Predatory Trading in Mutual Funds

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Abstract

I hypothesize that mutual fund managers sell shares to induce price pressure in stocks owned by competitor funds 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 relation is highly convex and in the fourth quarter when the 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.

JEL Classification: G11, G23

Key words: Mutual Fund, Predatory Trading

1. Introduction

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. Such rankings affect the investment decisions of investors. Mutual funds managers have incentives to take actions that increase the inflow of investments to maximize their fees. In this context, Chevalier and Ellison (1997) show that the flow-performance relationship is convex and 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 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 where they compete for higher rankings, which I refer to as predatory trading. I define predatory trading as the sale of stock that is commonly held by a predating fund and its higher-ranked competitor to hurt the competitor's return more than the predating fund's own. This definition differs from the traditional definition[1] of predatory trading in mutual funds. I derive the necessary condition for successful predation and hypothesize a direct channel through which predatory behavior affects trading by mutual funds. In this channel, predators are more likely to sell the common positions that have the potential benefit of predation. I test this channel empirically and find evidence of predatory trading. I find the strongest evidence of predatory trading in top-ranked funds that satisfy the necessary conditions of predatory trading close to year-end. Due to the strict necessary

[1] Traditionally, the literature on predatory trading has focused on front running in buying or selling, consuming available liquidity, and subsequently providing liquidity at a worse price.

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 predated. I show that the threat of predation affects the portfolio choice of funds. Specifically, funds would hold fewer common positions and fewer shares in common positions toward the end of the year when the threat is high.

The intuition 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 for A than for 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 portfolio weights and fund 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 portfolio and trading strategies both directly and indirectly (threat). A lower-ranked fund could trade predatorily on the common positions with its competitor(s) directly. In my analysis, I define funds as competitors if they follow the same benchmark reported in the fund prospectus and create fund pairs with consecutive ranks (*i.e.*, rank 1 & 2, 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 the 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 predate when the fund return difference is lower and when the relative portfolio impact from selling the stock is higher, or lower value of the variable, $Decision_{Stock}$[2]. 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' incentive to improve relative performance is the strongest in the last quarter of the year (Brown, Harlow, and Starks, 1996; Carhart, Kaniel, Musto, and Reed, 2002; Kemf, Ruenzi, and Thiele, 2009).

Predatory trading also affects portfolio choices of funds indirectly because of the threat it poses. 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 such commonly held positions before predatory trading takes place or reduce the 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 predate others or to react to predatory trading.

[2] $\mathrm{Decision_{Stock}} = \frac{\text{Return difference of the two funds}}{\text{Illiquidity ratio of the stock} * \text{Weight difference of the stock}}$

Consequently, I predict that small funds react to the threat of predatory trading and reduce or exit illiquid and common positions with their, especially, larger competitors.

My results support that funds trade predatorily 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[3]. 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 predate the higher-ranked fund by selling up to all the common positions. I find that $Decision_{Stock}$ is negative and significant only in the top 20% ranked funds. One standard deviation increase in $Decision_{Stock}$ reduce the likelihood of the sale of the stock by 57%. Overall, the evidence supports that top-ranked funds are more likely to predate their higher-ranked peers when they satisfy the necessary condition. 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 affect funds' portfolio choices and holding size. First, I find evidence of funds reduce 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. Additionally, I find cyclical changes in the average number of overlapped stock positions in fund pairs (Figure 2). Second, I show that when funds cannot avoid holdings in common, they hold

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

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 if 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 1, the small funds ranked 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 differences in changes in liquidity across the fund ranks for larger funds.

I conduct several robustness tests. First, I examine how reliable is the reported benchmark in grouping competitors by examining non-competing funds. I find no evidence of predatory trading when I group fund pairs with consecutive ranks but do not follow the same benchmark. Second, I repeat similar regressions on the sample of commonly held stocks with negative weight difference (higher weights in the lower-ranked funds) and show no evidence of predatory trading. Lastly, I use the alternative measures of illiquidity, estimated by dollar volume instead of the number of shares traded, and performance, and my main results are robust.

My paper is related to the literature on the 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 riskiness (Brown, Harlow, and Starks, 1996; Kemf, Ruenzi, and Thiele, 2009) and portfolio pumping (Carhart, Kaniel, Musto, and Reed, 2002; Wang, 2018).

My paper is also related to the literature on predatory trading and predatory pricing. Previous literation on the topic mostly focuses on the 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 the 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, there are interesting policy implications to discuss. From the regulator's perspective, predatory trading could hurt short-term investors and be considered as unfair competition. The quarterly reporting requirement increases the risk of predatory trading with more updated holdings information compared to semi-annual reporting. One way to solve such issue while preserving the timely report of funds' holdings could be to change the year-end performance calculation. Instead of using the last trading day's portfolio value, we could require the use of 10-day average value. The price pressure is short-lived, so the impact from price manipulation could be significantly reduced by averaging fund performance in a longer time window.

