Statistics

My sample consists of all-equity mutual funds between 1999 and 2009. I obtain the list of active equity funds and the benchmarks reported in fund prospectus, from Cremers and Petajisto (2009). The authors use the investment objective codes to screen for equity funds and require the stock holdings to be at least 80% of total net assets. I obtain mutual fund holdings from Thomson Reuters and merge them with fund-level characteristics, such as fund return and total net assets (TNA). The detailed steps are explained in Appendix A1 and A2. Most of the funds offer multiple share classes, but the composition of holdings is the same for each share class. In the calculation of TNA and fund return, I aggregate the observations pertaining to different share classes into one observation using the sum and the weighted average measures. Duplicate observations for the same stock in the same fund during the same period are deleted. I define fund peer groups based on the reported benchmark in funds' prospectus. I collect stock-level data from CRSP and COMPUSTAT. My final sample includes 10,956 fund pairs with 209,287 common holdings with positive weight differences.

[Table 1 Here]

Table 1 and 2 present the summary statistics of my sample. Table 1 summarizes the key variables in $\text{Decision}_{\text{Stock i}} = \frac{\Delta \text{R}}{\text{Ill}_i * \Delta \text{W}_i}$ of consecutively ranked fund pairs under the constraint that $\Delta \text{W}_i > 0$.

The median number of shares needed for successful predation is 329,000, while the average number of shares is much higher. Although the return difference is small because the funds in pairs are ranked consecutively, the variable, $Decision_{Stock}$, is large due to the illiquidity ratio and small weight difference, likely the result of portfolio diversification. In practice, it is very unlikely that a fund can satisfy the necessary condition of predatory trading with a single common position.

[Table 2 Panel A & B Here]

Table 2 reports stock characteristics of common holdings with positive weight differences in Panel A and all holdings in Panel B. The common holdings with positive weight differences are roughly half of all common holdings. On average, fund pairs overlap in roughly a third of stock holdings. To calculate the book equity in B/M ratio, I use total shareholders' equity plus deferred taxes and investment tax credit minus the book value of the preferred stock:

BE = SEQQ (or CEQQ + PSTKQ when not available) + TXDITCQ – PSTKQ

When neither SEQQ nor CEQQ is available, I use total assets minus total liabilities as a proxy for book equity. Following Falkenstein (1996) and Schwarz (2012), I include the measures of the stocks' riskiness, beta, and total standard deviation using daily return. To capture the most recent changes in beta, I adopt the time frame of 60 days before the end of the quarter. The common holdings are characterized by stocks that have more total shares outstanding and that are larger, riskier, and more liquid. Such features may indicate that in equilibrium, funds try to reduce their exposure to predatory trading by choosing more liquid stocks in their common holdings, but there are other explanations to these observations.

2.4 Main Results

2.4.1 Direct Channel: Evidence of Predatory Trading in the Last Quarter

2.4.1.1 Which Commonly Held Stocks Do Funds Sell?

Stock characteristics, such as size, B/M, previous performance, liquidity, and riskiness, are related to mutual funds' choices of their portfolios in general, but how does the selling decision change when it comes to the common holdings with positive weight differences? I present the first result with a linear probability regression on the factors related to mutual fund selling. The dependent variable *Sell* is a dummy variable, set to one if the stock is sold by the lower-ranked fund during the fourth quarter; otherwise, it is set to zero. *Sell* is regressed on stock characteristics, such as size, B/M, previous month's return, previous month's return standard deviation, and 60-day beta. I also control for the year fixed effect and cluster the standard errors at fund-level.

Using the sample of fund pairs with consecutive ranking, I break down three components in $\mathrm{Decision}_{\mathrm{Stock\ i}} = \frac{\Delta \mathrm{R}}{\mathrm{Ill}_i * \Delta \mathrm{W}_i}$ and include them separately in Regression (1) to (3). I further consider two dummy variables, *NC* and *Top-ranked*, to indicate if the fund pair satisfies the necessary condition in Equation (1) and if the fund ranks in the top 20% in the peer group at the end of the third quarter.

[Table 3 Here]

In Table 3, when included separately, the coefficients on $\Delta R, \frac{1}{Ill}$, and $\frac{1}{\Delta W}$ do not seem to be consistent with the predatory story. ΔR and $\frac{1}{Ill}$ are related to predatory trading but are the opposite of the prediction of Equation (1). The coefficient on $\frac{1}{\Delta W}$ is negative as expected but insignificant. In Regression (4), the coefficient on *Top-ranked* is significant and positive; it indicates that the funds are more likely to sell the common positions if they are top-ranked. In Regression (5) and (6), neither *NC* nor $Decision_{Stock}$ is significant, but when I interact the two variables in Regression (7), the coefficient on the interaction is negative and significant. It indicates that funds are more likely to sell the common positions when they satisfy the necessary condition of predatory trading, or Equation (1), and when the stock creates higher relative portfolio impact, or with lower $Decision_{Stock}$.

2.4.1.2 Do Funds Trade Predatorily in the Laster Quarter?

The Regression (7) in Table 3 suggests the evidence of predatory trading. Next, I move on to test H1 more strictly by conditioning on fund-pair-year and then compare the common positions in the same fund pair. H1 states that with all else equal, funds are more likely to sell the common positions when the fund return difference is smaller and when the stock's relative portfolio impact is more significant, that is with lower $Decision_{Stock}$. In other words, H1 predicts a negative coefficient on $Decision_{Stock}$. ΔR and the interaction terms involving ΔR are omitted because the condition on fund-pair-year removes the common variation in the fund pair.

$$Sell = \alpha + \mathrm{Decision}_{\mathrm{Stock}} + \frac{1}{\Delta W} + \frac{1}{Ill} + Holdings\ in\ Q3 + Pre_{return} + \frac{\mathrm{B}}{\mathrm{M}} + Size + \beta + \sigma + FE + \varepsilon \quad (3)$$

[Table 4 Panel A Here]

In Table 4 Panel A, the negative coefficient on $Decision_{Stock}$ indicates that funds are more likely to sell the stocks that have greater relative portfolio impact. The coefficient declines as I include more lower ranking quintiles into the sample, and the variable is significant at the 10% level, except for the top 20% ranked funds. The insignificant coefficient in the top 20% ranked funds is not consistent with H1-Extention 1, which predicts that predatory trading is more likely to happen among top-ranked funds. Top-ranked funds with good performance in the first three quarters of the year may be cautious about the strategies they take. On the one hand, those funds have the incentives to move up in the ranking due to the high marginal benefit. On the other hand, top-ranked funds also have more to lose if the predatory trading strategy fails and the return of the portfolio declines. Thus top-ranked funds are more likely to trade predatorily when the probability of success is high. I approximate the probability of success by checking if the top-ranked predator satisfies the necessary condition of predatory trading. The intuition is that because the quarterly reports provide noisy information about the true holdings, the more overlaps in holdings, the less likely that the target will exit all predatory positions and the predatory trading is more likely to succeed.

To address the issue that top-ranked funds are less likely to trade predatorily if the likelihood of success is low, I use the subsample of fund-pairs where the lower-ranked funds satisfy the necessary condition and present the results in Panel B. As shown in the summary statistics, the lower-ranked fund must sell a large number of shares when it is trying to trade predatorily by selling a single position. Most likely, the lower-ranked funds need to sell a handful of commonly held stocks to create enough relative portfolio impact. Starting with all fund-pair-stock observations, I sum up the relative portfolio impact if the lower-ranked fund sells all common positions with positive weight differences. If the total impact is greater than the actual fund return difference at the end of the third quarter, I keep the fund pair in the sample. Not surprisingly, the screening process ends up with fund pairs that have a greater number of stocks in common and a much smaller sample of fund pairs. On average, there are 83 fund pairs annually where the lower-ranked funds satisfy the necessary condition of predatory trading.

[Table 4 Panel B & C Here]

In Panel B, the coefficient on $Decision_{Stock}$ is negative in all quintiles, but significant only in the top 20% ranked funds. Consistent with the convex flow-performance relationship, top-ranked funds are more likely to sell stocks that generate greater relative portfolio impact. Further, the result is strongest in the top 20% ranked funds, and both the coefficient and significance for $Decision_{Stock}$ decrease monotonically when I include funds in the lower-ranking quintiles. One standard deviation increase in $Decision_{Stock}$ reduces the likelihood of the sale of the stock by 57%. As a comparison, I run the same logistic regression with fund pairs where the lower-ranked funds do not satisfy the necessary condition. The results are reported in Panel C. In Panel C, the coefficient on $Decision_{Stock}$ is insignificant only in the subsample of the top 20% ranked funds, similar to the full sample results in Panel A. The overall evidence shows that funds trade predatorily by selling common positions with higher relative portfolio impact and top-ranked funds are more likely to trade predatorily when they satisfy the necessary condition of predatory trading.

2.4.1.3 Do Funds Succeed with Predatory Trading?

Funds are unlikely to trade predatorily if there is little chance of a favorable outcome, such as an improvement in the ranking. In this section, I examine the year-end results of predatory trading in the subsample of fund pairs where the lower-ranked fund satisfies the necessary condition. I define the dependent variable of the conditional logistic regression, *Success*, as a dummy set to one if the lower-ranked fund outperforms the higher-ranked fund at the end of the year (relative ranking is reversed).

$$Success = \alpha + Predate + Rank\ Quintile + Fund\ Size\ (Low) + Fund\ Size\ (High)$$
$$+ Pre_{performance}(Low) + (FE) + \varepsilon$$

The variable of interest, *Predate*, is set to one if the lower-ranked fund sells any of the common positions over the last quarter of the year[10]. I define *Predate* conservatively because the timing of predation is not observable. Mutual fund quarterly holdings are required to be submitted within 60 days after the quarter ends, so predatory trading could take place in any trading day of December, most likely in the end of the month. The return difference and, thus, the shares needed for predation will vary with the changing performance difference between the two funds. Further, predatory trading could be combined with other strategies that boost short-term performance such as portfolio pumping as documented in Carhart et al. (2002) and Wang (2018).

[Table 5 Here]

[10] The results are robust when using a stricter definition of *Predate*, where it is set to one if the actual portfolio impact is at least half of the return difference. The actual portfolio impact is defined as the sum of relative portfolio impact of each common stock sold by the lower-ranked fund over the last quarter.

Table 5 shows the logistic regression results without any conditional effect in column (1); conditional on year in column (2); conditional on the benchmark in column (3); and conditional on both year and the benchmark in column (4). I present the evidence that among the 923 fund pairs, the lower-ranked funds are more likely to reverse the relative rankings within the pairs if they become predatory on their higher-ranked peers. The number of observations in column (4) drops because in some benchmark-year groups, there are too few observations or observations do not vary within the groups. Based on the results of column (4), the probability of relative ranking reversal, or *Success*, increases by 29% (from 43% to 72%) if funds trade predatorily. The evidence suggests funds are more likely to improve the relative ranking if they implement predatory trading.

2.4.2 Indirect Channel: Are Funds Sitting Ducks?

2.4.2.1 Do Higher-ranked Funds React to Predatory Trading?

In the repeated game of mutual fund ranking, fund managers should be aware of predatory trading and are likely to take responsive strategies. I consider two strategies that are available to the targets. First, when the predator sells the common positions, the target fund could buy more of the stocks to offset or reduce the negative price impact. The plausibility of the strategy depends on the cash holding of the fund and the size of the fund. Second, the target funds could avoid being targeted by exiting the positions before predatory trading happens. The first strategy puts more constraints on the fund size and portfolio holdings, while the second strategy can be applied more easily and is less costly. Based on the two options, I further develop two testable hypotheses.

<u>H2: The target fund is more likely to buy more of the common holdings when a competitor trades predatorily and when it holds more cash.</u>

H3: The fund that is more likely to become the target of predatory trading will hold fewer common positions or fewer shares in the common positions when the threat of predatory trading is higher.

2.4.2.2 Do Target Funds React to Predatory Trading with the First Strategy?

To test the first strategy (H2), I start with fund pairs where the lower-ranked funds satisfy the necessary condition. In the conditional logistic regression, the dependent variable is set to one if the higher-ranked fund increases the stock positions that are exposed to predatory trading. The independent variable, *Predate*, is set to one if the lower-ranked fund sells any of the stock(s) the higher-ranked fund buys. *Cash Holding* is calculated by subtracting the market value of all stock holdings at the end of the third quarter from the total net assets reported at the same time point. I further control for relative fund size and rank quintile of the higher-ranked fund. Although I cannot completely rule out alternative explanations, the variable of interest is *Predate * Cash Holding*, and it is expected to be positive and significant if H2 holds as funds are more likely to buy more of the common holdings, especially when they hold more cash and when the lower-ranked fund trades predatorily.

[Table 6 Here]

Table 6 reports the regression results. The coefficient on the interaction term, however, is insignificant and negative. Also, the negative coefficient on *Cash Holding* shows that cash is negatively related to a fund's decision of increasing its holdings in the common positions in the next period. The coefficient on *Predate* is negative and significant, indicating that instead of buying more of the commonly held stocks, the target reduces its position on common holdings that are subject to predatory trading. Despite the noisy empirical test, I find no support for the first strategy. The reason could be that the strategy is simply too costly for funds to adopt, and the fund size and cash or cash-like assets needed put further constraints on funds to make it unlikely to happen in practice.

2.4.2.3 Do Target Funds React to Predatory Trading with the Second Strategy?

Compared to the first strategy, there is more evidence supporting the second strategy with both the number of common positions and size of common positions. First, the average number of fund pairs that satisfy the necessary condition of predatory trading decreases from 138 pairs at the end of the first quarter to 117 pairs at the end of the second quarter and, lastly, to 83 pairs at the end of the third quarter. Further, the number of common positions, both positive weigh difference positions and all positions, are decreasing across the quarters as shown in Figure 2.

[Figures 2 and 3 Here]

In Figure 3, the graph exhibits a time series movement of the average number of common holdings in fund pairs that satisfy the necessary condition for predatory trading. The graph shows a cyclical pattern that decreases in the beginning of the year to the end of the third quarter and rises during the last quarter. The number of common positions picks up at the end of the last quarter, indicating there may be the effect of window dressing, where funds want to report their year-end holdings with star stocks. In the theory of window dressing, funds buy the "hot issues" before reporting portfolio holdings to convince investors of their stock selection ability because the timing of the stock purchase is not reported. The decrease in fund pairs that satisfy the necessary condition and the average number of common positions indicates that funds are moving away from common positions when the threat of predatory trading close to the end of the year. Such behavior supports the second strategy that funds react to predatory trading by shifting away from common positions that are exposed to predatory trading.

Third, as shown in the summary statistics of stock characteristics, the common holdings are generally more liquid. In the second strategy (H3), the mutual funds that are vulnerable to predatory trading should foresee the threat and are likely to make strategic changes in portfolio holdings. Fund size comes into the picture because a large number of shares need to be sold for predatory trading. Small funds are limited by their size and lack in the ability to target others, compared to large funds, so they are more likely to be targets rather than predators. Further, as shown in the previous results and indicated by the convex flow-performance relationship, top-ranked funds have stronger incentives to trade predatorily. Thus, top-ranked small funds are more likely to adjust the average liquidity of their portfolios. I define the small and large funds in each benchmark. I divide all funds into three groups, and the group with the smallest TNA is categorized as small funds and the biggest as large funds. Funds are competing with others that share similar goals and benchmarks, so it is the relative size within each peer group that matters. Next, both the set of small funds and the set of large funds are divided into three groups based on their rankings at the end of the third quarter and their benchmarks.

[Figure 4 (A) & (B) Here]

In Figure 4 (A), I report the change in average illiquidity of small funds' holdings in the top- and bottom-ranked groups. The graph shows that top-ranked small funds improve the liquidity of their portfolios towards the end of the year, while the bottom group changes little. In Figure 4 (B), I present a similar graph using the subsample of large funds. Large funds, regardless of their rankings, increase the average liquidity of their portfolios toward the end of the year. However, there is no difference between the top- and the bottom-ranked large funds. From the adjusted illiquidity ratio, small funds hold about seven times more liquid stock on average when compared to large funds. The evidence that higher-ranked small funds will tilt their portfolios toward more liquid stocks near the end of the year, suggests that they may be strategically avoiding being targeted by large funds. Previous literature looks at how fund size affects the liquidity of holdings and provides two sets of opinions. One explanation is that small funds may face greater flow volatility and thus choose to hold more liquid stocks (Hanouna et al., 2015). Nevertheless, a more prevalent explanation to the holding liquidity differences between small and large funds is that large funds are limited in their choice of stocks because of trading costs associated with liquidity or price impact, while a small fund can easily put all its money into its best ideas (Chen, Hong, Huang, and Kubik, 2004; Yan, 2008). If the asset base is more constrained on the choice of stocks in large funds, such an explanation should contradict my result that small funds are more likely to hold the illiquid stocks compared to large funds.