2. Literature and Hypotheses

2.1 Literature

This paper relies on three strands of findings. First, Chevalier and Ellison (1997) and Sirri and Tufano (1998) find a positive and convex relationship between performance rank and flows. These authors show that the flow performance relationship generates incentives for mutual funds to make strategic portfolio decisions to increase the funds' relative rank. Brown, Harlow, and Starks (1996) demonstrate that mid-year losers tend to increase portfolio volatility compared to the mid-year winners. Similarly, Kemf, Ruenzi, and Thiele (2009) find empirical evidence that fund managers with poor mid-year performance tend to decrease portfolio riskiness to prevent job loss and increase riskiness when employment risk is low. My results further complement the findings of Carhart, Kaniel, Musto, and Reed (2002). They show that mutual funds push up the stock price of their major holdings at the end of the year, but they do not explore the source of cash. My findings complement the story that when funds are boosting the stock prices of their major holdings, the source of cash could be drawn from selling the predatory positions when their cash on hand is insufficient. In a recent working paper, Wang (2018) documents evidence that non-star fund managers pump the prices of stocks held by star funds to inflate performance at quarter-end.

Second, several studies show that mutual fund trading could lead to price pressure on stocks and make the trading prices deviate from the fundamentals. For example, Warther (1995), Wermers (1999) and Edelen and Warner (2001) capture the effect of mutual fund flows on market return and individual stocks. Edelen and Warner (2001) document a positive relation between large fund flows and returns on the stocks held by the fund and 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 cause the price pressure purposefully and affect returns of themselves and other funds holding the same stocks to different levels depending on portfolio weights of the stocks. Research in hedge fund shows such findings. Ahoniemi and Jylha (2014) observe flow-induced price pressure and the 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 that 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), and Mitchell, Pulvino, and Stafford (2004)) while slightly longer-lived price pressure up to a few weeks is presented in Greenwood (2005).

Third, my paper relates to the empirical evidence of predation theory. 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 focuses on theoretical models in predation. Fudenberg and Tirole (1986), Poitevin (1988), and Bolton and Sharfstein (1990) investigate capital market imperfections that affect product market competition and thus create the potential for predation. Other papers apply predatory pricing to the setting of merger and acquisition. 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 the 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 (1986) 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) look at the evidence of predatory pricing in the airline industry and the effectiveness of the Department of Transportation's approach in addressing such issue.

Brunnermeier and Pedersen (2005) is the first paper to introduce the idea of predatory trading in the setting of traders. They refer it to the trading that induces or exploits the need of other investors to reduce their positions and 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, Lobo, and Viswanathan (2007) model how illiquidity could arise from a breakdown in cooperation among market participants. However, there is little empirical evidence. Eisele, Nefedova, and Parise (2014) is the only other paper on 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 the case that affiliated funds exploit the information on liquidity constraints of other funds and thus refers to selling stock positions before the distressed fund does. Further, they only find predatory trading inside large fund families.

Finally, my results are related to two working papers on mutual fund holding overlaps. Basak and Markov (2015) and Nanda and Wei (2018). Basak and Markov (2015) focus on the theoretical analysis of the holdings of portfolio managers. They find that managers will be better off if they hold different stocks. Nanda and Wei (2018) show that funds can reduce their exposure to liquidity risk by engaging in overlap management. They show that funds benefit from avoiding stocks that are more vulnerable to flow-driven trading. My finding of predatory trading in common positions also suggest that less overlapped holdings may be optimal for fund managers.

2.2 Hypotheses 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. Morningstar and similar companies, such as Lipper and Standard's and Poor, 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 funds companies, and fund managers, in particular, have incentives to take actions that increase the inflow of investments in order to maximize their fees. In this context, Chevalier and Ellison (1997) show that the flow-performance relationship is convex and 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 ranks, 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 weight 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[4] 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 $\mathrm{Ill}_i * (\mathrm{W}_{\mathrm{Ai}} - \mathrm{W}_{\mathrm{Bi}})$, where Illiquidity ratio is defined based on Amihud (2002) with a modification.

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

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

$R_{i,t}$ is the daily return for stock i in day t, $Vol_{i,t}$ is the respective daily trading volume on that day. Different from the dollar trading volume used in Amihud (2002), here I use the number of shares traded to simplify the calculation of portfolio impact. Because the timing of predatory trading is unobservable and the using the dollar trading volume would require 9io8the stock price on the day when the stock is sold to calculate the portfolio impact[5], 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:

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

The left-hand side of Equation (1) is the 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 predate, 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 predate 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 different relative portfolio impact calculated by Equation (2):

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[5] 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 the Appendix A2, I replicate my main results using dollar trading volume and estimate the selling price using the average stock price in December.

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

where $\Delta \text{R} = \text{R}_\text{A} - \text{R}_\text{B}, and\ \Delta \text{W}_i = \text{W}_{\text{Ai}} - \text{W}_{\text{Bi}}$

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 $\text{Ill} * \Delta \text{W}$. Thus $\text{Decision}_{\text{Stock}}$ is expected to be negatively related to the likelihood of selling the stock.

According to Equation (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 predate 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 that when the portfolio return difference is lower and when the relative portfolio impact is higher, which means lower $Decision_{Stock}$.

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

H1 Extension 2: I predict that the 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). Lastly, a specific compensation structure may affect incentives. For example, fund managers with career concerns may be more aggressive in the trading behavior, and funds belong to larger fund families may involve more in predatory trading due to the more commonly used relative performance-linked compensation structure (Ma, Tang, and Gomez, 2017).

2.3 Empirical Methodology

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 funds could obtain is quarterly holdings. I create pairs of predators and targets with consecutive rankings based on their cumulative return[6], i.e., rank 1 & 2 and rank 2 & 3. Such treatment allows me to simplify the predatory trading story to the most intuitive case because a predator is most likely targeting those ranked nearby and above. The choice of targets should be considered on a combination of factors, including return difference, holding overlaps, weight

[6] 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. I choose raw return instead of net return because flow-performance relationship indicates that investors use performance to infer managerial skill from past returns (Gruber,1996; Sirri and Tufano, 1998; Berk and Green, 2004). As a robustness check, I use the net return and replicate my main findings in the Appendix A3.

difference in those overlapped holdings, and the stock liquidity. Thus the range of targets cannot be readily determined with some absolute value of rank distance or return difference.

Further, it is crucial to notice that predatory trading only exists among funds that are competing for flows. For instance, a fund 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 seen from 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 Pitajisto, 2009; Pitajisto, 2013)[7].

Third, based on the convex flow-performance relationships, the marginal benefit of moving up one place is higher for top-ranked funds. To distinguish funds ranked top from those 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 a 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

[7] The data on fund reported benchmark is obtained from Petajisto's website (https://www.petajisto.net/data.html).

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 resources allocation 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 difference (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 stocks where 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 return of its holdings, it will avoid the positions commonly held by its competitors.

3. Data and Summary Statistics

My sample consists of all-equity mutual funds between 1999 and 2009. I obtain mutual fund holdings from Thomson Reuters and merge them with fund-level characteristics, such as fund return and total net asset (TNA). The detailed steps are explained in Appendix A1. 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. When multiple positions for the same stock are reported for the same fund during the same period, I exclude the duplicated observations. 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 $\mathrm{Decision}_{\mathrm{Stock\ i}} = \frac{\Delta \mathrm{R}}{\mathrm{Ill}_i * \Delta \mathrm{W}_i}$ of consecutively ranked fund pairs, under the constraint that $\Delta \mathrm{W}_i > 0$.

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, $Decision_{Stock}$ 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, the fund pairs have about a third of stocks in common. In the calculation of 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 not available, I use total asset minus total liability as a proxy for book equity. Following Falkenstein (1996) and Schwarz (2012), I include the measures of the stock riskiness,s 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, higher-ranked funds try to reduce their exposure to predatory trading by choosing more liquid stocks in their common holdings.

4. Direct Channel: Do Funds Predate in the Last Quarter?

4.1 Which Commonly Held Stocks Do Funds Sell During the Last Quarter?

Stock characteristics, such as size, B/M, the previous performance, liquidity, and riskiness, are related to mutual funds' choices of their portfolios in general, but how does the 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, and otherwise, 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 (quarter) fixed effect and fund-level clustered standard errors.

Using the sample of fund pairs with consecutive ranking, I break down three components in $\text{Decision}_{\text{Stock i}} = \frac{\Delta \text{R}}{\text{Ill}_i * \Delta \text{W}_i}$, 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 ΔR, $\frac{1}{Ill}$, 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 in the opposite to 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 that 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 $Decision_{Stock}$.

4.2 Do Funds Predate 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 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 short words, H1 predicts a negative coefficient on $Decision_{Stock}$. The interaction terms involving ΔR and ΔR are omitted because the regression focuses on the choice of sale within a fund pair by conditioning on fund-pair-year.

$$Sell = \alpha + \mathrm{Decision_{Stock}} + \frac{1}{\Delta W} + \frac{1}{Ill} + Holdings\ in\ Q3 + Pre_{return} + \frac{\mathrm{B}}{\mathrm{M}} + Size + \beta + \sigma + FE + \varepsilon$$

[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 lower ranking quintiles into the sample, and the variable is significant at 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. First, a generally decreasing coefficient indicates weaker results in bottom quintiles as the incentives decline. Second, 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 would prefer to move further up in the rankings due to the high marginal benefit associated with their top rankings. 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 predate 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 holdings provide noisy information about the true holdings, the more overlap in holdings, the less likely that the target, or the higher-ranked fund, will exit all predatory positions. The necessary condition provides an estimate of the level of portfolio overlap that could benefit the predator which is the lower-ranked fund, so the top-ranked predator may predate only when the necessary condition is satisfied.

To address the issue that top-ranked funds are less likely to predate if the likelihood of success if low, I use the sub-sample 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 predate by selling a single position. More commonly, the lower-ranked funds need to break down the number and sell a handful of commonly held stocks. Starting with all fund-pair-stock observations, I sum up the relative portfolio impact if the lower-ranked fund sells each common position with positive weight difference. 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. 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 weak evidence in the lower-ranked quintiles in the full sample or the subsample in Panel C may seem inconsistent with the predatory trading story because these funds do not satisfy the necessary condition. There are two explanations for that. First, $Decision_{Stock}$, is calculated based on the funds' holdings at the end of the third quarter. The timing of predatory trading, however, is more likely to happen around the last few trading days of the year if managers believe the price pressure is short-lived. It is also possible that funds may choose to sell at an earlier date so that the target is less likely to change the positions. Funds' holdings could change a lot during the time period, and it also changes the fund pairs that satisfy the necessary condition in Equation (1). Second, the predatory trading strategy can be further combined with other trading schemes. The relative return gain can be further enhanced if the funds use the proceeds from selling to pump their own holdings. For example, Carhart et al. (2002) show that funds pump up the stock price of their major holdings during the last trading day of the year to achieve a better end of year performance. Wang (2018) also documents evidence that non-star fund managers pump the prices of stocks held by star funds to inflate the star funds' performance.