Given that I define peer groups based on the benchmark funds follow, it is impossible for funds to avoid all common holdings and it is sometimes costly to avoid certain stocks. Thus, I predict that small funds hold fewer shares in commonly held stocks when the threat of predatory trading is high. In Table 7, I compare the small funds' common holdings with varying levels of threat. I define *Threat* as the rank distance between the small fund and the closest ranked large fund that also holds the stock, and the rank distance is standardized by the number of funds in each benchmark in the given year. *Threat*, by definition, is negatively related to the threat of predatory trading. The greater the distance between the small fund and the large fund, the less likely that the large fund is going to target the small fund.

[Table 7 Here]

I regress the number of shares held by small funds on a set of variables, including controls for size, book-to-market equity, and stock's previous return. Small funds are expected to hold fewer shares when the stock is also held by a large competitor ranked nearby and when the stock is more illiquid. In Regression (1), small funds hold more shares when the threat is low, shown by the positive and significant coefficient on *Threat*. The coefficient on the interaction of *Threat* and *Illiquidity Ratio* is not significant in Regression (2). There are two explanations to the insignificance. First, given that the average liquidity is about seven times higher for portfolios of small funds than for large funds, the difference in liquidity is potentially less important in a small fund when facing the threat of predatory trading. Second, the size difference between small and large funds could lead to the case where small differences in liquidity do not prevent the large funds from predating. The overall result in Table 7 shows that small funds hold fewer shares in the illiquid common holdings when the threat of predatory trading is higher.

In summary, I test two trading strategies to impede predatory trading and find support for the second strategy that funds avoid being targeted by strategically changing their portfolio holdings. Toward the end of the year, funds hold fewer stocks in common, hold stocks with better liquidity, and when it is too costly to avoid certain common positions, funds hold fewer shares when the threat of predatory trading is high.

2.4.3 Robustness Tests

2.4.3.1 Other Explanations to Stock Sale

There are many explanations for stock sale other than predatory trading. For instance, the fund manager may decide that the stock is no longer a good investment or harvest the investment losses at the end of the year for tax purposes. Those trading strategies differ from predatory trading in that a fund manager will minimize price impact rather than purposefully create price pressure. Thus, I examine stock performance around the end of the year to address this concern. In the subsample of fund pairs that satisfy the necessary condition, I identify the commonly held stocks that are sold during the last quarter as "Predator Stocks" (denotes as PS afterward) and the other common holdings as "Non-predator Stocks" (denotes as NPS afterward). I check the cumulative abnormal returns of both groups during the ten trading days before the end of the year and ten trading days after.

[Figure 5 (A) & (B) Here]

In Figure 5 (A), the graph captures the movements in cumulative abnormal return of PS and NPS in Figure 5 (B). In the last trading day of the year, there is a decline in the cumulative abnormal return of PS, but an increase in the cumulative abnormal return of NPS. Further, I test the 1-day, 3-day, and 5-day cumulative abnormal return differences at the end of December and find that there is a significant difference between PS and NPS only in the last trading day of the year (1-day difference). The NPS outperforms PS by 0.0972% or 9.72 basis points in the last trading day of the year. The difference is significant at the 1% level, and 76% of the difference comes from the underperformance of PS. The evidence suggests that the sale of PS aims at creating price pressure rather than minimize price impact and weakens other explanations to the stock sale of funds at the end of the year.

2.4.3.2 Classification of Peer Groups

A second concern is that the effect captured in the previous regression is not related to competition among peers. To check the validity of the peer group classification, I turn to a falsification test that uses fund pairs with consecutive rankings ***but are not competing for flows***.

Specifically, I rank all funds together regardless of their reported benchmarks and create fund pairs with consecutive ranks. Next, I drop the fund pair if both funds belong to the same benchmark, and I identify common stock positions with the fund pairs left. The final data contains common positions in fund pairs that have consecutive ranks but are not competing against each other. I restrict the sample to fund pairs where the lower-ranked funds satisfy the necessary condition of predatory trading and where the evidence of predatory trading is the strongest. The number of common positions is lower as the two funds in each fund pair belong to different peer groups.

[Table 8 Panel A Here]

Reported in Table 8 Panel A, the variable of interest, $Decision_{Stock}$, is either insignificant or positive. It shows contradictory findings to Table 4 Panel B, where similar tests are performed. The falsification test confirms that predation only occurs among funds that are competing for flows, and the benchmarks reported in prospectus identify funds that are competing for flows.

2.4.3.3 Common Positions with Negative Weight Difference

In addition to non-competing fund pairs, I run a falsification test using the common positions with negative weight differences that are excluded in the main tests. The predatory trading hypotheses suggest the selling of common positions is only rational when the weight of the stock is higher in the target's portfolio. Given such reasoning, the lower-ranked funds, or the predators, are not expected to sell those positions with negative weight differences (Target minus predator) because the target fund, or the higher-ranked fund, will be hurt less compared to the lower-ranked fund. It will end up with an even wider gap in fund returns.

[Table 8 Panel B Here]

The regression result is reported in Table 8 Panel B. Consistent with expectation, there is no evidence of predatory trading in the common positions with negative weight differences. It suggests that when funds adopt the predatory trading strategy, they are selectively choosing the ones that have the predatory benefit.

2.4.3.4 Do Funds Trade Predatorily in the Second or Third Quarter?

Fund families, in most of the cases, make family decisions on advertising, compensation, and promotions at the end of the year. For example, Gallaher, Kaniel, and Starks (2006) report that advertising budgets are decided annually. Therefore, fund managers would be expected to enhance their performance by year-end for higher annual bonus and favorable resources allocation within their families. I run a similar regression to Table 4 Panel B using the second quarter and the third quarter data. Both logistic regressions are limited to fund pairs that satisfy the necessary condition of predatory trading. Mutual fund managers usually receive bonuses, which are a significant part of their total compensation, based on their full year's performance. Presumably, the results should be the strongest at the end of the year.

[Table 9 Panel A & B Here]

In Table 9, I only find weaker evidence of predatory trading in the top 20% ranked funds in the second quarter. The coefficient on $Decision_{Stock}$ is negative and significant at the 10% level. The result indicates that predation exists but is weaker in other quarters of the year. The first half of the year performance may also be an indicator that matters to managers as it could influence their strategies in the second half of the year. For instance, Brown et al., (1996) show that the mid-year losers increase the portfolio's riskiness in the second half of the year. In the third-quarter data, the coefficient on $Decision_{Stock}$ is either insignificant or positive, which is contrary to the prediction of predatory trading. Overall, the incentives to trade predatorily is the strongest in the last quarter.

2.4.3.5 Which Stocks do Funds Pump at the End of the Year?

In the previous regressions, the fund-pair-stock observations where $\Delta W_i \leq 0$ are excluded because there is no intuitive prediction of how funds deal with such positions. I have shown that there is no evidence of predatory trading in the sample of common positions with negative weight differences. In this section, I connect my paper to the literature on portfolio pumping strategy. Pumping the stock price of the common holdings will give competitors a free ride on the benefit. I show that if funds choose to pump their portfolios, they are likely to avoid common holdings.

I follow Carhart et al. (2002) and show that the stocks that funds choose to boost the price of are stocks not held by competitors. Carhart et al. (2002) define *Inflation* as the difference between the excess return of a stock in the last trading day of the year and the excess return in the first trading day of the year. Higher *Inflation* indicates there is likely stock price manipulation around the end of the year. I create a sample of stocks that experience positive inflation. Following Carhart et al. (2002), I use the subsample with the top 5% performing funds starting from the beginning of the year to the second to last trading day. The dependent variable is a dummy set to one if the fund increases its holding of the stock in the last quarter; otherwise, the dependent variable is set to zero. A dummy variable, *Competitor*, is set to one if the nearby and above competing fund holds the stock; otherwise, it is set to zero. I use the actual rank of funds instead of rank quintiles in the previous tables because the funds involved in the test are top-ranked already.

[Table 10 Here]

Table 10 reports the logistic regression results, conditional on the year with fund-level clustered standard errors. The negative and significant coefficient on *Competitor* indicates that funds are more likely to be the drive behind those inflation stocks not held by a competitor. The negative and significant coefficient on *Rank* indicates that funds are more likely to be the drive behind those inflation stocks if they are top-ranked. The result is consistent with the convex flow-performance relationship that top-ranked funds have higher marginal benefits if they move up one place in the rankings. The results in Table 10 show that a fund is more likely to pump its portfolio when the fund is top-ranked. Further, when choosing which stock to pump, the fund will likely avoid those stocks commonly held by its nearby competitors to reduce the risk of free riding.

2.5 Conclusion

Mutual funds provide a unique setting for predation theory in that funds can directly affect the price of stocks in their competitors' portfolios. The convex flow-performance relationship gives mutual fund manager's pecuniary and non-pecuniary incentives to adopt trading strategies to achieve better end-of-year rankings. I hypothesize that mutual funds sell their positions in common with their higher-ranked competitors to improve their relative rankings within their peer groups. I define such a strategy as predatory trading in mutual funds and test it by creating fund pairs with consecutive rankings in each peer group. I find that the lower-ranked funds in pairs trade predatorily when they satisfy the necessary condition of predatory trading, and the result is the strongest for top-ranked funds. Such a trading strategy is not widely used by mutual funds because of the strict conditions needed to be satisfied. My main results are concentrated on a subsample of fund pairs that satisfy the necessary conditions.

Further, funds anticipate the threat of predatory trading and initiate strategies in response but making use of a strategy is less common. First, I show that funds reduce the number of common positions toward the end of the year. Second, when funds hold stocks in common with a competitor, they hold fewer shares when the competitor is ranked nearby and when the competitor is larger. Lastly, there are some interesting policy implications of the findings. From the regulator's perspective, predatory trading could hurt investors and be considered unfair competition. When compared to semi-annual reporting, the quarterly reporting requirement increases the risk of predatory trading because of the frequency of reporting updated holdings information. One way to solve such an issue while preserving the timely report of funds' holdings could be to change the year-end performance calculation. For example, we could require the use of a 10-day average portfolio value instead of the last trading day's value.

3.0 Second Essay: Mutual Fund Governance

3.1 Introduction

Investors' right to redeem the shares on any trading day and board of directors are two of the important governance mechanisms for mutual funds. While share redemption may be costly[11], the board of directors mitigates the agency problem by overseeing the fund's operation. The literature on corporate board governance generally finds that firms with smaller and more independent boards perform better and that diversified firms have larger and more independent boards (Boone et al., 2007; Coles et al., 2008; Linck et al., 2008). Given the diversified nature[12] of mutual funds families, funds with more independent boards should perform better, according to the literature. However, the research on mutual fund boards provides mixed findings on whether board independence matters to fund performance. On the one hand, Ferris and Yan (2007) discover that neither the probability of a fund scandal nor overall fund performance is related to board independence. Further, Kuhnen (2009) finds that the business connection between board and advisor does not affect fund performance. On the other hand, Tufano and Sevick (1997) and Del Guercio et al.(2003) show that smaller and more independent boards set lower fees or expenses. Ding and Wermers (2012) show that independent directors are crucial in terminating underperforming seasoned portfolio managers.

[11] Due to sales loads, redemption fees, capital gain taxes, or other personal reasons

[12] The multiple types of funds offered can be considered as a diversified product range.

In this paper, I use the setting of series trusts in the mutual fund industry as an alternative measure of board independence. I test the impact of board independence on mutual fund performance, and further compare it to the other important governance mechanism, investor's redemption right. Series trust is a form of mutual fund entity that funds within the trust share a board of trustees, chief compliance officer, and much of the infrastructure supporting compliance, reporting, shareholder services, transactions, and back-office functions. Each portfolio in the trust has its prospectus and is branded to the adviser that manages the funds. In such a setting, the board is not selected by the fund advisers. Thus, the connection between the board and advisers is weaker. Even in public firms, where directors are reelected regularly, the independence of boards could be compromised. Hwang and Kim (2009) show that 30% of conventionally independent corporate boards are not socially independent.

A similar situation could also apply to mutual funds for the given reasons. First, when a fund is initially set up, independent directors are selected and nominated by the management company/fund advisor. There will not be mandatory shareholder election of directors unless less than a majority of the board is shareholder-elected. Second, Kuhnen (2009) shows that fund directors and advisory firms that manage the funds hire each other preferentially based on the intensity of their past interactions. Third, the qualifications of an independent director do not cover some cases that could lead to the independent director to be an interested person. Lastly, there is a pecuniary benefit that the compensation of directors is closely related to the total size and number of portfolios they supervise. As shown in Graph 1 and 2, the median compensation for supervising 26 to 35 portfolios is $122,000[13]. Mutual fund families are aware of the independence issue and

[13] Source: 2012 MPI annual survey of mutual fund directors

adopt strategies to mitigate the problem by putting more investment constraints (Almazan et al., 2004) or increase director ownership in funds (Cremers et al., 2009). The setting of series trusts mitigates the independence issue in several ways. First, the board of directors is set up by the financial intermediary that provides the service of the series trust. It is unlikely that there are close ties between directors and fund advisors. Second, the board of series trusts is not related to the advisors' other standalone boards, and such a structure reduces the possibility of performance transfer (Nanda et al., 2004; Gaspar et al., 2006). The funds under the umbrella of series trusts are less connected to the other funds managed by the same adviser but are not in the series trusts. Because the directors do not overlap on the boards, they are unlikely to agree to cross-subsidization that could harm the performance of funds they oversee.

To compare the two governance mechanisms, board governance, and the redemption right, I compare the subsample of insurance series trusts to the subsample of non-insurance series trusts. Insurance series trusts are the series trusts that only open to insurance annuity contracts or retirement plans, while there is no restriction on the non-insurance series trusts. The funds in insurance and non-insurance series trusts are different in that the shareholders' ability to exit the funds is limited when investing in an insurance series trust. Because of the contract terms in insurance policies and retirement plans, investors are trapped in their investments due to a high exit penalty. A typical annuity contract specifies a surrender period, which could last up to 15 years. If the investor withdraws funds from the annuity before the surrender period ends, he or she will face a penalty, or deferred sales fee. The surrender fee often starts at 10 percent if the investor cashes in his or her investment in year one. It goes down to 1 percent if the investor cashes it in during year nine and no surrender fees in year ten or longer. As a comparison, the non-insurance series trust funds are open to retail investors and have the daily liquidity feature of traditional open-end mutual funds. Some funds charge a short-term trading fee or a redemption fee if the investor redeems the share in a short period after purchase, such as 30 days, and SEC requires that the redemption fee is capped at 2 percent.

In the empirical design, I compare funds in non-insurance series trusts with funds in traditional standalone trusts to test the effect of board independence on mutual fund performance. Because the board independence is similar in insurance and non-insurance series trusts, I compare the performance of the two subgroups to test the relative importance of costless redemption and board independence. I hypothesize that funds in non-insurance series trusts have better governance than the funds in traditional standalone trusts for the four reasons stated above. I start with a case study of BlackRock funds and manually collect the information on the board of directors of all trusts, both standalone and series trusts, managed by BlackRock. The case study confirms that in addition to the reduced connection between directors and fund advisors, the sets of directors are not overlapped between series trusts and standalone trusts. In the empirical tests, I collect the SEC Edgar filings and use a sample of 4,137 fund-years managed under series trusts. I use both a matched sample and multivariate regressions to compare the funds in standalone trusts and series trusts. In the matched sample tests, I first match the fund-years with funds from standalone trusts that have the same Lipper Objective Code and CRSP Index indicator. Further, I require the age of the matched fund to be between one year younger and one year older and choose the closest fund size.

I find that insurance series trust funds underperform in gross terms by 27 basis points annually, and they charge higher expense ratios to shareholders. In contrast, non-insurance series trust funds outperform 46 basis points in gross return and 23 basis points in net terms annually. In both samples, series trust funds have higher expense ratios due to high 12b-1 expenses. In addition to the matched sample t-test, I also test the difference in annual gross performance using multivariate regression. I find similar results to the matched sample tests. I show that insurance series trust funds underperform their standalone peers significantly in the gross return by 180 to 261 basis points. The non-insurance series trust funds outperform by 30 to 55 basis points annually. The results suggest that funds with more independent boards perform better. Further, costless redemption is a more critical governance mechanism than board governance.