4.3 Do Funds Succeed with Predatory Trading?

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

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

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[8]. I define Predate conservatively because the timing of predation could be any time point over the last month of the year (as mutual fund

[8] The results are robust to 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 stocks sold by the lower-ranked fund over the last quarter.

quarterly holdings are required to be submitted within 60 days after the quarter ends) and is not observable. The return difference and thus, the shares needed for predation will vary with the changing performance difference between the two funds.

[Table 5 Here]

Table 5 shows the logistic regression results without any fixed 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 predate 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 result of column (4), the probability of relative ranking reversal, or success, increases by 29% (from 43% to 72%) if funds predate. The evidence suggests funds are more likely to improve the relative ranking if they predate their closely-ranked peers.

5. Indirect Channel (Threats): Are Funds Sitting Ducks?

5.1 Do Higher-ranked Funds React to Predatory Trading?

In the repeated game of mutual fund ranking, fund managers should be aware of such probability of predatory trading and take strategies as a response. There are two strategies that the targeted funds can take. First, when the predator fund 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 simply avoid being predated by exiting the positions before predatory trading happens. Based on the two options, I further develop two testable hypotheses.

H2: A fund is more likely to buy more of the common holdings when a competitor predates and when it holds more cash.

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

The first strategy puts more constraints on the fund size, while the second strategy can be applied much easier and less costly.

5.2 Do 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 logistic regression, the dependent variable is set to one if the higher-ranked fund increased the stock positions that are exposed to predatory trading. The dependent variable, *Predate*, is set to one if the lower-ranked fund sells any of the stock(s) the higher-ranked fund buys. Although I cannot completely rule out alternative explanations such as mutual fund herding, I should pick up some effect of the first strategy as I define *Predate* loosely. *Cash Holding* is calculated by subtracting the market value of all stock holdings at the end of the third quarter from the total net asset reported at the same time point. I further control for relative fund size and rank quintile of the higher-ranked fund. 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 it holds more cash and when the lower-ranked fund predates.

[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 higher-ranked fund 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 further put constraints on funds to make it unlikely to happen in practice.

5.3 Do React to Predatory Trading with the Second Strategy?

Compared to the first strategy, there is more evidence supporting the second strategy. 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.

[Figure 1 Here]

Further, the numbers of common positions, both positive weigh difference positions and all positions, are decreasing across the quarters as well as shown in Figure 1.

[Figure 2 Here]

In Figure 2, the graph exhibits a cyclical movement of the average number of common holdings in fund pairs that satisfy the necessary condition of predatory trading. The graph shows a decreasing trend in the number of common holdings from the beginning of the year to the end of the third quarter. The number of common positions picks up at the end of the last quarter, indicating there may be the effect of window dressing that funds want to report their year-end holdings with the 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 decreasing fund pairs and common positions indicate that funds are moving away from common positions when the incentive for predatory trading gets stronger. Such behavior supports the second strategy that funds react to predatory trading by shifting away from or reducing the 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. First, those funds could hold fewer stocks in common as indicated by the cyclical movements in the number of common holdings. Second, when it is too costly for funds to avoid certain stocks, they could reduce the position by holding fewer shares when the threat of predatory trading is high. Fund size comes into the picture because a large number of shares needs to be sold for predatory trading. Small funds are limited by their size and lack in the ability to predate others, compared to large funds. In the test of H3, I focus on small funds because they are more likely to be targeted by large predators and unlikely to be predators themselves. Further, as shown in the previous results and indicated by the convex flow-performance relationship, top-ranked funds have stronger incentives to predate. 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 share similar goals and benchmarks, so it is the relative size within each peer group that matters. A small fund in benchmark A may be larger than a large fund in benchmark B. 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 quarter and their benchmarks.

[Figure 3 (A) & (B) Here]

In Figure 3 (A), I report the change in average illiquidity of small funds' holdings in the top and bottom rank 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 3 (B), I report a similar graph using the sub-sample 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 of 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 predated 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, Novak, Riley, and Stahel, 2015). Nevertheless, a more prevalent explanation to the holding liquidity differences between small and large funds is that large funds are limited on the choice of stocks because of trading costs associated with liquidity or price impart while a small fund can easily put all its money in its best ideas (Chen, Hong, Huang and Kubik, 2004; Yan, 2008). If the asset base constraints more on the choice of stocks in large funds, such explanation should go against my result that small funds are more likely to hold the illiquid stocks compared to large funds.

Based on Figure 3, 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, 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 as the greater the distance between the small fund and the large fund, the less likely that the large fund is going to predate on 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 four 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 potential trading strategies to predatory trading and find support for the strategy that funds avoid being predated by strategically change their portfolio holdings.

Toward the end of the year, funds hold fewer stocks in common, and when it is too costly to avoid certain common positions, funds hold fewer shares when the threat of predatory trading is high.

6. Robustness Tests

6.1 Classification of Peer Groups

One 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 using fund pairs with consecutive rankings ***but are not competing for flows***. In specific, 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 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 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. The falsification test confirms that predation only occurs among funds that are competing for flows, and the active benchmark identifies funds that are competing for flows.