In the next section, I explore whether superior or inferior performance is due to different managerial skills. I use the four-factor gross alpha to measure skill and find significant inferior skills in insurance series trusts, and no significant difference comparing non-insurance series trusts to their peers that are in standalone trusts. The results suggest that the superior performance of non-insurance series trusts is not because of better fund managers. However, the inferior performance of insurance series trusts could be explained by retaining low-skill managers.

In the last section of the paper, I examine the information sharing among funds in series trusts and the skill of fund managers. I use the return correlation to test information sharing among funds in series trusts. I calculate the average pairwise correlation between funds in the same series trusts and have the same Lipper classification and label it as an internal correlation. The external correlation is calculated as the average correlation between the series of trust funds and standalone trust funds with the same adviser and same Lipper classification. I use six measures, the gross return, the gross alpha, the gross residual, the net return, the net alpha, and the net residual, estimated by the Carhart four-factor model. I show that in all six measures, internal correlations are higher than external correlations. The empirical evidence suggests that there is enhanced information sharing among funds in series trusts.

This paper relates to three strands of literature. First, the paper is related to the literature on mutual fund governance that investigates the impact on performance and fee setting. In general, the literature finds no significant governance impact on performance and effectively set fees when funds have better governance. Tufano and Sevick (1997) find that smaller boards, a higher percentage of independent directors and fund directors that sit on a more substantial fraction of the fund family's boards tend to set lower fees. Del Guercio et al.(2003) use the sample of closed-end funds and show that funds with smaller boards and a higher percentage of independent directors have lower expenses. Board structure affects the fund's willingness to undertake activities favorable to shareholder value. The literature generally finds that actions of boards are insufficient to impact fund performance. Ferris and Yan (2007) find that neither the probability of a fund scandal nor overall fund performance is related to board independence. Kuhnen (2009) further explores the business connection between board and advisor and show that it does not affect fund performance. The effect of facilitating efficient information transfers cancels out with the channels for inefficient favoritism.

Second, the paper is related to the literature on director overlaps in mutual funds. Kong and Tang (2008) look at the particular case of one board that serves all funds in the family, unitary board. They show that the unitary board is an effective governance mechanism. Funds with unitary boards are associated with lower fees, are more likely to pass the economies of scale benefits to investors, are less likely to be involved in trading scandals, and rank higher on stewardship. In contrast, funds with larger or more independent boards charge higher fees and rank lower on stewardship. However, Hornstein et al. (2015) show that better return caused by higher director overlap is explained by window dressing and performance transfer. The literature suggests there is a trade-off between efficiency and performance transfer when the same group of directors monitors the funds.

Third, this paper is related to the literature on information flow among mutual funds. Cohen et al. (2008) focus on connections between mutual fund managers and corporate board members via shared education networks and find that portfolio managers place larger bets on connected firms and outperform up to 7.8 percent a year. Elton et al. (2007) find that mutual fund returns are more closely correlated within than between fund families, primarily due to common stock holdings and similar exposures to economic sectors and industries. Parwada and Yang (2009) show that the portfolios of managers based in the same country have stronger similarities than those of similar funds across different countries. In their model, Ozsoylev and Walden (2011) evaluate the implications of network connectedness for asset pricing and argue that the most observable effect of investors' connectedness is on portfolio holdings. They predict a positive relationship between the degree of network connectedness and the similarity in trading decisions. Consistently, Hong et al. (2005) provide empirical evidence on the tendency of fund managers to imitate trades of other managers in the same city and attribute this phenomenon to the so-called word-of-mouth effect.

My paper contributes to the literature on mutual fund board independence by first adopting the unique setting of series trusts to test the impact of board independence and comparing it to the importance of investors' right to redeem shares on any trading day. The major difference between this paper and the other papers on mutual fund board independence is that rather than measuring board independence directly the percentage of independent director, I use a subsample of funds where the connection between the board and fund advisors is greatly reduced. The subsamples of funds are, in the way they are organized, governed by a more independent board of directors. Further, the comparison between insurance and non-insurance series trusts sheds light on how the redemption right affects fund performance when combined with board independence. Although closed-end funds may serve as a potential comparison for the fund governance with and without the redemption right, there are more explanations to the closed-end fund discount in addition to the weak governance/agency problem. Recent papers have shown that unrealized capital gains, liquidity and tax concerns are factors that explain the premiums and discounts of a closed-end fund (Cherkes et al., 2009; Goldie et al., 2010; Day et al., 2011; Edwin J Elton et al., 2013). The increased cost of redemption creates a discouragement of redeeming shares in insurance series trusts. It does not change the nature of investments as closed-end funds usually invest in less liquid assets. The results indicate that board governance serves as a complement to investor's right to redeem in monitoring mutual fund performance rather than a substitute.

3.2 Institutional Details

By 2012, about 2,200 fund directors oversee around $12 trillion assets. These boards are overlapped to a great extent in that 280 directors in 25 complexes govern over 75% of all fund assets. The directors have an average age of 64 and tenor of 20 years. The typical directors' compensation program includes both an annual retainer and a separate fee provided for attending Board and Committee meetings. About 67% of directors' compensation structure includes both the retainer fee and the meeting fee, while the retainer fee makes up 72% of total compensation. In 2015, the median compensation for boards overseeing assets between $3 billion to $10 billion was $80,000, while the chairmen receive an additional $37,200 on average.

Some of the duties of mutual fund directors include approving the investment advisory and sub-advisory contracts, underwriting or distribution contract, trading practice and procedures, investment policies and objectives, 12b-1 plan, and multiple asset arrangements. The directors further monitor the investment in derivatives and liquidity of the portfolios and oversee personal investing by managers. To qualify as an independent director, one cannot be an employee of the adviser, or a member of the immediate family of an employee, or an employee or a 5-percent shareholder of a registered broker-dealer. Additionally, one cannot have an affiliation with any recent legal counsel to the fund.

In general, the empirical results of the literature suggest that more independent board sets lower fees but does not improve fund performance. Several papers question the board's independence that retail shareholders do not have much power in determining board members. The conflicts of interest between fund managers and investors may arise because investment firms/fund advisors often provide service to multiple funds simultaneously. As of 2016, 87% of fund families have unitary boards where a common board serves all funds. In large fund families, a cluster structure is more common; there are several boards within the families, each oversees a designated group of funds. Under such a relationship, directors may not be as independent because directors that are more supportive of the managers may be invited to sit on more boards and thus receive higher compensation. Further, a common board suffers from the concern of strategic performance transfer from low-value funds to high-value funds (Nanda et al., 2004; Gaspar et al., 2006).

A series trust is a form of mutual fund entity where funds within the trust share a board of trustees, chief compliance officer, and much of the infrastructure supporting compliance, reporting, shareholder services, transactions, and back-office functions. Each portfolio in the trust has its own prospectus and is branded to the advisor that manages the funds. There are several differences between series trusts and standalone trusts. First, the creation costs are about 25% lower because of negotiated agreements. Second, series trusts use the existing board of directors/trustees, legal counsel, and CCO. Third, the director compensation (trustee fee) is typically lower because of shared service. Fourth, the branding of funds happens at the fund level for series trusts while it happens at both fund and trust level for standalone trusts. Lastly, there is no seed audit required for series trusts and $100,000 required to begin audits for standalone trusts. When a series trust terminates, there are three options for the funds. The funds can choose from making a liquidation distribution to shareholders, merging with existing funds, or restarting as a new fund.

3.3 A Case Study of BlackRock Funds

When several fund advisors co-manage a series trust and brand it as a separate fund advisor, there could be some overlap between the board of the series trust and its co-managers. I use a case study using the funds managed by the investment company, BlackRock, to show that it is unlikely to be the case. Among all the fund advisers, BlackRock operates in the highest number of series trusts. I manually collected the director information and board characteristics on all 79 trusts and 403 funds of BlackRock, including the liquidated trusts and funds (shown in Figure 6).

[Figure 6 Here]

There are seven series trust-involved funds managed by BlackRock. None of the series trusts has directors that overlap with other standalone trusts managed by BlackRock. As additional evidence, the locations of series trusts are different from the standalone trusts. For instance, the "ADVANCED SERIES TRUST" locates in Newark, NJ, and "TRANSAMERICA SERIES TRUST" locates in Denver, CO, while the majority of BlackRock standalone trusts locate in Wilmington, DE.

[Figure 7 Here]

Further, the funds included in series trusts are mostly equity funds. Equity funds are riskier compared to fixed-income funds and thus need more monitoring. As shown in Figure 7, the average age, size of the board, and the percentage of independent directors are similar across the two types of set-ups. The significant difference between the currently existing two types of trusts is the number of portfolios overseen. The directors of standalone trusts, on average, monitor more portfolios. Although large fund families, such as BlackRock, adopt the structure of the clustered board, the directors still, on average, oversee more funds compared to the directors of series trusts. Similar to the busy board (i.e., Fich and Shivdasani, 2006) scenario in corporate governance, monitoring of the board may be further weakened.

The independence of boards in the traditional standalone trusts is likely to be compromised because of the following four reasons. First, independent directors are selected and nominated by the management firm. The 1940 Act dictates that shareholders elect fund directors, but only for the initial board and to fill vacancies if less than a majority of the board is shareholder-elected (there is no annual election). Second, fund directors and advisory firms that manage the funds hire each other preferentially based on the intensity of their past interactions (Kuhnen, 2009). Third, the definition of independence is not very strict. Executives of brokerage firms, banks, and other lenders are considered “not interested” so long as their firm has not executed trades for or conduct any business with the mutual fund group in the previous six months. Former officials or business associates of the management firm are considered independent after a two-year waiting period. Lastly, there is a considerable amount of pecuniary benefit. According to the 2012 MPI annual survey of mutual fund director compensation, director compensation is positively related to the number of funds and the total size of the assets that the board oversees. The median compensation of directors overseeing between 26 and 35 portfolios is $122,000, and the compensation would double if the number of portfolios overseen is above 80. Given the above reasons, the independence of the board in traditional standalone trusts is compromised. In contrast, series trusts ease the problem to the extent that the directors are less connected to the fund advisers.

3.4 Data

I obtain the list of investment companies (trust level) and funds under management from SEC Edgar for the year 2010 to 2017. Each trust is treated as an investment company/entity in the SEC filings with a unique CIK number. I only include observations with the entity type "30", which refers to mutual funds. If the investment company name contains "Series Trust", the company is labeled as a series trust, and the funds under the same trust are assigned to the target group. To drop the cases where the names coincidentally contain the two words, I further exclude series trusts where the same adviser manages all funds. To identify whether a series trust is an insurance or non-insurance series trust, I manually check the funds and advisers in each series trust and their prospectus (Form 485POSA and 485POSB). If the prospectus states that all funds in the trust are open to retail investors, the trust is defined as a non-insurance trust, and otherwise, an insurance series trust.

The sample of funds is matched to CRSP Mutual fund database, where I obtain fund characteristics such as age, size (total net assets), return, and different types of expenses and fees. I aggregate share class fund size, return, and fees to fund level by taking the sum and weighted average. Following the screening process of previous papers, I drop funds with total net assets of less than 5 million. Fund age is determined by the oldest share class.

In the matching funds from series trusts with those from standalone trusts, I first match the fund-years with funds from standalone trusts that have the same Lipper Objective Code and CRSP Index indicator. Further, I require the age of the matched fund to be between one year younger and one year older and choose the closest fund size. About 80% of the matched funds' size falls between 50% and 150% of the targeted series trust fund. In the final sample, I have 4,137 fund-year observations that are managed under series trusts.

[Table 11 Panel A Here]

Table 11 Panel A reports the number of series trusts and standalone trusts from 2010 to 2017 and the average number of funds in those trusts, respectively. In contrast to the 17% decline in the number of standalone trusts, the number of series trusts has grown by 23%. Further, the average number of funds in both types of trusts are growing, indicating that fund families are grouping more funds to reduce operating costs. The average number of funds in series trusts is significantly higher than that of standalone trusts. By 2017, series trusts hold on average 65% more funds in their structures compared to 2010. Although it may seem that boards of series trusts oversee more funds, many standalone trusts that belong to the same fund family have the same or overlapped boards. As shown in the case study of BlackRock, the same set of directors sit on several standalone trusts and thus the average number of funds a typical standalone trust board oversees could be higher.

[Table 11 Panel B Here]

Table 11 Panel B reports the fund-year summary statistics of the sample of series trust funds between 2010 and 2017. The portfolio turnover ratio is calculated as the minimum of aggregated sales or aggregated purchases of securities divided by the average 12-month Total Net Assets of the fund. Expense ratio and management fees are calculated on an actual basis. There may be reimbursements from the advisers that could result in a negative management fee. The data from SEC Edgar only starts from 2010, but some series trusts have been around much longer with an average fund age of 9.7 years.

3.5 Do Series Trust Funds Outperform?

There is a small number of series trust funds relative to the number of standalone trust funds, so I use a matched sample method to compare the two groups. In choosing the control group, I first restrict that the matched fund should have the same Lipper objective code and CRSP index fund identifier, and should be similar in age and fund size.

[Table 12 Here]

Table 12 reports the t-statistics of the matched sample. Overall, the series trust funds perform slightly better than standalone trusts in both net and gross terms, but the difference is not significant. In the meanwhile, the series trust funds are associated with significantly lower portfolio turnover and management fee while significantly higher total expense ratio and 12b-1 fee. The expense ratio covers administrative, management, advertising (12b-1), and all other expenses.

3.5.1 Insurance and Non-insurance Series Trusts

The funds in insurance and non-insurance series trusts are different in that the shareholders' ability to exit the funds without bearing significant costs is limited when investing in an insurance series trust. Because of the contract terms in insurance policies and retirement plans, investors are trapped in their investments due to a high exit penalty. As a comparison, non-insurance series trust funds are open to retail investors and have the daily liquidity feature of traditional open-end mutual funds. An example of an insurance series trust is Advanced Series Trust. The list of advisers in the trust is provided in Appendix D. An example of non-insurance series trust is Investment Managers Series Trust. The list of advisers in the trust is provided in Appendix E.

[Table 13 Here]

Table 13 Panel A reports the differences between funds in insurance series trusts and the matched sample in standalone trusts. The portfolio turnover ratio, expense ratio, management fee, and 12b-1 fee are missing for 90% of the insurance series trust funds in CRSP, so I manually collect the information from funds' annual reports and fill in over 90% of the fund-years. Still, there are missing variables from the control group that contains standalone trust funds and cause differences in the number of observations in the tested variables. The t-test results show that the insurance series trust funds underperform in gross terms by 27 basis points annually, and they charge higher expense ratios to shareholders. The management fee is significantly lower, while the 12b-1 fee is significantly higher, consistent with the full sample results except for the little difference in portfolio turnover.

Table 13 Panel B reports the matched sample results with non-insurance trusts. In contrast to insurance series trust funds, non-insurance series trust funds outperform their standalone trust peers in both raw and gross terms though the difference is not significant for the net returns. The non-insurance series trust funds outperform 46 basis points in gross return and 23 basis points in net terms annually. For the expense ratios, the non-insurance series trust funds have significantly lower management fees and portfolio turnover compared to the standalone ones, but significantly higher expense ratio and 12b-1 fee, consistent with the full sample results. The t-test results of the matched sample show outperformance of non-insurance series trust funds and underperformance of insurance series trust funds in gross terms. Further, the more independent boards are effective in setting lower management fees, which is directly charged by the fund advisors. The higher total expense ratio is mainly due to the absence of an economy of scale, which leads to operational costs, including administrative costs.

3.5.2 Multivariate Regressions

In addition to a matched sample t-test, I run an OLS regression with the dependent variable as the gross return. The variable of interest is a dummy variable, *Series Trust*, that indicates whether the fund is managed in a series trust or not. The independent variables include fund age, fund size, portfolio turnover, expense ratio, actual 12b-1 fees with year-Lipper Objective Code fixed effects, and clustered standard errors at the adviser level.

[Table 14 Here]

Table 14 reports the regression results of the full sample in the first two columns and a subsample of equity funds in the last two columns with all series trust funds. In all four columns, I find series trust fund significantly outperform the standalone trust funds after controlling for fund characteristics. Funds that are older and larger perform better generally. Additionally, gross performance is negatively related to portfolio turnover in all four columns, suggesting lower turnover, in general, is associated with better fund performance. In the subsample of only equity funds, the series trust funds outperform the standalone peers by between 39 and 59 basis points annually.

In the next table, I split the sample by insurance and non-insurance series trust funds and find similar results to the matched sample t-test.

[Table 15 Here]

Table 15 Panel A reports the full sample and equity fund subsample regression results of insurance series trust funds and all standalone trust funds. In the first and third columns, I find insurance series trust funds significantly underperform standalone trust funds after controlling for fund characteristics such as size and age. In the full sample, insurance series trust funds underperform by 180 basis points annually, and equity funds in insurance series trust underperform by 261 basis points annually. The multivariate regressions produce similar and stronger evidence of underperformance as compared to standalone peers.

Table 15 Panel B reports the full sample and equity fund subsample regression results of non-insurance series trust funds and all standalone trust funds. Similar to the full sample results, I find series trust fund significantly outperform the standalone trust funds in all four columns. On average, funds in non-insurance series trusts outperform their standalone peers between 37 and 53 basis points per year. The equity funds outperform their standalone peers between 40 to 61 basis points per year.

Both the matched sample and the multivariate results indicate that insurance series trust funds underperform their standalone peers significantly in the gross return by 180 to 261 basis points while the non-insurance series trust funds outperform by 37 to 61 basis points annually.

3.6 What Explains the Differences in Performance?

3.6.1 Internal and External Correlations

Elton et al. (2007) find that mutual fund returns are more closely correlated within than between fund families, primarily due to common stock holdings and similar exposures to economic sectors and industries. In this section, I test the information sharing channel using monthly performance correlations. If there is no information sharing in series trusts, the performance of funds should correlate more with standalone trust funds managed by the same adviser. I obtain the adviser information from CRSP Mutual Fund Database.

I calculate the average pairwise correlation between funds in the same series trusts and have the same Lipper classification and label it as an internal correlation. The external correlation is calculated as the average correlation between series trust funds and standalone trust funds that have the same adviser and same Lipper classification. Alpha and residual are calculated based on a Carhart four-factor model with 24-month rolling regressions.

[Table 16 Here]

Table 16 reports the differences between internal and external correlations. I report six types of correlations, gross return, gross residual risk, gross alpha, net return, net residual risk, and net alpha, with all funds and only equity funds. In six measures, internal correlations are stronger than external correlations. The internal correlation in gross alpha is about 16 basis points higher than external correlation and 30 basis points for equity funds. The internal gross residual correlation is about 11 basis points higher than the external correlation and 17 basis points higher for equity funds. The net terms produce a similar magnitude of differences. These findings indicate that the structure of series trusts enhance the information sharing among the funds in the trust, and such information sharing is related to the superior performance of the funds in series trusts.

[Table 17 Here]

In Table 17, I split the sample by insurance and non-insurance series trusts to further explore the difference in information sharing between two types of series trusts. In all, except for the net return correlation, I find non-insurance series trusts have significantly higher internal correlation, while the insurance series trusts do not exhibit a significant difference between internal and external correlation. Further, except for net return correlation, non-insurance series trusts show more considerable differences between internal and external correlations compared to insurance series trusts. The evidence suggests that funds in insurance series trusts generally engage in information sharing through a shared board of directors, and such information sharing is significantly higher for non-insurance series trust funds.

3.6.2 Managerial Abilities

Aside from information sharing among different fund advisers, the difference in performance could also be interpreted as the fund managers in the non-insurance series trust funds are better-skilled professionals while the managers of insurance series trust are less skilled. To test this inference, I use gross alpha estimated with a Carhart four-factor model as the managerial ability.

[Table 18 Here]

In Table 18 Panel A, I report the OLS regression results with the four-factor alpha as the dependent variable. The variable of interest is a dummy variable, Series Trust, indicating whether a fund is managed under a series trust or not. I control for other fund characteristics such as fund size, age, and fees. The first two columns report the results with all funds, and the last two reports the subsample of equity funds. I find that insurance series trust funds, especially equity funds, have significantly lower alphas. The coefficient on Series Trust is negative and significant in the second column of the full sample while I add more controls and negative and significant in both two columns of equity funds. The equity funds in insurance series trusts have an average alpha that is 30 basis points lower than their standalone peers on an annual basis.

As a comparison, in Table 18 Panel B, I report the regression results of non-insurance trust funds. There is no evidence of better skill in the full sample or the subsample of equity funds. However, the coefficient on Series Trust is positive, opposite to the results in Panel A. The evidence shows that the skill of managers in non-insurance series trusts does not differ significantly from its standalone peers while the managers in insurance series trusts exhibit inferior skill.

The above analysis indicates that poorer governance in insurance series trusts can be explained by lower managerial skill or ineffectiveness in terminating underperforming managers. As a comparison, the outperformance of the non-insurance series trust funds could be related to better information sharing among different advisers while there is no significant difference in managerial skill.

3.7 Conclusion

In this paper, I examine the two important governance mechanisms in the mutual fund industry, investors' right to redeem shares on any trading day, and the board of directors. The setting of series trusts in mutual funds allows me to identify funds with more independent boards compared to mutual funds governed by a traditional standalone trust. A series trust is a turnkey setup service provided by a third party to provide certain services (e.g., audit, trustee, some legal) to fund advisers. The board of directors in a series trust is set up by the third-party service provider, and the connection between the directors and advisors is significantly reduced, making the board of directors more independent than traditional standalone trusts. Further, a case study using BlackRock funds shows no overlap between directors of a series trusts and the directors of standalone trusts belonging to the advisors participating in series trusts. The difference between the two types of series trusts further allows me to compare the impact of investors' redemption right to board governance. There are two major types of series trusts, insurance series trusts, and non-insurance series trusts. Insurance series trusts are those only open to insurance companies or retirement plans while the non-insurance series trusts do not have such investment limitations. Due to the difference in clientele, investors of funds in insurance series trusts face much higher redemption costs than traditional mutual fund investors.

Using the fund-year data between 2010 and 2017, I find that insurance series trust funds underperform, and non-insurance trust funds outperform in both matched sample and multivariate regression. The empirical findings support that board independence has an impact on mutual fund performance. A more independent board leads to better gross performance. Additionally, the comparison between insurance series trusts and non-insurance series trusts indicates that costless redemption is a stronger and more effective governance mechanism than board governance. The two mechanisms work as complements rather than substitutes. I further examine the information sharing and managerial skill of funds in series trusts. I find that fund managers of insurance series trust funds have lower gross alphas or lower managerial skill. In contrast, those of non-insurance series trust funds do not differ significantly from the other standalone trust funds in skill. The outperformance of the non-insurance series trust funds could also relate to better information sharing among different advisers.

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Table 1 Summary Statistics on Fund Pair Characteristics

The table reports the statistics of the main variables estimated from equation $\mathrm{Decision}_{\mathrm{Stock\ i}} = \frac{\Delta \mathrm{R}}{\mathrm{Ill}_i * \Delta \mathrm{W}_i}$. To simplify the model, I create fund pairs with consecutive ranks within each peer group (same active benchmark reported in fund prospectus) at the end of the third quarter, eg. Rank 1 and Rank 2, Rank 2 and Rank 3 in benchmark R1G. The common positions are restricted to those with positive weight differences (higher-ranked minus lower-ranked) according to the constraint of predatory trading. The number of common holdings with positive weight differences is roughly the same as the number with negative weight differences.

ΔW is the weight difference of the common positions, measured by the weight of the stock in the higher-ranked fund minus the weight in the lower-ranked fund in each pair. ΔR is the fund cumulative return difference between the higher-ranked fund and the lowered-ranked fund, measured from the first trading day of the year to the last trading day of the third quarter. *Shares Sold* refers to the number of shares sold by the lower ranked funds during the last quarter of the year. A negative number indicates that the fund increases the holding of the stock during the last quarter. *Shares Held* is the number of shares held by the lower ranked fund at the end of the third quarter. On average, there are 19 peer groups and on average 87 funds in a group annually.

Variable	Mean	Median	Std	Min	Max
Decision$_{stock}$ (in 10^{11})	0.058	<0.001	5.71	<0.001	1,890
ΔW	0.48%	0.11%	20.75%	<0.001%	48.50%
ΔR	0.24%	0.01%	0.84%	<0.001%	33.91%
Ill (in 10^{-7})	4.23	2.4	42.6	0	3,509
Shares Sold	432	0	389,219	-94,200,000	43,300,000
Shares Held	207,733	19,900	1,284,422	100	98,700,000
N	209,240				

Table 2 Summary Statistics on Stock Characteristics

Panel A reports the stock characteristics of common holdings with positive weight differences, and Panel B reports stock characteristics of all holdings. Size is measured as the total market equity at the end of third quarter. B/M is the book to market equity ratio. Pre return is calculated over the last month in the third quarter. Shares Outstanding is the total number of shares of the stock. β is the measured based on 60 days prior to the end of the third quarter. Stock Standard Deviation (Stock Std) is the stock daily return standard deviation over the last month in the third quarter. Ill refers to the average illiquidity ratio in the last month of the third quarter.

Panel A: Common Holdings

Variable	Mean	Median	Std	Min	Max
Size (in millions)	25,484	3,086	59,176	27	604,415
B/M	0.50	0.46	0.4	-0.16	3.50
Pre return	0.85%	-0.02%	20.75%	-41.7%	44.03%
Shares Outstanding (in thousands)	641,890	104,670	1,577,103	883	22,900,000
β	2.07	1.13	6.72	-11.03	22.42
Stock Std	0.63	0.03	0.12	0.01	2.62
Ill (in 10^{-7})	4.2	2.4	42.6	<0.1	3,509
N	209,240				

Panel B: All Holdings

Variable	Mean	Median	Std	Min	Max
Size (in millions)	16,607	2,495	40,031	11.54	274,430
B/M	0.51	0.42	0.41	-0.24	5.37
Pre return	0.69%	0.13%	19.11%	-19.10%	266.47%
Shares Outstanding (in thousands)	414,960	80,707	1,118,499	50	22,900,000
β	1.10	0.96	0.98	-2.20	5.30
Stock Std	0.05	0.04	0.07	0.01	1.39
Ill (in 10^{-7})	7.9	2.6	84.7	<0.1	18,136
N	1,355,520				

Table 3 Which Stocks Do Funds Sell in the Last Quarter?

This table reports the linear probability regression results of which stocks are more likely to be sold. The dependent variable is a dummy variable, *Sell*, which is set to one if the lower-ranked fund sells part or all of the stock. The regression is based on the fund-pair-stock observations with consecutive ranks in each benchmark. Ranks are calculated with fund raw return from the beginning of the year to the end of third quarter. $1/\Delta W$, ΔR and

1/Ill are components of $Decision_{stock}$ ($Decision_{stock} = \frac{\Delta R}{Ill * \Delta W}$). Top-ranked is a dummy variable set to one if the lower-ranked fund ranks in the top 20% of funds in its peer group. Standard errors are clustered at fund level. NC is a dummy variable set to one if the necessary condition of predatory trading is satisfied. *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Decision $Decision_{stock}$ * NC							-0.0253***
							(-3.587)
$Decision_{stock}$						-1.74E-4	-1.93E-3
						(-0.704)	(-0.831)
$1/\Delta W$	-4.46E-10					-3.16E-10	-2.43E-10
	(-1.335)					(-0.704)	(-0.548)
1/Ill		2.08E-11***				2.03E-11***	2.03E-11***
		(5.538)				(5.516)	(5.516)
ΔR			1.107**			0.592	0.592
			(2.040)			(1.156)	(1.156)
Top-ranked				0.0673***		0.0598***	0.0598***
				(3.350)		(2.843)	(2.843)
NC					-0.032	-0.026	-0.026
					(-1.045)	(-0.869)	(-0.863)
Fund ret	-0.302**	-0.302**	-0.323***	-0.404***	-0.289**	-0.393***	-0.393***
	(-2.562)	(-2.565)	(-2.753)	(-3.268)	(-2.400)	(-3.086)	(-3.086)
Shares Held in Q3	-4.47E-10	-1.49E-9	-4.07E-10	-3.10E-10	1.18E-9	0	5.58E-11
	(-0.130)	(-0.429)	(-0.119)	(-0.0906)	(0.351)	(0.00897)	(0.0166)
Size	4.71E-07***	2.90E-07***	4.75E-07***	4.44E-07***	4.55E-07***	2.58E-07***	2.58E-07***
	(5.252)	(3.376)	(5.287)	(5.073)	(5.057)	(3.046)	(3.046)
B/M	5.65E-7	5.49E-7	5.72E-7	5.38E-7	5.83E-7	5.42E-7	5.42E-7
	(1.249)	(1.214)	(1.264)	(1.177)	(1.297)	(1.198)	(1.198)
Pre return	-0.108***	-0.111***	-0.108***	-0.106***	-0.109***	-0.110***	-0.110***
	(-3.517)	(-3.622)	(-3.517)	(-3.466)	(-3.540)	(-3.594)	(-3.596)
β	-0.000126*	-0.000132*	-0.000129*	-0.000135*	-0.000125*	-0.000139*	-0.000139*
	(-1.705)	(-1.783)	(-1.745)	(-1.811)	(-1.716)	(-1.902)	(-1.901)
Stock Std	0.0151***	0.0155***	0.0151***	0.0148***	0.0152***	0.0153***	0.0153***

	(3.226)	(3.336)	(3.229)	(3.174)	(3.259)	(3.317)	(3.319)
Constant	0.650***	0.650***	0.666***	0.750***	0.643***	0.743***	0.743***
	(3.756)	(3.763)	(3.848)	(4.238)	(3.737)	(4.213)	(4.213)
Observations	209,240	209,240	209,240	209,240	209,240	209,240	209,240
R-squared	0.013	0.014	0.014	0.015	0.014	0.017	0.017
Year FE	Y	Y	Y	Y	Y	Y	Y

Table 4 Direct Channel: Evidence of Predatory Trading in the Last Quarter of the Year

This table reports the results of conditional logistic regressions with the dependent variable is a dummy variable, *Sell*, which is set to one if the lower-ranked fund sells part or all of the stock over the last quarter. All panels are based on fund-pair-stock observations with consecutive ranks in each benchmark. Ranks are calculated with fund raw return from the beginning of the year to the end of third quarter.

Panel A reports the regression results in all fund pairs. Panel B reports the results of fund pairs where the necessary condition of predatory trading is satisfied. Panel C is based on the fund pairs where the necessary condition is not satisfied.