6.2 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 previously. The predatory trading hypotheses suggest the selling of common positions is limited to the ones that create positive relative portfolio impact, which is to hurt the competing fund's performance more than the predator's. Given such reasoning, the lower-ranked fund in the pair is not expected to sell those positions with negative weight differences (higher-ranked fund minus lower-ranked fund), 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 difference. It suggests that when funds sell common positions to predate, they are selectively choosing the ones that have the predatory benefit.

6.3 Do Funds Predate 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 as 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.

Intuitively, the results should be the strongest at the end of the year. The number of lower-ranked funds that satisfies the necessary condition is on average 138 at the end of the first quarter and decreased to 117 at the end of the second quarter. It indicates that funds are moving away from common positions toward the end of the year to avoid being predated by their competitors.

[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, Harlow, and Starks (1996) show that the mid-year losers increase the portfolio riskiness in the second half of the year. In the third-quarter data, the coefficient on is $Decision_{Stock}$ either insignificant or positive, which is contrary to the prediction of predatory trading. Overall, the incentives to predate is the strongest in the last quarter.

6.4 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 and show that if funds choose to pump their portfolios, they are likely to avoid common holdings when selecting stocks. Pumping the stock price of the common holdings will let competitors free ride the benefit and thus will not achieve the goal of creating a wider performance gap between a fund and its competitors.

I follow Carhart et al. (2002) and show that the stocks that funds choose to boost the price of stocks that are 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 and zero otherwise. A dummy variable, *Competitor*, is set to one if the nearby and above competing fund holds the stock, and otherwise, 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 result 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 the stock is 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 benefit if they move up one place in the ranking. 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.

7. Conclusion

Mutual funds provide a unique setting for predation theory in that funds can affect the price of stocks in their competitors' portfolio directly. 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 strategy as predatory trading in mutual funds and test it by creating fund pairs with consecutive ranking 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 with a sub-sample of fund pairs that satisfy the necessary conditions.

Further, funds anticipate the threat of predatory trading and take strategies in response, making use of the strategy less common. First, I show that funds reduce the number of common positions towards 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 as unfair competition. The quarterly reporting requirement increases the risk of predatory trading with more updated holdings information compared to semi-annual reporting. One way to solve such 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 10-day average portfolio value instead of the last trading day's value.

Reference

Ahoniemi, K., & Jylhä, P. (2014). Flows, Price Pressure, and Hedge Fund Returns. Financial Analysts Journal, 70(5), 73–93.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. Journal of financial markets, 5(1), 31-56.

Barber, B. M., Huang, X., & Odean, T. (2016). Which Factors Matter to Investors? Evidence from Mutual Fund Flows. The Review of Financial Studies, 29(10), 2600–2642.

Basak, S., & Markov, D. (2015). Competition Among Portfolio Managers and Asset Specialization.

Ben-Rephael, A., Kandel, S., & Wohl, A. (2011). The Price Pressure of Aggregate Mutual Fund Flows. The Journal of Financial and Quantitative Analysis, 46(2), 585–603.

Berger, R. G., & Mitchell, S. J. (1983). Predatory Pricing in the Airline Industry: A Case Study. Transportation Law Journal.

Brady, S. P., & Cunningham, W. A. (2001). Exploring predatory pricing in the airline industry. Transportation Journal, 41, 5+.

Brown, K. C., Harlow, W. V, & Starks, L. T. (1996). Of Tournaments and Temptations: An Analysis of Managerial Incentives in the Mutual Fund Industry. The Journal of Finance, 51(1), 85–110.

Brunnermeier, M.K., & Pedersen, L. H. (2005). Predatory Trading. The Journal of Finance, 60(4), 1825–1863.

Bolton, Patrick, and David Scharfstein (1990). "A Theory of Predation Based on Agency Problems in Financial Contracting." American Economic Review 80, no. 1, 93-106.

Burns, M. R. (1986). Predatory Pricing and the Acquisition Cost of Competitors. Journal of Political Economy, 94(2), 266–296.

Capon, N., Fitzsimons, G. J., & Prince, R. A. (1996). An Individual Level Analysis of the Mutual Fund Investment Decision. Journal of Financial Services Research, 10(1), 59–82.

Carhart, M. M., Kaniel, R., Musto, D. K., & Reed, A. V. (2002). Leaning for the Tape: Evidence of Gaming Behavior in Equity Mutual Funds. The Journal of Finance, 57(2), 661–693.

Carlin, Bruce, Ian, Lobo, Miguel, and Viswanathan, S.(2007). Episodic Liquidity Crises: Cooperative and Predatory Trading. The Journal of Finance, 62(5), 2235–2274.

Caves, R. E. (1981). Diversification and Seller Concentration: Evidence From Changes, 1963-72. The Review of Economics and Statistics, 63(2), 289–293.

Chen, H.-L., Jegadeesh, N., & Wermers, R. (2000). The Value of Active Mutual Fund Management: An Examination of the Stockholdings and Trades of Fund Managers. The Journal of Financial and Quantitative Analysis, 35(3), 343–368.

Chen, J., G. Hong, H., Huang, M., & D. Kubik, J. (2004). Does Fund Size Erode Mutual Fund Performance? The Role of Liquidity and Organization. American Economic Review (Vol. 94).