$Decision_{stock}$ is the variable of interest and funds are expected to sell the stock when $Decision_{stock}$ is low. ΔR and its interaction terms are omitted because of the fund pair year fixed effect. Previous Return, Size, and Book-to-Market Equity control for stock characteristic and stock return standard deviation, and β control for the total and standard risk of stocks. Standard errors are clustered at fund level. *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: All Fund Pairs

Variable	Top 20%	Top 40%	Top 60%	Top 80%	Full Sample
$Decision_{stock}$	-0.0259	-0.0157*	-0.0159*	-0.0211*	-0.0133*
	(-1.494)	(-1.889)	(-1.881)	(-1.933)	(-1.650)
$1/\Delta W$	1.95E-08***	6.42E-09***	4.65E-09***	6.61E-09***	5.29E-09***
	(4.312)	(2.973)	(3.298)	(2.693)	(2.815)
1/Ill	- 3.39E-11*	5.51E-12	5.38E-12	2.49E-12	1.11E-11
	(-1.656)	(0.291)	(0.334)	(0.147)	(0.795)
Shares Held in Q3	3.56E-08***	1.34	1.66E-08**	1.70E-08**	1.50E-08***
	(2.957)	(1.445)	(2.482)	(2.525)	(2.629)
Pre return	-1.276	-1.290	-1.074*	-1.460**	-0.926**
	(-1.114)	(-1.510)	(-1.783)	(-2.428)	(-2.001)
Stock Std	0.158	0.163	0.135*	0.183**	0.116*
	(1.089)	(1.500)	(1.761)	(2.372)	(1.952)
β	0.00195	-0.00027	-0.00056	-0.00078	-0.00104**
	(1.287)	(-0.425)	(-0.994)	(-1.530)	(-2.176)
B/M	-0.0704**	5.55E-06**	4.00E-06*	5.55E-06***	5.35E-06***
	(-2.331)	(2.098)	(1.799)	(2.691)	(2.751)
Size	-7.36E-07**	-3.47E-7	-1.35E-7	2.35E-8	-3.16E-7
	(-1.975)	(-0.828)	(-0.348)	(0.0606)	(-1.033)
Observations	30,097	68,831	102,043	143,389	175,639
Pseudo R-squared	0.0015	0.0003	0.0003	0.0004	0.0003
Conditional on Fund pair year	Y	Y	Y	Y	Y

Panel B: Fund Pairs that Satisfy Necessary Condition

Variable	Top 20%	Top 40%	Top 60%	Top 80%	Full Sample
$Decision_{stock}$	-4.147***	-0.523	5.67E-2	0.059	0.063
	(-3.407)	(-0.975)	(1.153)	(1.162)	(1.247)
$1/\Delta W$	3.03E-06***	2.55E-7	1.14E-9	7.27E-10	2.59E-10
	(4.982)	(0.866)	(0.126)	(0.0769)	(0.0274)
1/Ill	-7.88E-11	2.50E-11	3.87E-11	3.08E-11	1.51E-11
	(-0.778)	(0.433)	(0.732)	(0.655)	(0.361)
Shares Held in Q3	1.25E-8	1.29E-8	5.68E-9	9.80E-9	6.44E-9
	(0.982)	(1.468)	(0.732)	(1.324)	(0.916)
Pre return	1.422	-1.967	-2.000	-2.255	-1.409
	(0.248)	(-0.570)	(-0.925)	(-1.228)	(-0.907)
Stock Std	-0.395	0.237	0.244	0.274	0.175
	(-0.390)	(0.547)	(0.892)	(1.176)	(0.890)
β	0.0190*	-0.0043	-0.0006	-0.00133**	-0.00144***
	(1.700)	(-1.069)	(-0.736)	(-2.288)	(-2.605)
B/M	0.025	-0.030	-0.013	-3.13E-4	7.90E-06**
	(0.414)	(-0.459)	(-1.386)	(-0.403)	(2.300)
Size	8.48E-7	7.24E-7	3.88E-7	2.60E-7	3.67E-7
	(0.562)	(0.784)	(0.402)	(0.306)	(0.480)
Observations	2,780	7,841	26,344	35,534	38,578
Pseudo R-squared	0.0076	0.0021	0.0006	0.0007	0.0006
Conditional on Fund pair year	Y	Y	Y	Y	Y

Panel C: Fund Pairs that Don't Satisfy Necessary Condition

Variable	Top 20%	Top 40%	Top 60%	Top 80%	Full Sample
$Decision_{stock}$	-0.0394	-0.0221*	-0.0152*	-0.0173**	-0.0136*
	(-0.973)	(-1.832)	(-1.898)	(-2.080)	(-1.645)
$1/\Delta W$	7.61E-08**	2.82E-9	6.61E-09***	6.13E-09***	5.26E-09***
	(2.258)	(0.660)	(3.045)	(2.810)	(2.808)
1/Ill	-2.50E-11	-1.82E-11	-1.54E-11	1.26E-12	9.03E-12
	(-0.781)	(-0.843)	(-0.897)	(0.0767)	(0.626)
Shares Held in Q3	2.70E-07*	1.05E-07**	8.64E-08***	7.02E-08**	6.46E-08***
	(1.924)	(2.257)	(2.690)	(2.446)	(2.867)
Pre return	-1.354	-1.377	-1.823	-0.552	-0.861*
	(-0.868)	(-1.105)	(-1.495)	(-1.012)	(-1.747)
Stock Std	0.175	0.177	0.233	0.066	0.109*
	(0.879)	(1.109)	(1.497)	(0.883)	(1.672)
β	0.00267	0.00064	-0.00062	-0.00115*	-0.00076
	(1.007)	(0.343)	(-0.938)	(-1.722)	(-1.160)
B/M	-2.37E-05***	6.00E-06*	6.13E-06*	5.91E-06**	4.32E-06*
	(-3.004)	(1.872)	(1.903)	(2.119)	(1.929)
Size	-1.20E-06**	-9.78E-07**	-4.10E-7	-2.26E-7	-4.96E-07*
	(-2.066)	(-2.123)	(-1.069)	(-0.675)	(-1.649)
Observations	11,648	35,202	76,364	112,868	137,061
Pseudo R-squared	0.0024	0.0014	0.0006	0.0005	0.0004
Conditional on Fund pair year	Y	Y	Y	Y	Y

Table 5 Direct Channel: Do Funds' Predatory Practices Succeed?

This table reports the fund-level logistic regression results of whether the relative rankings are reversed after predatory trading. The sample contains 923 fund pairs where the lower-ranked fund satisfies the necessary condition of predatory trading at the end of the third quarter. The dependent variable, *Success*, is a dummy set to one if the lower-ranked fund in the pair ends up with higher year-end return relative to the higher-ranked fund. I define *Predate* as a dummy equal to one if the lower-ranked fund trades predatorily by selling any number of shares of the common holdings.

ΔR is the return difference within each pair of funds. *Rank Quintile* indicates whether the lower-ranked fund is ranked in top 20%, 40%, 60%, 80% or 100% in its peer group. *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

VARIABLES	Regression(1)	Regression(2)	Regression(3)	Regression(4)
Predate	0.251*	0.219	0.247*	0.256*
	(1.714)	(1.479)	(1.682)	(1.678)
ΔR	-71.82*	-65.39	-67.96	-48.32
	(-1.682)	(-1.543)	(-1.555)	(-1.108)
Rank Quintile	-0.049	-0.048	-0.047	-0.041
	(-1.006)	(-0.974)	(-0.952)	(-0.839)
Fund Size (low)	-2.32E-6	-2.88E-6	-1.81E-6	-1.58E-6
	(-0.542)	(-0.663)	(-0.395)	(-0.332)
Fund Size (high)	-9.60E-6	-9.46E-6	-1.11E-5	-8.87E-6
	(-0.814)	(-0.800)	(-0.932)	(-0.746)
Constant	0.013			
	(0.0826)			
Observations	923	923	923	888
Pseudo R-Squared	0.007	0.006	0.007	0.006
Conditional on Year	N	Y	N	N
Conditional on Benchmark	N	N	Y	N
Conditional on Benchmark year	N	N	N	Y

Table 6 How do Funds React to the Threat of Predatory Trading? Strategy 1

This table reports conditional logistic regression results of the first strategy of higher-ranked funds as a response to predatory trading. Such strategy predicts that the higher-ranked fund will increase the holding of the stock when facing predatory trading. The dependent variable is the probability of increasing a stock position when the lower-ranked fund trades predatorily. The sample is limited to fund pairs where the lower-ranked fund satisfies the necessary condition of predatory trading.

ΔR is the return difference within each pair of funds. *Rank Quintile* indicates whether the lower-ranked fund is ranked in the top 20%, 40%, 60%, 80% or 100% in its peer group. *Relative size (High/Low)* is the ratio of fund size (TNA), higher-ranked fund divided by lower-ranked fund. Standard errors are clustered at benchmark level. *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

VARIABLES	Regression(1)	Regression(2)
Predate * Cash Holding	-6.549	-3.431
	(-0.686)	(-0.638)
Predate	-6.079***	-6.137***
	(-14.62)	(-9.900)
Cash Holding	-0.0732***	-0.0953***
	(-3.348)	(-4.488)
Rank Quintile	-0.135*	-0.114*
	(-1.668)	(-1.936)
ΔR	-51.38***	-57.86*
	(-3.554)	(-1.888)
Relative size (High/Low)	0.0416	0.0505
	(1.131)	(1.587)
Observations	923	879
Pseudo R-Squared	0.558	0.599
Conditional on Benchmark year	N	Y

Table 7 How do Funds React to the Threat of Predatory Trading? Strategy 2

This table reports the OLS regression results of number of shares held by small funds on the threat of predatory trading across every quarter. For each stock observation in a small fund's holdings, I identify the closest-ranked large competitor that holds the same stock. *Threat* is measured as the rank distance between the large competitor and the small fund. The distance is the absolute difference between the small fund and the closest-ranked large fund adjusted by the total number of funds in each benchmark. The higher the value is, the smaller the threat of predatory trading. In Regression (2), Threat is interacted with Illiquidity ratio.

Previous Return, Size, and Book-to-Market Equity control for stock characteristic and stock return standard deviation, and β control for the total and standard risk of stocks. Rank takes the value of 0, 1, and 2, indicating whether the fund is in top, middle, and bottom third of its peer group. Standard errors are clustered at fund level. *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

VARIABLES	Regression(1)	Regression(2)
Threat	8,184***	8,190***
	(2.980)	(2.984)
Threat*Ill		-206,198
		(-1.131)
Fund Size	141.1***	141.4***
	(4.725)	(4.725)
Fund Size large	-0.0324*	-0.0324*
	(-1.936)	(-1.936)
Ill	-77,804	-11,047
	(-1.255)	(-0.176)
B/M	393	393
	(1.480)	(1.480)
Size	0.0906***	0.0906***
	(9.088)	(9.088)
Pre return	-2,997***	-2,997***
	(-2.677)	(-2.676)
Stock Std	37,530**	37,533**
	(2.464)	(2.464)
β	1.149	1.149
	(0.922)	(0.922)
Rank	-934.6*	-934.4*
	(-1.731)	(-1.731)
Constant	4964	4963
	(1.232)	(1.232)
Observations	720,359	720,359
R-Squared	0.03	0.03
Year-quarter FE	Y	Y

Table 8 Falsification Tests

In Panel A, the sample contains fund pairs where the lower-ranked funds satisfy the necessary condition of predatory trading but are not directly competing for flows. Funds are ranked together instead of in each benchmark. If both funds in the pair belong to the same benchmark, the pair is excluded from the sample. In Panel B, the sample includes all common positions with negative weigh differences (weights of stocks are higher in the lower-ranked funds' portfolios). Both samples use the end of the third quarter holdings to predict which common holdings are more likely to be sold in the last quarter of the year. The β in Top 40% is omitted due to the concavity requirement with conditional logistic estimation.

The dependent variable in the logistic regression, *Sell*, is a dummy variable set to one if the lower-ranked fund sells part or all of the stock. Previous Return, Size, and Book-to-Market Equity control for stock characteristic and stock return standard deviation, and β control for the total and standard risk of stocks. Standard errors are clustered at fund level. *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Non-competing Fund Pairs

Variable	Top 20%	Top 40%	Top 60%	Top 80%	Full Sample
$Decision_{stock}$	73.44**	18.43	18.83***	12.31*	4.51
	(2.146)	(0.880)	(2.671)	(1.940)	(0.575)
$1/\Delta W$	-1.11E-4***	-1.95E-5	-8.93E-06**	-4.19E-06**	-1.12E-6
	(-4.136)	(-1.521)	(-2.014)	(-2.029)	(-0.710)
1/Ill	1.33E-10	-7.05E-11	1.86E-12	1.69E-11	2.52E-12
	(0.774)	(-0.940)	(0.0341)	(0.380)	(0.0627)
Shares Held in Q3	-1.46E-8	3.72E-9	-8.42E-9	-2.91E-9	3.23E-9
	(-0.774)	(0.209)	(-0.665)	(-0.279)	(0.356)
Pre return	1.284	-3.958	0.624	0.622	0.811
	(0.243)	(-1.176)	(0.635)	(1.255)	(1.193)
Stock Std	-0.264	0.472	-0.172	-0.147*	-0.169
	(-0.383)	(1.098)	(-1.143)	(-1.707)	(-1.527)
β	0.047	0.005	-0.001	-0.001	-0.001
	(1.072)	(0.972)	(-0.653)	(-0.639)	(-0.776)
B/M	-0.322*	-0.258*	-0.151	-0.082	-0.066
	(-1.897)	(-1.845)	(-1.058)	(-0.730)	(-0.627)
Size	-5.04E-06***	-1.87E-06*	-1.25E-06*	-5.84E-7	-8.04E-7
	(-2.830)	(-1.860)	(-1.652)	(-0.815)	(-1.262)
Observations	1,905	5,224	10,082	14,254	17,452
Pseudo R-squared	0.0298	0.0091	0.0041	0.0019	0.0013
Conditional on Fund pair year	Y	Y	Y	Y	Y

Panel B: Common Holdings with Negative Weight Differences

Variable	Top 20%	Top 40%	Top 60%	Top 80%	Full Sample
Decision$_{stock}$	0.031	0.025	0.016	0.012	0.011
	(1.191)	(1.213)	(1.231)	(0.860)	(0.884)
$1/\Delta W$	-7.68E-9	-7.02E-9*	-5.66E-09**	-1.21E-10	-7.97E-11
	(-1.494)	(-1.658)	(-1.998)	(-0.865)	(-0.505)
1/Ill	1.16E-11	2.40E-11	2.76E-11 *	3.03E-11*	1.89E-11
	(0.508)	(1.285)	(1.652)	(1.837)	(1.317)
Shares Held in Q3	1.76E-08**	1.21E-08*	1.14E-08**	1.83E-08***	1.81E-08***
	(2.417)	(1.900)	(1.968)	(3.254)	(3.455)
Pre return	0.764	0.105	0.109	0.084	0.069
	(0.876)	(1.533)	(1.573)	(1.219)	(1.003)
Stock Std	-0.0.90	-0.019	-0.202	-0.0.14	-0.012
	(-0.740)	(-1.518)	(-1.603)	(-1.483)	(-1.215)
β	0.00519		0.00196***	0.00105*	0.00124*
	(1.368)		(2.776)	(1.805)	(1.914)
B/M	-0.0363**	-3.96E-6	-6.40E-7	-1.16E-6	-1.20E-6
	(-2.403)	(-1.226)	(-0.259)	(-0.512)	(-0.557)
Size	-2.21E-8	2.490E-7	3.86E-7	3.83E-7	2.87E-7
	(-0.0457)	(0.601)	(0.988)	(1.060)	(0.983)
Observations	34,497	71,532	108,716	145,608	181,994
Pseudo R-squared	0.0298	0.0091	0.0041	0.0019	0.0013
Conditional on Fund pair year	Y	Y	Y	Y	Y

Table 9 Do Funds Trade Predatorily in the Second or the Third Quarter?

Panel A and Panel B report the results of conditional logistic regression results of predatory trading in the second and the third quarters respectively. Both samples are limited to the fund pairs where the lower ranked fund satisfies the necessary condition of predatory trading, similar to Table 4 Panel B. In Panel A, fund pairs are created based on their performance from the beginning of the year to the end of the first quarter. In Panel B, fund pairs are created based on their performance from the beginning of the year to the end of the second quarter.

$Decision_{stock}$ is the variable of interest and funds are expect to sell the stock when $Decision_{stock}$ is low. Previous Return, Size, and Book-to-Market Equity are stock characteristic controls. Illiquidity, stock standard deviation, and β are additional factors that affect mutual funds' portfolio choices. Standard errors are clustered at fund level. In the last three columns of Panel A, the control variable *B/M* is replaced with *Tobin's q* due to the concavity requirement with conditional logistic estimation. *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Second Quarter

Variable	Top 20%	Top 40%	Top 60%	Top 80%	Full Sample
$Decision_{stock}$ (in 10^{11})	-20.58*	0.069	0.005	0.006	-0.128
	(-1.750)	(0.807)	(0.0813)	(0.101)	(-1.262)
$1/\Delta W$	1.87E-6	-2.36E-8	2.58E-8	2.49E-8	1.41E-7
	(1.383)	(-0.344)	(0.457)	(0.458)	(1.622)
1/Ill	5.8E-11	3.95E-11	6.11E-11	6.11E-11**	4.87E-11**
	(1.210)	(0.476)	(1.249)	(2.416)	(2.174)
Shares Held in Q1	2.57E-08***	1.54E-08***	9.72E-09**	7.53E-9	9.46E-09**
	(3.373)	(2.740)	(2.242)	(1.551)	(2.241)
Pre return	-0.464	2.798	-2.130	-2.724	-4.067**
	(-0.122)	(1.153)	(-1.056)	(-1.606)	(-1.977)
Stock Std	0.099	-0.570	0.468	0.591*	0.872**
	(0.124)	(-1.122)	(1.108)	(1.661)	(2.022)
β	-0.0658**	0.006	0.010	0.004	0.008
	(-2.311)	(0.420)	(0.891)	(0.407)	(0.918)
B/M	-0.082	0.015			
	(-1.141)	(1.234)			
Size	-2.42E-06**	-1.76E-06***	-4.81E-8	2.07E-7	-8.31E-8
	(-2.540)	(-2.591)	(-0.0630)	(0.321)	(-0.145)
Tobin's q			-0.099	-0.145	-0.134
			(-0.709)	(-1.392)	(-1.423)
Observations	3,483	10,973	29,649	47,111	53,243
Pseudo R-squared	0.0056	0.0025	0.0012	0.0015	0.0017
Conditional on Fund pair year	Y	Y	Y	Y	Y

Panel B: Third Quarter

Variable	Top 20%	Top 40%	Top 60%	Top 80%	Full Sample
$Decision_{stock}$ (in 10^{11})	-4.540	-0.176	0.401**	0.281*	0.281*
	(-1.289)	(-0.0935)	(2.434)	(1.921)	(1.906)
$1/\Delta W$	2.36E-6	-1.71E-06***	-2.42E-8	6.25E-10	6.29E-10
	(0.939)	(-3.140)	(-1.369)	(0.233)	(0.235)
1/Ill	4.43E-11	1.85E-12	4.98E-11	3.77E-11	2.9E-11
	(0.629)	(0.0428)	(1.394)	(1.147)	(1.108)
Shares Held in Q2	-2.53E-9	1.89E-9	2.4E-9	-3.17E-9	2.42E-9
	(-0.236)	(0.202)	(0.340)	(-0.455)	(0.385)
Pre return	2.657	3.485	-0.095	-3.487	-3.910
	(0.289)	(0.701)	(-0.0234)	(-0.979)	(-1.229)
Stock Std	4.458*	2.940*	0.464	0.786	0.868
	(1.827)	(1.749)	(0.544)	(0.981)	(1.213)
β	0.0279	-0.0192***	0.0001	0.0001	0.0001
	(0.752)	(-2.626)	(0.817)	(0.653)	(0.879)
B/M	-9.64E-2	-3.36E-2	-4.52E-3	-5.28E-06*	-6.72E-06**
	(-1.093)	(-0.906)	(-0.400)	(-1.950)	(-2.535)
Size	-1.34E-6	-1.46E-06*	-6.52E-7	1.11E-7	8.28E-8
	(-1.058)	(-1.882)	(-0.926)	(0.154)	(0.133)
Observations	3,101	8,604	25,336	41,695	47,628
Pseudo R-squared	0.0063	0.0056	0.0009	0.0005	0.0005
Conditional on Fund pair year	Y	Y	Y	Y	Y

Table 10 Which Stocks Do Funds Buy?