Chevalier, J., & Ellison, G. (1997). Risk Taking by Mutual Funds as a Response to Incentives. Journal of Political Economy, 105(6), 1167–1200.

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

Cremers, K. J. M., & Petajisto, A. (2009). How Active Is Your Fund Manager? A New Measure That Predicts Performance. The Review of Financial Studies, 22(9), 3329–3365.

Edelen, R. M., & Warner, J. B. (2001). Aggregate price effects of institutional trading: a study of mutual fund flow and market returns. Journal of Financial Economics, 59(2), 195–220.

Eisele, A., Tamara Nefedova and Gianpaolo Parise. (2014). "Predation versus Cooperation in Mutual Fund Families."

Fumagalli, C., & Motta, M. (2013). A Simple Theory of Predation. The Journal of Law & Economics, 56(3), 595–631.

Gibson, S., Safieddine, A., & Titman, S. (2000). Tax-Motivated Trading and Price Pressure: An Analysis of Mutual Fund Holdings. The Journal of Financial and Quantitative Analysis, 35(3), 369–386.

Hanouna, P., Novak, J., Riley, T., & Stahel, C. (2015). Liquidity and Flows of U.S. Mutual Funds. SEC White Paper.

Kempf, A., Ruenzi, S., & Thiele, T. (2009). Employment risk, compensation incentives, and managerial risk taking: Evidence from the mutual fund industry. Journal of Financial Economics, 92(1), 92–108.

Koller, R. H. I. I. (1970). The Myth of Predatory Pricing: An Empirical Study . Antitrust Law & Economics Review.

Koller, R. H. I. I., Caves, R. E., Burns, M. R., Brady, S. P., Cunningham, W. A., Berger, R. G., & Mitchell, S. J. (1986). Predatory Pricing and the Acquisition Cost of Competitors. Transportation Law Journal, 4(2), 105–124.

Ma, L., Tang, Y., & Gómez, J.-P. (Forthcoming). Portfolio manager compensation in the US mutual fund industry. Journal of Finance.

Miller, R. A. (1973).Concentration and marginal concentration advertising and diversity: three issues in structure-performance tests. Industrial Organization Review, 1(1), pp. 15-24.

Nanda, V., Wang, Z. J., & Zheng, L. (2004). Family Values and the Star Phenomenon: Strategies of Mutual Fund Families. The Review of Financial Studies, 17(3), 667–698.

Nanda, V., & Wei, K. (2018). Correlated Flows, Portfolio Similarity and Mutual Fund Liquidity Management.

Ordover, J. A., & Willig, R. D. (1981). An Economic Definition of Predation: Pricing and Product Innovation. The Yale Law Journal, 91(1), 8–53.

Petajisto, A. (2013). Active Share and Mutual Fund Performance. Financial Analysts Journal, 69(4), 73–93.

Saloner, G. (1987). Predation, Mergers, and Incomplete Information. The RAND Journal of Economics, 18(2), 165–186.

Shive, S., & Yun, H. (2013). Are mutual funds sitting ducks? Journal of Financial Economics, 107(1), 220–237.

Sirri, E. R., & Tufano, P. (1998). Costly Search and Mutual Fund Flows. The Journal of Finance, 53(5), 1589–1622.

Wang, P. (2018). Portfolio Pumping in Mutual Fund Families.

Warther, V. A. (1995). Aggregate mutual fund flows and security returns. Journal of Financial Economics, 39(2), 209–235.

Wermers, R. (1999). Mutual Fund Herding and the Impact on Stock Prices. The Journal of Finance, 54(2), 581–622.

Yan, X. Sterling. (2008). Liquidity, Investment Style, and the Relation between Fund Size and Fund Performance. Journal of Financial and Quantitative Analysis, 43(3), 741–767.

Table 1: Summary Statistics on Fund Pair Characteristics

The table reports the statistics of the main variables estimated from equation $Decision_{stock} = \frac{\Delta R}{Ill*\Delta W}$. To simplify the model, I create fund pairs with consecutive ranks within each peer group (same active share benchmark) at the end of the third quarter, eg. Rank 1 and Rank 2, Rank 2 and Rank 3 in active share benchmark R1G. The common positions are restricted to those with positive weight differences (higher-ranked minus lower-ranked) according to the model constraint. The number of common holdings with positive weight differences is roughly the same as the ones with negative 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. Shared 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 result 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 partly or all of the stock. The regression is based on the 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. $1/\Delta W$, 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.

$$Necessary\ Condition : \sum_{i=1}^{n} N_{Bi} * Ill_i * (W_{Ai} - W_{Bi}) > R_A - R_B \quad (1)$$

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Decision_{stock}$ * NC							-0.0253***
							(-3.587)
$Decision_{stock}$						-1.74E-4	-1.93E-4
						(-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: Do funds Predate in the Last Quarter of the Year?

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. All 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.

Panel A reports the regression results in all fund pairs. Panel B is limited to the fund pairs where the lower-ranked fund satisfies the necessary condition of predatory trading. Panel C is based on the fund pairs where the lower-ranked fund does not satisfy the necessary condition of predatory trading.

$Decision_{stock}$ is the variable of interest and funds are expect 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 Predate Succeed?