This table reports the results of conditional logistic regression with the set of stocks experienced positive inflation from the last trading day of the year to the first trading day of the next year. The dependent variable is a dummy set to one if the fund buys the stock in the last quarter of the year and otherwise zero. The independent variable, *Competitor*, is set to one if the stock is also held by the fund ranks one place above. *Rank* is measured within each benchmark. Previous Return, Size, Illiquidity Ratio, Book-to-Market Equity, β, and Stock Std are stock characteristic controls. Standard errors are clustered at stock level. *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

VARIABLES	(1)	(2)
Rank	-0.00997***	-0.00939***
	(-13.02)	(-12.32)
Competitor	-0.460***	-0.343***
	(-10.31)	(-7.535)
Rank*Competitor	0.0125***	0.00938***
	(9.529)	(7.235)
Ill	-686***	-722***
	(-4.629)	(-4.696)
$\boldsymbol{\beta}$	2.25E-4	3.04E-4
	(0.353)	(0.467)
Stock Std	-2.939***	-2.474***
	(-3.914)	(-2.934)
B/M	-0.118***	-0.154***
	(-2.985)	(-3.486)
Size	-1.07E-6	-2.17E-06***
	(-1.285)	(-2.732)
Pre return	-0.365***	-0.282**
	(-3.343)	(-2.440)
Constant	-0.533***	-0.918***
	(-14.23)	(-4.999)
Observations	32,589	32,589
Pseudo R-Squared	0.009	0.020
Conditional on Year	N	Y

Table 11 Summary Statistics (Series Trusts)

Panel A reports time series changes in the number of series trusts and standalone trusts. A standalone trust refers to the traditional set up of mutual funds by a fund advisor. A series trust is a turnkey setup service provided by a third party to provide certain services (e.g., audit, trustee, some legal) to fund advisers. When a fund advisor joins a series trust, it will share the trust with other unaffiliated fund advisors. Panel A also reports the average number of funds in the two types of trusts. Panel B reports the summary statistics of fund characteristics of funds in series trusts.

Panel A: Number of Funds in Series Trusts and Standalone Trusts

Year	Market Share (Series)	Series Trust	Ave Funds (Series)	Standalone Trust	Ave Funds (Standalone)
2010	2.7%	46	37.7	1,897	18.0
2011	4.6%	41	42.7	1,804	18.5
2012	4.6%	39	45.7	1,706	19.6
2013	5.6%	42	45.7	1,641	20.5
2014	6.4%	44	45.5	1,626	20.8
2015	5.5%	44	46.9	1,608	22.1
2016	6.1%	40	50.5	1,587	22.9
2017	4.1%	51	41.4	1560	24.6

Panel B: Series Trust Fund Characteristics

VARIABLES	Obs	Mean	Std. Dev.	Min	Max
Annual Gross Return	3,851	8.58%	11.68%	-46.60%	74.52%
Annual Net Return	4,137	7.48%	11.73%	-1.69%	1.73%
Fund Size	4,139	2,939	7,556	5	119,475
Fund Age	4,117	9.7	8.7	0	71
Expense Ratio	3,852	1.06%	0.41%	0%	7.74%
Mgmt Fee	3,860	0.13%	1.37%	-49.55%	3.67%
12b-1 Fee	3,421	0.15%	0.12%	0%	0.67%
Portfolio Turnover	3,607	87.81%	126.84%	0%	2213%

Table 12 Matched Sample T-tests

This table reports the matched sample results of funds in series trusts and their comparable funds in standalone trusts. Each fund belongs to a series trust is matched with a fund in standalone trust by fund size, age, Lipper classification and whether it is an index fund. Turnover refers to the portfolio turnover of the funds, which is the minimum of aggregated sales or aggregated purchases of securities divided by the average 12-month Total Net Assets of the fund. Management fee sometimes takes a negative value due to expense reimbursement. *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

VARIABLES	Target	Control	Diff	T-stat	N
Gross Return	8.88%	8.84%	0.04%	0.25	2,969
Net Return	7.50%	7.47%	0.02% 4	0.19	4,126
Turnover	87.51%	106.40%	-18.89%	-1.65	2,745
Expense Ratio	1.06%	0.96%	0.10%	10.26***	2,969
Mgmt Fee	0.15%	0.34%	-0.10%	-4.99***	3,000
Actual 12b-1	0.16%	0.15%	0.01%	2.44***	1,820

Table 13 Matched Sample T-tests: Insurance and Non-insurance Series Trusts

Panel A reports the matched sample t-test results of matched sample of insurance series trusts. Panel B reports the results of non-insurance series trusts. A insurance series trust is the type of trust that only opens to insurance company annuity plans and/or retirement plans. A non-insurance series trust has no limitation on the investors of the funds in the trust. Each fund belonging to a series trust is matched with a standalone trust fund by fund size, age, Lipper classification and whether it is an index fund. *Turnover* refers to the portfolio turnover of the funds, which is the minimum of aggregated sales or aggregated purchases of securities divided by the average 12-month Total Net Assets of the fund. Management fee sometimes takes a negative value due to expense reimbursement. *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Insurance Series Trusts

VARIABLES	Target	Control	Diff	T-stat	N
Gross Return	8.18%	8.45%	-0.27%	-1.45*	1,460
Net Return	7.06%	7.22%	-0.16%	-1.02	2,181
Turnover	88.58%	104.08%	-15.50%	-0.72	1,379
Expense Ratio	0.98%	0.88%	0.10%	8.20***	1,460
Mgmt Fee	0.23%	0.81%	0.59%	-2.42***	1,471
12b-1 Fee	0.20%	0.15%	0.04%	9.83***	986

Panel B: Non-insurance Series Trusts

VARIABLES	Target	Control	Diff	T-stat	N
Gross Return	9.59%	9.14%	0.46%	2.20**	1,543
Net Return	7.88%	7.65%	0.23%	1.17	2,027
Turnover	86.84%	108.81%	-21.96%	-2.95***	1,401
Expense Ratio	1.13%	1.04%	0.09%	6.71***	1,543
Mgmt Fee	-0.13%	0.28%	-0.42%	-2.96***	1,562
12b-1 Fee	0.19%	0.14%	0.05%	8.32***	853

Table 14 Do Funds in Series Trusts Perform Better?

This table reports the OLS regression results with the dependent variable as annual gross return. The dummy variable, *Series Trust*, is set to one if the fund belongs to a series trust and zero otherwise. *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

VARIABLES	**All Funds**	**All Funds**	**Equity Funds**	**Equity Funds**
Series Trust	0.00369**	0.00514***	0.00392**	0.00591***
	(2.460)	(3.362)	(2.124)	(3.165)
Fund Age	0.000257***	0.000258***	0.000323***	0.000336***
	(6.362)	(7.040)	(6.815)	(8.072)
Fund Size	7.31E-09***	7.69E-09***	7.26E-09***	7.70E-09***
	(3.548)	(4.311)	(2.594)	(3.153)
Portfolio Turnover	-0.000482***	-0.000309***	-0.000558***	-0.000378***
	(-2.926)	(-3.723)	(-2.715)	(-6.178)
Expense Ratio	0.247	0.625***	0.224	0.655***
	(1.602)	(3.071)	(1.364)	(3.160)
Mgmt Fee		1.31E-4		9.12E-5
		(0.983)		(0.684)
12b-1 Fee		-1.740***		-2.243***
		(-4.336)		(-5.075)
Constant	1.089***	1.085***	1.105***	1.100***
	(623.7)	(521.5)	(544.9)	(479.5)
Observations	46,435	31,326	34,510	22,960
R-squared	0.71	0.78	0.70	0.77
Year-Lipper FE	Y	Y	Y	Y
Adviser Cluster	Y	Y	Y	Y

Table 15 Performance Differences Between Insurance and Non-insurance Series Trusts

This table reports the OLS regression results with the dependent variable as annual gross return. The dummy variable, *Series Trust*, is set to one if the fund belongs to a series trust and zero otherwise. Panel A reports the results with funds in insurance series trusts and all standalone trusts. Panel B reports the results with funds in non-insurance series trusts and all standalone trusts. An insurance series trust is the type of trust that is only open to insurance company annuity plans and/or retirement plans. A non-insurance series trust has no limitation on the investors of the funds in the trust. *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Insurance Series Trusts

VARIABLES	All Funds	All Funds	Equity Funds	Equity Funds
Series Trust	-0.0180**	-0.0109	-0.0261**	-0.0178
	(-1.980)	(-1.047)	(-2.209)	(-1.494)
Fund Age	0.000276***	0.000273***	0.000343***	0.000354***
	(6.414)	(7.193)	(6.812)	(8.161)
Fund Size	5.95e-09***	4.94e-09***	5.95e-09**	4.80e-09**
	(3.352)	(3.765)	(2.370)	(2.575)
Portfolio Turnover	-0.000465***	-0.000284***	-0.000543***	-0.000353***
	(-2.925)	(-3.174)	(-2.737)	(-6.052)
Expense Ratio	0.236	0.580***	0.197	0.586***
	(1.52)	(2.99)	(1.20)	(2.93)
Mgmt Fee		0.000309*		0.000260
		(1.791)		(1.503)
12b-1 Fee		-0.811**		-1.246***
		(-2.455)		(-3.183)
Constant	1.091***	1.089***	1.107***	1.106***
	(1,214)	(1,130)	(1,040)	(989.8)
Observations	44,667	30,024	33,162	21,971
R-squared	0.71	0.78	0.70	0.77
Year-Lipper FE	Y	Y	Y	Y
Adviser Cluster	Y	Y	Y	Y

Panel B: Non-insurance Series Trusts

VARIABLES	All Funds	All Funds	Equity Funds	Equity Funds
Series Trust	0.00374**	0.00528***	0.00405**	0.00611***
	(2.472)	(3.419)	(2.179)	(3.255)
Fund Age	0.000257***	0.000258***	0.000324***	0.000336***
	(6.363)	(7.038)	(6.813)	(8.067)
Fund Size	7.31E-09***	7.68E-09***	7.25E-09***	7.69E-09***
	(3.548)	(4.320)	(2.595)	(3.160)
Portfolio Turnover	-0.000482***	-0.000309***	-0.000558***	-0.000378***
	(-2.926)	(-3.721)	(-2.715)	(-6.178)
Expense Ratio	0.246	0.625***	0.223	0.655***
	(1.597)	(3.069)	(1.358)	(3.158)
Mgmt Fee		1.32E-4		9.23E-5
		(0.992)		(0.694)
12b-1 Fee		-1.744***		-2.248***
		(-4.337)		(-5.076)
Constant	1.089***	1.085***	1.105***	1.100***
	(623.7)	(521.9)	(544.9)	(480.0)
Observations	46,423	31,319	34,503	22,953
R-squared	0.71	0.78	0.70	0.77
Year-Lipper FE	Y	Y	Y	Y
Adviser Cluster	Y	Y	Y	Y

Table 16 Fund Performance Correlation

This table reports the t-test results of fund correlations with funds within the same trust, internal, and fund correlations with funds outside the trust but with the same adviser. The correlation is calculated pair-wised and only between funds with the same Lipper classification. I calculate the average pairwise correlation between funds in the same series trusts and have the same Lipper classification and label it as internal correlation. The external correlation is calculated as the average correlation between the series trust funds and standalone trust funds that have the same advisor and same Lipper classification. Alpha and residual are calculated based on the four-factor model with 24-month rolling regressions. *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Type	N	Internal Correlation	External Correlation	Diff	T
Gross Return					
All Funds	655	0.8981	0.8848	0.0133	2.35***
Equity Funds	529	0.9101	0.8905	0.0196	3.21***
Gross Residual					
All Funds	557	0.3322	0.2986	0.0336	1.63**
Equity Funds	448	0.2450	0.2086	0.0363	1.46*
Gross Alpha					
All Funds	557	0.3909	0.3377	0.0531	2.38***
Equity Funds	448	0.3210	0.2464	0.0746	2.78***
Net Return					
All Funds	1,159	0.8686	0.8502	0.0184	4.81***
Equity Funds	977	0.8777	0.8529	0.0248	5.88***
Net Residual					
All Funds	1,052	0.3046	0.2641	0.0406	2.72***
Equity Funds	887	0.2381	0.2020	0.0361	2.10**
Net Alpha					
All Funds	1,052	0.3651	0.3275	0.0377	2.44***
Equity Funds	887	0.3105	0.2685	0.0420	2.38***

Table 17 Matched Sample T-tests: Insurance and Non-insurance Series Trusts

This table reports the t-test results of fund correlations with funds within the same trust, internal, and fund correlations with funds outside the trust but the same adviser in insurance series trusts and non-insurance series trusts. The correlation is calculated pair-wised and only between funds with the same Lipper classification. I calculate the average pairwise correlation between funds in the same series trusts and have the same Lipper classification and label it as *Internal Correlation*. *External Correlation* is calculated as the average pair-wise correlation between a series trust fund and all standalone trust funds that have the same advisor and same Lipper classification. Alpha and residual are calculated based on a four-factor model with 24-month rolling regressions. *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Type	N	Internal Correlation	External Correlation	Diff	T
Gross Return					
Insurance ST	462	0.8879	0.8851	0.0028	0.50
Non-insurance ST	200	0.9250	0.8850	0.0400	3.03**
Gross Residual					
Insurance ST	397	0.2737	0.2567	0.0170	1.29
Non-insurance ST	165	0.5485	0.4383	0.0823	2.10**
Gross Alpha					
Insurance ST	397	0.3319	0.2989	0.0330	1.29
Non-insurance ST	165	0.4918	0.4095	0.1102	2.51**
Net Return					
Insurance ST	832	0.8379	0.8178	0.0201	3.81***
Non-insurance ST	355	0.9190	0.9146	0.0043	0.88
Net Residual					
Insurance ST	748	0.2411	0.2028	0.0382	2.22**
Non-insurance ST	309	0.4727	0.3994	0.0734	2.41**
Net Alpha					
Insurance ST	748	0.3197	0.2846	0.0351	1.92**
Non-insurance ST	309	0.4753	0.4101	0.0652	2.19**

Table 18 Do Managers in Series Trusts Have Superior Skill?