This table reports the logistic regression on fund level. 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 predates 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. The sample is limited to fund pairs where the lower-ranked fund satisfies the necessary condition of predatory trading. The probability of the higher-ranked fund increasing the holding of the stock is regressed on whether the lower-ranked fund predates and the cash holding (percentage of TNA) of the higher-ranked fund.

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. 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 of number of shares held by small funds on the threat of predatory trading across every quarter. For each stock observation in each 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 active share benchmark every period. The higher the value is, the smaller threat of predatory trading is. 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 is limited to the fund pairs where the lower-ranked funds satisfy the necessary condition of predatory trading but are not directly competing for flows. Instead of ranking funds in each active benchmark, the funds are ranked together. If both funds in the pair belong to the same active 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 adopt same timeline as the main results in Table 4. 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 partly 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-09*	-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	-0.090	-0.019	-0.020	-0.014	-0.012
	(-0.740)	(-1.518)	(-1.603)	(-1.483)	(-1.215)
β	5.19E-3		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 Predate 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 relatively. 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)
Tobins 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 active share benchmark. Previous Return, Size, Illiquidity Ratio, Book-to-Market Equity, β, and Stock Std are stock characteristics 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)
β	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

Figure 1: Funds' Reaction to the Threat of Predatory Trading

Figure 1 shows the change of the average number of funds 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 difference from the end of the first quarter to the end of the third quarter.

Necessary Condition: $\sum_{i=1}^{n} N_{Bi} * Ill_i * (W_{Ai} - W_{Bi}) > R_A - R_B$

Figure 2: Funds' Reaction to the Threat of Predatory Trading

Figure 2 shows the quarterly movements of the average number of common positions in fund-pairs that satisfies the necessary condition of predatory trading.

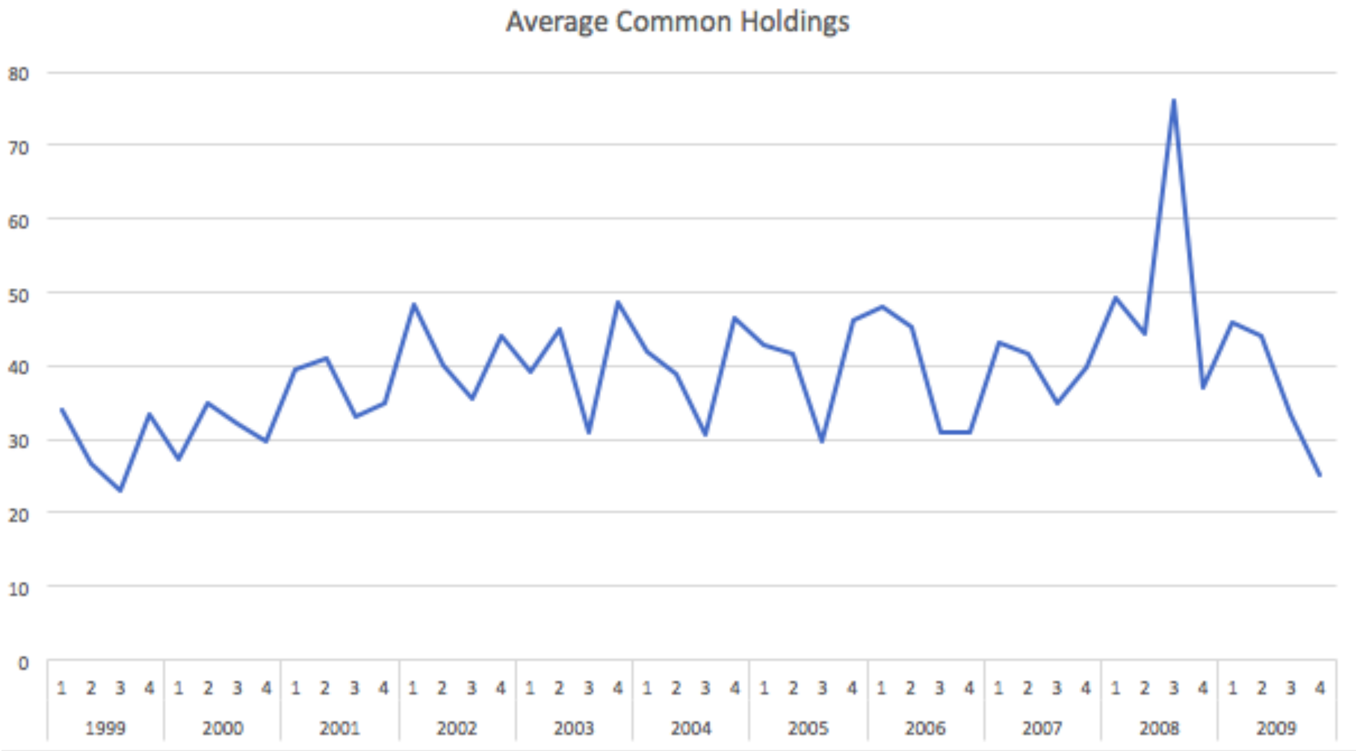

Figure 3: Changes in Average Portfolio Illiquidity Ratio

Figure 3 (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 3 (b) exhibits the changes in average illiquidity ratio for top-ranked and bottom-ranked large funds from the third quarter to the fourth quarter.