This table reports the OLS regression results with the dependent variable as the gross four-factor alpha. The dummy variable, *Series Trust*, is set to one if the fund belongs to a series trust and zero otherwise. Panel A reports the regression results of insurance series trusts while Panel B reports the results of non-insurance series trusts. *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Insurance Series Trusts

VARIABLES	All Funds	All Funds	Equity Funds	Equity Funds
Series Trust	-0.00254	-0.00434***	-0.00296*	-0.00300**
	(-0.844)	(-2.632)	(-1.908)	(-2.156)
Fund Age	1.67e-3	-4.27e-5	-7.20e-5	-7.60e-05*
	(1.105)	(-1.218)	(-1.546)	(-1.839)
Fund Size	-3.34e-8	5.77e-09***	7.00e-09***	6.82e-09***
	(-0.922)	(4.455)	(4.004)	(4.269)
Portfolio Turnover	-0.000158	-0.000046	-0.000157*	-0.000131**
	(-1.309)	(-0.860)	(-1.750)	(-2.059)
Expense Ratio	-1.155	0.188	0.214*	0.275**
	(-0.93)	(1.46)	(1.72)	(2.16)
Mgmt Fee		-1.06e-4		-1.75e-4
		(-0.557)		(-0.852)
12b-1 Fee		-0.777***		-1.094***
		(-2.939)		(-3.401)
Constant	0.993***	1.005***	0.992***	0.994***
	(95.07)	(1,182)	(1,140)	(1,057)
Observations	41,840	29,286	31,072	21,459
R-squared	0.13	0.56	0.35	0.46
Year-Lipper FE	Y	Y	Y	Y
Adviser Cluster	Y	Y	Y	Y

Panel B: Non-insurance Series Trusts

VARIABLES	All Funds	All Funds	Equity Funds	Equity Funds
Series Trust	0.00614	0.00135	0.00204	0.00335
	(1.082)	(0.532)	(0.921)	(1.215)
Fund Age	1.67E-3	-4.07E-5	-6.90E-5	-7.96E-05*
	(1.109)	(-1.167)	(-1.498)	(-1.927)
Fund Size	-3.38E-8	6.03E-09***	7.28E-09***	7.21E-09***
	(-0.920)	(4.474)	(3.968)	(4.320)
Portfolio Turnover	-0.000173	-0.000038	-0.000166*	-0.000119**
	(-1.314)	(-0.713)	(-1.723)	(-2.339)
Expense Ratio	-1.146	0.174	0.171	0.262**
	(-0.95)	(1.40)	(1.35)	(2.12)
Mgmt Fee		2.04E-5		2.23E-6
		(0.149)		(0.0151)
12b-1 Fee		-0.891***		-1.227***
		(-3.066)		(-3.591)
Constant	0.993***	1.006***	0.991***	0.994***
	(97.29)	(1,194)	(1,128)	(1,070)
Observations	40,788	27,817	30,282	20,344
R-squared	0.13	0.55	0.34	0.45
Year-Lipper FE	Y	Y	Y	Y
Adviser Cluster	Y	Y	Y	Y

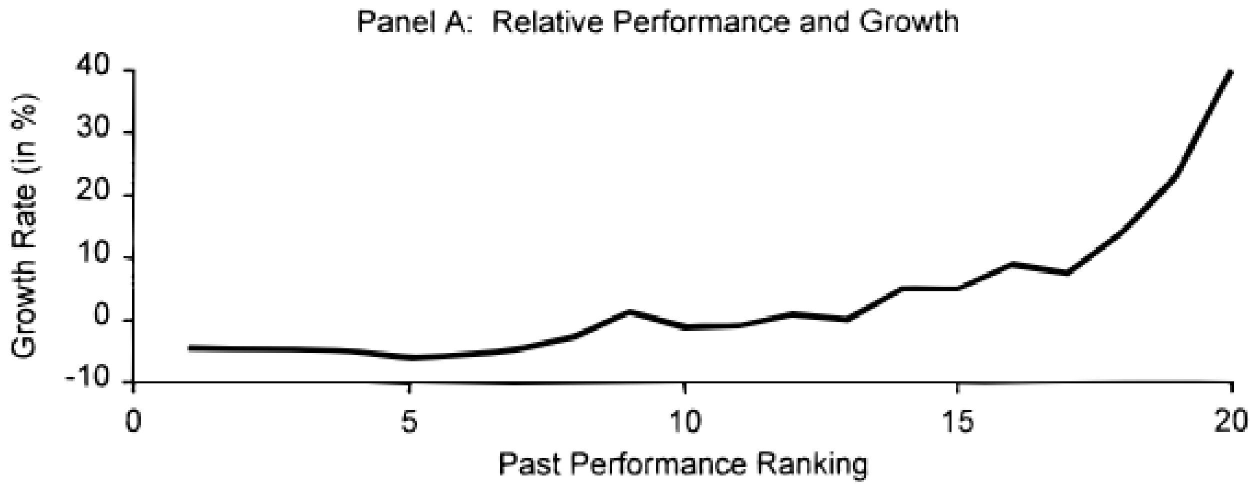


Figure 1 Convex Flow-Performance Relationship (Sirri and Tufano, 1998)

Figure 1 shows the convex flow-performance relationship documented in Sirri and Tufano (1998). The funds are sorted into 20 portfolios based on their prior performance.

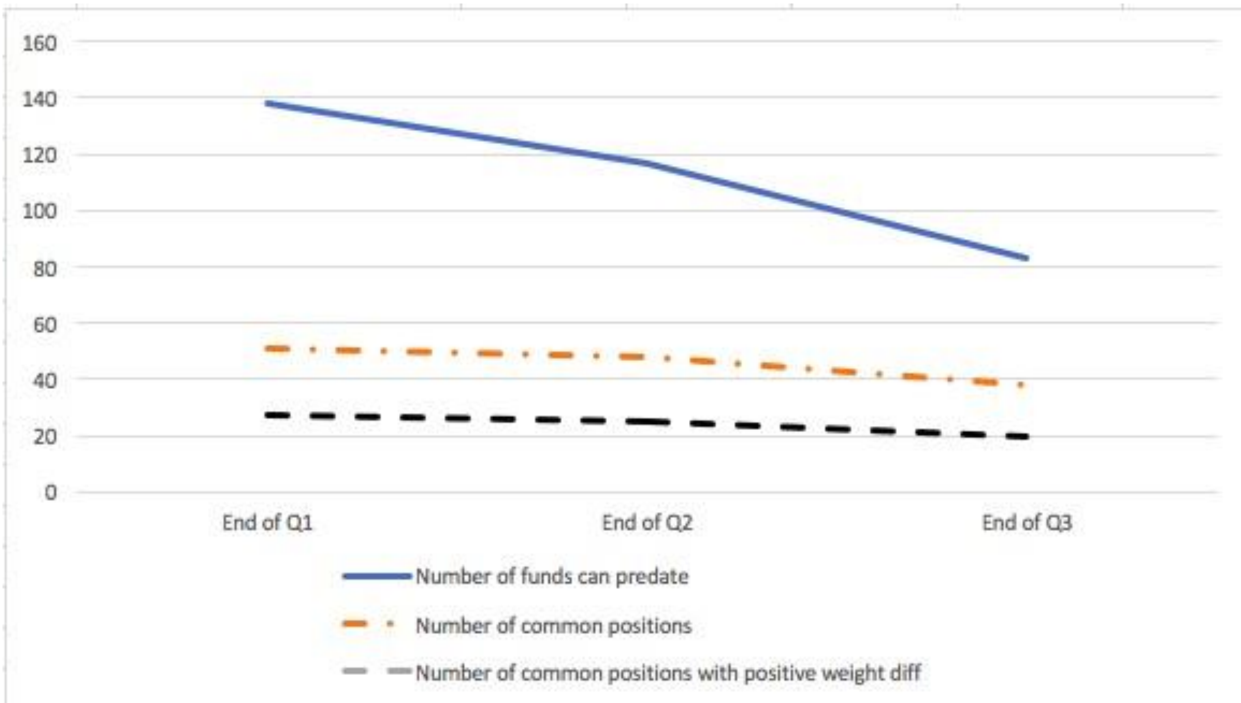
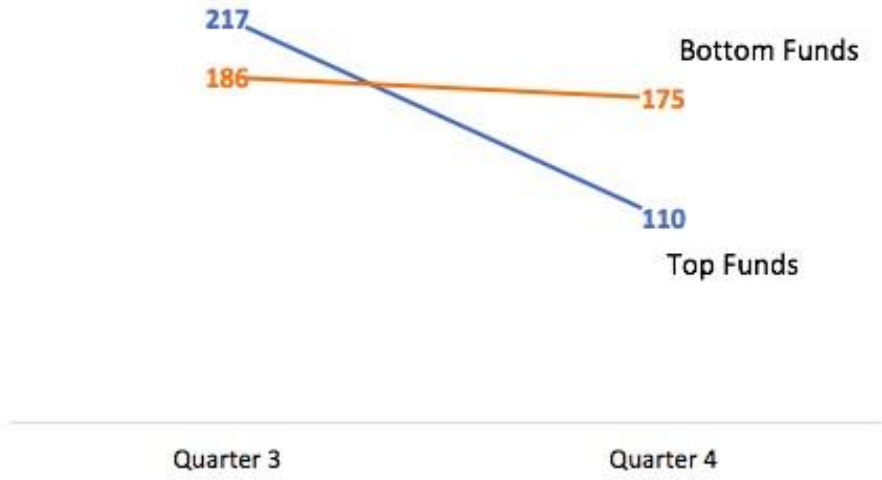


Figure 2 Funds' Reaction to the Threat of Predatory Trading (1)

Figure 2 shows the change of the average number of fund-pairs that satisfies the necessary condition of predatory trading, the average number of all common positions and the average number of common positions with positive weight differences from the end of the first quarter to the end of the third quarter.

Figure 3 Funds' Reaction to the Threat of Predatory Trading (2)

Figure 3 shows the quarterly movements of the average number of common positions through time. The number of common positions is calculated in fund-pairs that satisfy the necessary condition of predatory trading.

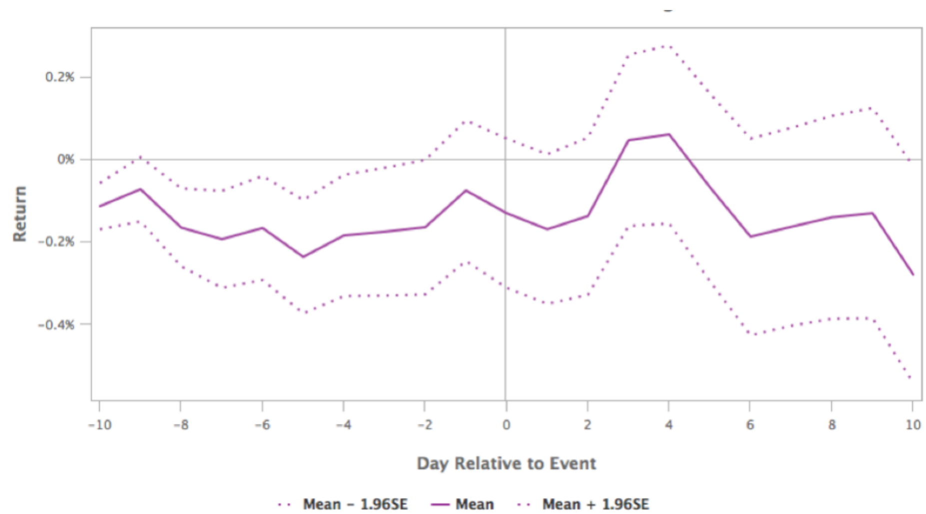


(a) Average Illiquidity Ratio of Small Funds

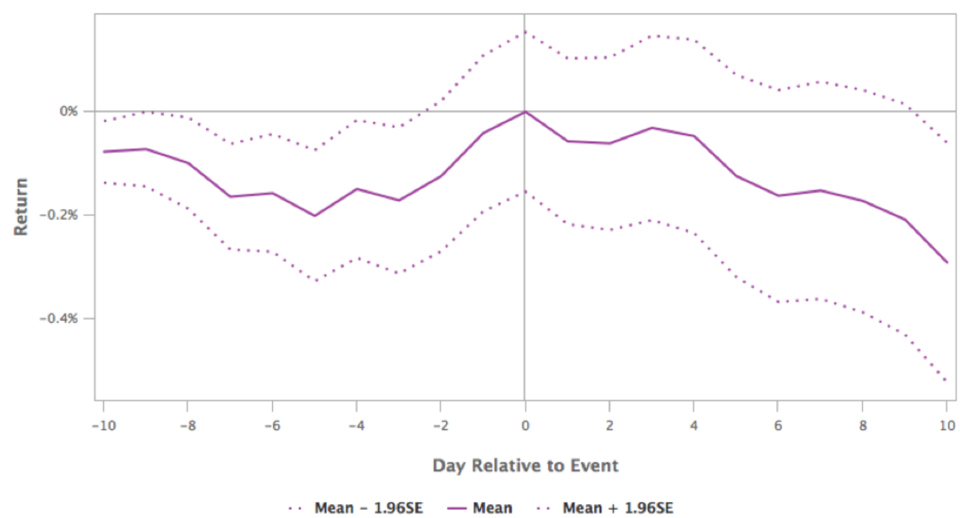
(b) Average Illiquidity Ratio of Large Funds

Figure 4 Changes in Average Portfolio Illiquidity Ratio

Figure 4 (a) exhibits the changes in average illiquidity ratio for top-ranked and bottom-ranked small funds from the third quarter to the fourth quarter. Figure 4 (b) exhibits the changes in average illiquidity ratio for top-ranked and bottom-ranked large funds from the third quarter to the fourth quarter.



(a) Cumulative Abnormal Return: Predator Stocks



(b) Cumulative Abnormal Return: Non-predator Stocks

Figure 5 Cumulative Return of Predator and Non-predator Stocks

Figure 5 (a) exhibits the changes in average cumulative abnormal return of "Predator Stocks". Figure 5 (b) exhibits the changes in changes in average cumulative abnormal return of "Non-predator Stocks". In the sub-sample of fund pairs that satisfy the necessary condition, I identify the commonly held stocks that are sold during the last quarter as Predator Stocks and the other common holdings as Non-predator Stocks. I check the cumulative abnormal returns of both groups during the ten trading days before the end of the year and ten trading days after.

CIK	Trust Names	Director Overlap
814679	ADVANCED SERIES TRUST	0
726735	ANCHOR SERIES TRUST	0
1413032	COLUMBIA FUNDS VARIABLE SERIES TRUST II	0
1532747	JACKSON VARIABLE SERIES TRUST	0
778207	TRANSAMERICA SERIES TRUST	0
892538	SUNAMERICA SERIES TRUST	0
933691	JNL SERIES TRUST	0
*Note	JNL and JACKSON shares same board directors	

Figure 6 The List of All BlackRock Trusts

Figure 6 provides a list of all series trusts that contain funds managed by BlackRock. I compare the board of directors of those series trusts to the directors of BlackRock standalone trusts (managed in-house). The variable, *Director Overlap*, is set to one if there is at least one director overlap.

ALL FUNDS

	Series Trust	Standalone
AGE	65.68	66.37
# OF PORTFOLIOS	113.6	126.38
# OF DIRECTORS	10.18	9.84
# OF TRUSTS	11	67
% OF INDEPENDENT DIRECTORS	84.82%	83.31%
N	112	659

CURRENT FUNDS

	Series Trust	Standalone
AGE	65.68	66.97
# OF PORTFOLIOS	113.6	130.91
# OF DIRECTORS	10.18	9.72
# OF TRUSTS	11	53
% OF INDEPENDENT DIRECTORS	84.82%	83.30%
N	112	515

Figure 7 BlackRock Board Characteristics

Figure 7 reports the summarized characteristics of BlackRock funds in series trusts and standalone trusts, respectively. The sample of all funds includes both current funds and terminated funds.

Appendix A Method of Merging Active Share, CRSP and Thomson Reuters

The Active Share data is obtained from the website of Antti Petajisto, at http://www.petajisto.net/data.html. The data covers a time period from 1980 to 2009. For each of the fund included, there are both Fund_no from Thomson Reuters and Crsp_fundno from CRSP, which are two fund identifiers of the latter two databases. However, Fund_no and Crsp_fundno are not onE-to-one matched. Fund_no is at fund level while Crsp_fundno is at fund share class level. It means that I still need to aggregate all share classes into one observation from CRSP.

To start with, I give each fund a unique ID, Fund id, based on the Active Share data. To aggregate the share classes, I first use the Crsp_portno, which is a unique id for each fund. The issue with Crsp_portno is that it is incomplete and is available for about 80% of the fund share classes in my active share funds. For the funds/share classes missing Crsp_portno, I use the Fund name to manually identify different share classes and match Fund id to Crsp_fundno.

Once I combine data using Crsp_portno and Fund name, I generate a one-to-one matching using Fund id and Crsp_fundno. Using both Fund id and Crsp_fundno, I do a manual check a total of 8,638 observations to make sure the match is correct. I obtain the fund name from Fund id as the reference and check the name obtained from Crsp_fundno, and drop the ones that do not match.

Appendix A.1 Example: Active Share Matched with Crsp_portno

Fund_no is the fund identifier from Thomson Reuters. ACrsp_fundno is the original CRSP Fund_no from Active Share data. Fund id the unique fund level identifier I generate. Crsp_fundno and Crsp_portno are the two fund share class and fund portfolio identifiers. Correct Name is the fund name matched from CRSP using ACrsp_fundno, while NAME is the fund share class name matched from CRSP using Crsp_fundno.

Fund_no	ACrsp_fundno	Fund_id	Crsp_fundno	Crsp_portno	Correct NAME	NAME
55002	2932	1580	2929	1004046	AIM Equity Funds: AIM Emerging Growth Fund; Class A Shares	AIM Equity Funds, Inc.: AIM Emerging Growth Fund; Class C Shares
55002	2932	1580	2930	1004046	AIM Equity Funds: AIM Emerging Growth Fund; Class A Shares	AIM Equity Funds, Inc.: AIM Emerging Growth Fund; Class B Shares
55002	2932	1580	2932	1004046	AIM Equity Funds: AIM Emerging Growth Fund; Class A Shares	AIM Equity Funds, Inc.: AIM Emerging Growth Fund; Class A Shares
51241	2933	1521	2933	1003990	AIM Equity Funds: AIM Mid Cap Growth Fund; Class A Shares	AIM Equity Funds, Inc.: AIM Mid Cap Growth Fund; Class A Shares
51241	2933	1521	2934	1003990	AIM Equity Funds, Inc.: AIM Mid Cap Growth Fund; Class A Shares	AIM Equity Funds, Inc.: AIM Mid Cap Growth Fund; Class B Shares
51241	2933	1521	2935	1003990	AIM Equity Funds: AIM Mid Cap Growth Fund; Class A Shares	AIM Equity Funds, Inc.: AIM Mid Cap Growth Fund; Class C Shares
50323	2937	1500	2936	1003942	AIM Equity Funds: AIM Dent Demographic Trends Fund; Class B Shares	AIM Equity Funds, Inc.: AIM Dent Demographic Trends Fund; Class A Shares
50323	2937	1500	2937	1003942	AIM Equity Funds: AIM Dent Demographic Trends Fund; Class B Shares	AIM Equity Funds, Inc.: AIM Dent Demographic Trends Fund; Class B Shares
50323	2937	1500	2938	1003942	AIM Equity Funds: AIM Dent Demographic Trends Fund; Class B Shares	AIM Equity Funds, Inc.: AIM Dent Demographic Trends Fund; Class C Shares

Appendix A.2 Example: Match Fund id and Share Classes

Fund id	Crspfundno	Correct NAME	NAME
10	7350	Acorn Investment Trust: Acorn Fund	Columbia Acorn Trust: Columbia Acorn Fund; Class A Shares
10	7351	Acorn Investment Trust: Acorn Fund	Columbia Acorn Trust: Columbia Acorn Fund; Class B Shares
10	7352	Acorn Investment Trust: Acorn Fund	Columbia Acorn Trust: Columbia Acorn Fund; Class C Shares
10	7353	Acorn Investment Trust: Acorn Fund	Acorn Investment Trust: Acorn Fund
11	6800	Addison Capital Shares, Inc.	Addison Capital Shares, Inc.
12	15500	ING Equity Trust: ING Growth Opportunities Fund; Class A Shares	ING Equity Trust: ING Growth Opportunities Fund; Class Q Shares
12	15501	ING Equity Trust: ING Growth Opportunities Fund; Class A Shares	ING Equity Trust: ING Growth Opportunities Fund; Class I Shares
12	15502	ING Equity Trust: ING Growth Opportunities Fund; Class A Shares	ING Equity Trust: ING Growth Opportunities Fund; Class C Shares
12	15504	ING Equity Trust: ING Growth Opportunities Fund; Class A Shares	ING Equity Trust: ING Growth Opportunities Fund; Class B Shares
12	15505	ING Equity Trust: ING Growth Opportunities Fund; Class A Shares	ING Equity Trust: ING Growth Opportunities Fund; Class A Shares
13	15474	ING Equity Trust: ING SmallCap Opportunities Fund; Class A Shares	ING Equity Trust: ING SmallCap Opportunities Fund; Class I Shares

13	15475	ING Equity Trust: ING SmallCap Opportunities Fund; Class A Shares	ING Equity Trust: ING SmallCap Opportunities Fund; Class C Shares
13	15476	ING Equity Trust: ING SmallCap Opportunities Fund; Class A Shares	ING Equity Trust: ING SmallCap Opportunities Fund; Class B Shares
13	15477	ING Equity Trust: ING SmallCap Opportunities Fund; Class A Shares	ING Equity Trust: ING SmallCap Opportunities Fund; Class A Shares
13	16076	ING Equity Trust: ING SmallCap Opportunities Fund; Class A Shares	ING Equity Trust: ING SmallCap Opportunities Fund; Class Q Shares
13	16077	ING Equity Trust: ING SmallCap Opportunities Fund; Class A Shares	ING Equity Trust: ING SmallCap Opportunities Fund; Class T Shares
13	36782	ING Equity Trust: ING SmallCap Opportunities Fund; Class A Shares	ING Equity Trust: ING SmallCap Opportunities Fund; Class W Shares

Appendix B Robustness Test with Amihud Illiquidity Ratio

This table reports the results of conditional logistic regressions with the dependent variable as a dummy variable, Sell, which is set to one if the lower-ranked fund sells partly or all of the stock. The two panels are presented as the robustness tests to Table 4 Panel A and Panel B, but with the illiquidity ratio calculated as Amihud (2002), using the dollar volume. Both panels are based on fund-pair-stock observations with consecutive ranks in each active share benchmark. Ranks are calculated with fund raw return from the beginning of the year to the end of third quarter. Previous Return, Size, and Book-to-Market Equity control for stock characteristic and stock return standard deviation, and β control for the total and standard risk of stocks. Standard errors are clustered at fund level. *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Full Sample

Variable	Top 20%	Top 40%	Top 60%	Top 80%	Full Sample
$Decision_{stock}$	-3.37E-5	-6.57E-5	-7.90E-5	-1.67E-4	-7.57E-5
	(-0.28)	(-0.56)	(-0.67)	(-1.09)	(-1.57)
$1/\Delta W$	7.35E-11	2.05E-10	2.42E-10	5.49E-10	3.78E-10
	(0.20)	(0.57)	(0.67)	(1.11)	(1.34)
1/Ill	8.13E-14	4.64E-12*	6.09E-12**	6.15E-12***	5.45E-12***
	(0.02)	(1.76)	(2.52)	(2.78)	(2.89)
Shares Held in Q3	4.32E-09**	1.54E-09	1.01E-09	8.16E-10	1.64E-09
	(1.99)	(1.27)	(0.91)	(0.75)	(1.57)
Std	0.0629	0.0846***	0.0673***	0.0483***	0.0428***
	(1.64)	(3.70)	(3.38)	(3.44)	(3.48)
β	1.66E-4	1.55E-4	1.50E-4	1.47E-4	1.43E-4
	(0.98)	(1.07)	(1.05)	(1.04)	(1.02)
B/M	-2.17E-7***	-2.25E-7	-2.61E-7	-2.37E-8	-6.96E-08
	(-10.68)	(-0.30)	(-0.47)	(-0.58)	(-0.21)
Size	-2.29E-7***	-2.15E-7***	-1.79E-7***	-1.23E-7***	-1.38E-7***
	(-4.91)	(-5.34)	(-4.38)	(-3.15)	(-3.54)
Previous Return	-0.396	-0.551***	-0.429***	-0.303***	-0.271***
	(-1.57)	(-3.53)	(-3.19)	(-3.24)	(-3.30)
Observations	25,513	59,782	88,168	124,684	152,766
Pseudo R-squared	0.0024	0.0004	0.0004	0.0006	0.0006
Conditional on Fund pair year	Y	Y	Y	Y	Y

Panel B: Fund-pairs that Satisfy the Necessary Condition

Variable	Top 20%	Top 40%	Top 60%	Top 80%	Full Sample
$Decision_{stock}$	-4.304***	-2.302	-1.179	-0.742	-0.618
	(-5.196)	(-0.966)	(-1.640)	(-1.541)	(-1.328)
$1/\Delta W$	3.38e-06***	1.66E-6	1.40e-07**	9.10E-8	8.49E-8
	(8.591)	(0.842)	(2.445)	(1.415)	(1.268)
1/Ill	-1.82E-12	2.95E-12	4.03e-12*	3.44e-12*	1.64E-12
	(-0.409)	(1.021)	(1.852)	(1.877)	(1.018)
Shares Held in Q3	1.10E-8	1.18E-8	7.39E-9	1.30e-08**	8.47E-9
	(0.942)	(1.546)	(0.979)	(1.961)	(1.329)
Std	-0.185	0.358	0.317	0.393	0.269
	(-0.692)	(0.740)	(1.068)	(1.454)	(1.022)
β	0.0228**	-0.0033	-0.0004	-0.0012**	-0.0013**
	(2.074)	(-0.799)	(-0.361)	(-2.054)	(-2.428)
B/M	-3.96E-2	-6.32E-2	-9.75E-3	-1.49E-4	9.87e-06***
	(-0.397)	(-0.528)	(-0.232)	(-0.141)	(2.768)
Size	9.25E-7	-3.21E-7	-4.71E-7	-4.26E-7	1.13E-7
	(0.463)	(-0.292)	(-0.433)	(-0.427)	(0.128)
Previous Return	-7.178	-2.923	-2.574	-3.184	-2.147
	(-0.504)	(-0.763)	(-1.094)	(-1.488)	(-1.032)
Observations	2,721	7,057	23,337	31,683	34,645
Pseudo R-squared	0.011	0.002	0.001	0.001	0.001
Conditional on Fund pair year	Y	Y	Y	Y	Y

Appendix C Robustness Test with Net Return

This table reports the results of linear probability regressions with the dependent variable as a dummy variable, Sell, which is set to one if the lower-ranked fund sells partly or all of the stock. The two panels are presented as the robustness tests to Table 4 Panel A and Panel B, but with the funds ranked using net return instead of gross return. Both panels are based on fund-pair-stock observations with consecutive ranks in each active share benchmark. Ranks are calculated with fund raw return from the beginning of the year to the end of third quarter. Previous Return, Size, and Book-to-Market Equity control for stock characteristic and stock return standard deviation, and β control for the total and standard risk of stocks. Standard errors are clustered at fund level. *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Full Sample

Variable	Top 20%	Top 40%	Top 60%	Top 80%	Full Sample
Decision$_{stock}$	-0.0294	-0.0155*	-0.0175*	-0.0235*	-0.0165
	(-0.629)	(-1.876)	(-1.871)	(-1.674)	(-1.561)
$1/\Delta W$	-1.3E-7	7.30E-09***	5.47E-09***	7.59E-09***	7.11E-09***
	(-0.683)	(3.945)	(3.997)	(3.020)	(2.836)
1/Ill	-1.47E-12	1.47E-12	1.11E-12	8.72E-13	8.92E-13
	(-1.518)	(1.641)	(1.371)	(1.156)	(1.400)
Shares Held in Q3	2.77E-08***	1.62E-8	2.17E-08***	2.12E-08***	1.80E-08***
	(2.969)	(1.631)	(3.263)	(3.208)	(3.290)
Std	-0.014	0.234	0.201*	0.276***	0.188*
	(-0.749)	(1.621)	(1.820)	(2.643)	(1.696)
β	0.0016	-0.0004	-0.0006	-0.0008	-0.0011**
	(1.131)	(-0.577)	(-1.136)	(-1.539)	(-2.276)
B/M	-7.95 E-2	6.88E-06**	4.99E-06**	6.64E-06***	6.52E-06***
	(-1.361)	(2.308)	(2.154)	(2.996)	(3.096)
Size	-4.29E-7	-6.16E-7	-3.22E-7	-1.36E-7	-4.22E-7
	(-0.969)	(-1.403)	(-0.766)	(-0.340)	(-1.386)
Previous Return	-12.77***	-1.861	-1.600*	-2.201***	-1.492*
	(-2.704)	(-1.639)	(-1.838)	(-2.686)	(-1.712)
Constant	0.319***	0.315***	0.317***	0.319***	0.338***
	(37.84)	(43.82)	(47.04)	(50.12)	(57.04)
Observations	35,378	77,958	113,309	154,484	187,988
R-squared	0.001	0.001	0.001	0.001	0.001
Fund _pair year FE	Y	Y	Y	Y	Y

Panel B: Fund-pairs that Satisfy the Necessary Condition

Variable	Top 20%	Top 40%	Top 60%	Top 80%	Full Sample
$Decision_{stock}$	-0.384***	-0.00340	0.00778***	0.00810***	0.00703*
	(-6.22)	(-0.40)	(2.70)	(2.89)	(1.95)
$1/\Delta W$	2.80E-7***	8.71E-10	-1.54E-10	-2.71E-11	1.08E-09
	(7.20)	(0.38)	(-0.66)	(-0.10)	(0.74)
1/Ill	-3.66E-12	7.85E-12	1.28E-11**	1.09E-11**	1.04E-11**
	(-0.31)	(1.06)	(2.08)	(2.18)	(2.28)
Shares Held in Q3	4.45E-09	8.03E-10	-9.83E-10	-2.98E-10	-1.74E-10
	(1.02)	(0.59)	(-0.93)	(-0.36)	(-0.18)
Std	0.274***	0.158**	0.0424**	0.0353*	0.0101
	(3.30)	(2.24)	(2.10)	(1.94)	(0.54)
β	3.44E-5	1.81E-4	4.26E-4	4.69E-4	1.43E-3
	(0.18)	(0.51)	(0.70)	(0.72)	(1.06)
B/M	4.10E-3	-1.18E-7***	-6.75E-08	-2.00E-6**	-2.14E-7**
	(0.11)	(-5.89)	(-1.54)	(-2.02)	(-2.19)
Size	-3.16E-08	-1.15E-7	-4.83E-08	-1.34E-08	-4.30E-08
	(-0.17)	(-1.37)	(-0.66)	(-0.22)	(-0.77)
Previous Return	-1.776***	-1.019**	-0.254*	-0.209*	-0.0501
	(-3.27)	(-2.20)	(-1.96)	(-1.78)	(-0.41)
Constant	0.240***	0.254***	0.265***	0.278***	0.299***
	(9.69)	(13.59)	(16.55)	(18.48)	(21.29)
Observations	3,586	10,067	24,726	33,013	37,732
R-squared	0.001	0.001	0.001	0.001	0.001
Fund _pair year FE	Y	Y	Y	Y	Y

Appendix D An Example of Insurance Series Trust

This table reports an example of an insurance series trust, Advanced Series Trust, with the list of fund advisers and the number of funds included by each advisor under the trust.

Name of Adviser	Number of Funds
AQR Capital Management	2
Allianz Global Investors	1
BlackRock Financial Management	6
Clear Bridge Investments	1
Cohen & Steers Capital Management	1
Franklin Advisers	1
Goldman Sachs Asset Management	7
Hotchkis and Wiley Capital Management	1
J.P. Morgan Investment Management	7
Jennison Associates LLC	3
LSV Asset Management	1
Loomis, Sayles & Company	1
Lord, Abbett & Co	2
Massachusetts Financial Services Comp.	3
Neuberger Berman Investment Advisers	1
PGIM Fixed Income	15
PGIM Investments LLC	2
Parametric Portfolio Associates	1
Quantitative Management Associates	9
T. Rowe Price Associates	4
UBS Asset Management	1

Victory Capital Management	1
WEDGE Capital Management	1
Wellington Management Company	3
Western Asset Management Company	2
Multiple Adviser Co-owned	3

Appendix E An Example of Non-insurance Series Trust

This table reports an example of a non-insurance series trust, Investment Managers Series Trust, with the list of fund advisers and the number of funds by each advisor under the trust.

Name of Adviser	Number of Funds
361 Capital LLC	7
Advisors Asset Management Inc	4
Advisory Research Inc	15
Aristotle Atlantic Partners LLC	1
Aristotle Capital Boston LLC	1
Aristotle Capital Management LLC	4
Aristotle Credit Partners LLC	1
B&T Capital Management Inc	1
Bernzott Capital Advisors	1
Chartwell Investment Partners Inc	1
Chartwell Investment Partners LLC	3
Chartwell Investment Partners LP	1
Euro Pacific Asset Management LLC	7
Fiduciary Asset Management LLC	2
GaveKal Capital LLC	5
Gratry & Company LLC	1
Ironclad Investments LLC	1
Jackson Park Capital LLC	1
Liberty Street Advisors Inc	8