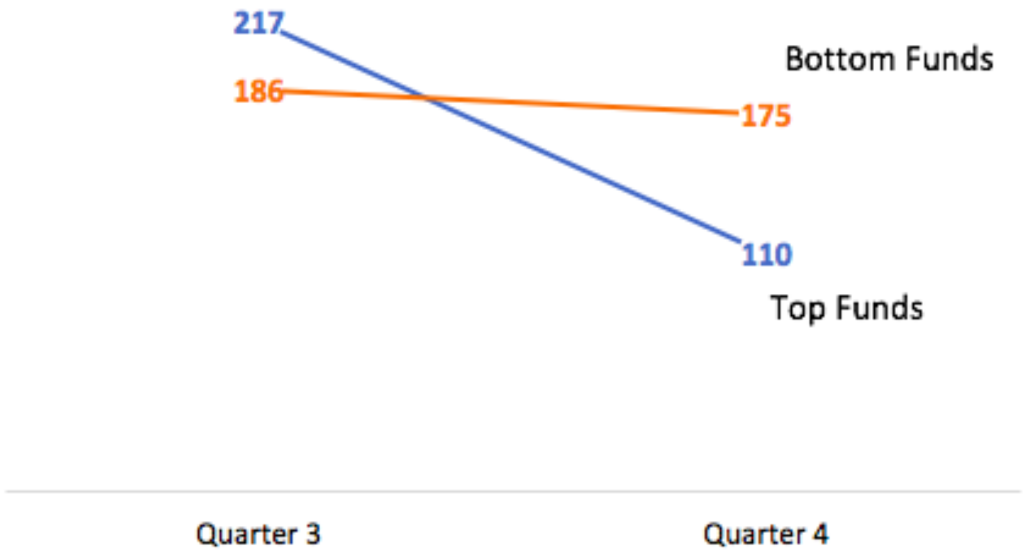

Figure 3 (a): Average Illiquidity Ratio of Small Funds

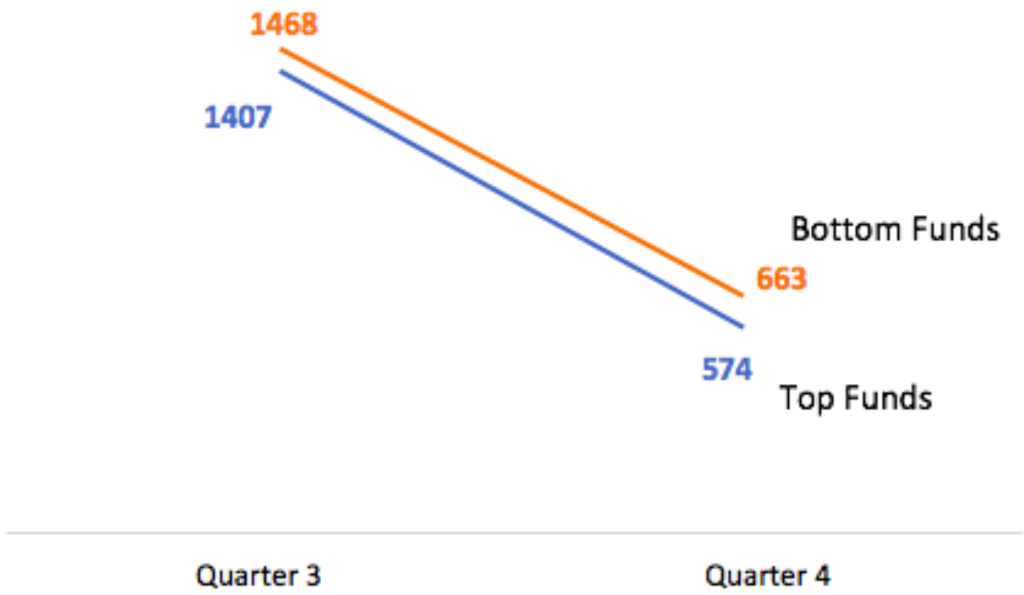

Figure 3 (b): Average Illiquidity Ratio of Large Funds

Appendix: Table A1

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 Fundno from Thomson Reuters and Crsp_fundno from CRSP, which are two fund identifiers of the latter two databases. However, Fundno and Crsp_fundno are not one-to-one matched. Fundno 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.

Example: Active Share Matched with Crsp_portno

Fundno is the fund identifier from Thomson Reuters. ACrspfundno is the original CRSP_Fundno from Active Share data. Fund_id the unique fund level identifier I generate. Crspfundno and Crspportno are the two fund share class and fund portfolio identifiers. Correct_Name is the fund name matched from CRSP using ACrspfundno, while NAME is the fund share class name matched from CRSP using Crspfundno.

Fundno	ACrspfundno	Fund_id	Crspfundno	Crspportno	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

Example: Matched 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: Table A2 (Amihud Illiquidity Ratio)

Panel A: Full Sample

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.

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)
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: Table A3 (Net Return)

Panel A: Full Sample

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.

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)
Previous Return	-0.396	-0.551***	-0.429***	-0.303***	-0.271***
	(-1.57)	(-3.53)	(-3.19)	(-3.24)	(-3.30)
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)
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)
Previous Return	-1.776***	-1.019**	-0.254*	-0.209*	-0.0501
	(-3.27)	(-2.20)	(-1.96)	(-1.78)	(-0.41)
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)
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