Coordinated Betting by Multi-Fund Managers

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Abstract

I study the investment behaviour of managers that manage multiple mutual funds simultaneously. Consistent with incentives in the mutual fund industry to generate outperformance, I find that multi-fund managers engage in an investment coordination strategy by placing negatively correlated investment bets across their funds. This strategy increases the probability that at least one fund will generate extreme positive performance, though, it does not maximize the performance of each individual fund. I also find that these coordinating multi-fund managers take on more idiosyncratic risk, have more active portfolios, trade more aggresively, and invest more in lottery-like stocks. This risk-taking behavior is consistent with coordinating multi-fund managers taking larger investment bets in order to make the potential return pay-offs of the individual funds more extreme. All in all, my paper documents a new potential agency problem in the mutual fund industry caused by the organizational structure at the manager level.

Keywords: Mutual Funds, Agency Problems, Investment Behaviour, Risk-Taking

JEL classifications: G11, G23

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1 Introduction

In this paper, I show that mutual fund managers deviate from optimizing risk versus returns when they manage multiple mutual funds simultaneously. The main incentive comes from asymmetric compensation contracts widely used in the mutual fund industry that reward outperformance but do not penalize underperformance. A consequence of this contracting is that it is often better for multi-fund managers to focus on generating extreme outperformance for at least one fund as opposed to trying to maximize the performance of each individual fund. I find that multi-fund managers invest according to this principle by strategically coordinating investments between their funds.

This investment coordination strategy entails that multi-fund managers coordinate risky investments in one of their funds with negatively correlated risky investments in their other funds, thus, increasing the probability that at least one fund holds investments with high positive returns. The multi-fund managers therefore alleviate uncertainties on when or whether risky investment bets are going to pay off by strategically distributing the risk across the funds as opposed to diversifying the risk away within each individual fund. As a result, the funds are taking more undiversified risk which benefits the multi-fund managers with a higher likelihood in generating outperformance, though, it hurts investors since they expect the managers to create risk-return optimized portfolios for each individual fund. So the organizational structure of assigning multiple mutual funds to the same managers creates potential agency problems.

I use several data sources to construct a comprehensive data set of U.S. domestic active equity mutual funds over the period from 2000 until 2018. The market share captured by multi-fund managers has been steadily increasing over this sample period to the point that they manage 39% of all assets in the active equity fund industry. This indicates the growing importance of researching the investment behaviour of multi-fund managers. I exploit quarterly disclosed portfolio holdings to test whether multi-fund managers are strategically coordinating investments, more specifically, I construct pairs of multi-funds with identical managers and analyze the idiosyncratic correlations of the investment bets between the funds. The investment bets are identified as the stock holdings that are unique to each portfolio between the fund pairs. I compare the investment bet correlations between multi-fund pairs against matched fund pairs with similar characteristics in terms of investment style and fund size.

I find that the investment bets between multi-fund pairs have 8.0% lower idiosyncratic correlations than matched fund pairs, thus, indicating that multi-fund managers are coordinating negatively correlated investments between their funds. This result does not hold for multi-fund pairs with slightly different manager team compositions. This is most likely due to fact that the managers that are unique to each fund are against the investment coordination strategy, because they do not stand to gain from taking undiversified risk if they are only a member in only one multi-fund manager team. These findings show that the exact commonality in manager team compositions plays an important role in the multi-fund manager's investment behaviour and therefore provides powerful evidence supporting the investment coordination strategy.

Furthermore, I find that the portfolios of multi-fund pairs have a 15.8% difference in industry weightings with most of the differences coming from more volatile industries. This is consistent with multi-fund managers overweighting different industries across the funds to not only make the potential return pay-off for each fund more extreme, i.e. the overweighted industries overperform, but also to increase the likelihood that such favourable return outcome occurs for one of their funds. I also find similar results for differences in factor styles. These findings indicate that multi-fund managers also apply the investment coordination strategy to more macro-level investments in addition to the idiosyncratic investment bets.

Next, I use the aforementioned methodology to construct a measure that evaluates which multi-fund managers are more likely to strategically coordinate investments. Using this measure, I find that coordinating multi-fund managers take on 0.30% higher volatility risk levels in their funds compared to the average fund. This risk-taking behaviour is mainly driven from idiosyncratic risk which is consistent with multi-fund managers taking on more undiversified risk in accordance with the investment coordination strategy. Additionally, I find that coordinating multi-fund managers have more active fund portfolios, trade more aggressively, and invest more in lottery-like stocks compared to other mutual fund managers. These findings support the idea that the investment coordination strategy is more effective when the fund portfolios have more extreme performance outcomes, because the key feature of the investment coordination strategy is that it increases the probability of at least one favourable extreme outcome.

My last set of results show that the investment coordination strategy is effective in generating outperformance, more specifically, coordinating multi-fund managers are 44% more likely to produce star funds compared to other mutual fund managers. The multi-fund managers are therefore more likely to receive substantial compensation rewards as a result of strategically coordinating investments. Furthermore, the strategy also benefits the mutual fund family, as I find that star performing multi-fund managers not only attract substantial investment flows to the star fund itself, but they also draw significant spillover investment flows to their other non-star funds in the family. These findings provide therefore a rationale as to why mutual fund families assign multiple mutual funds to the same manager.

Lastly, I find there is no persistence in the star fund outcome, that is, it is unlikely that coordinating multi-fund managers generate star performance for the same fund in consecutive years. This is because the investment coordination strategy relies on the assumption that multi-fund managers are uncertain about the future performance outcome of investment bets, hence why they distribute these investment bets strategically among their funds, as a result it is unknown to the multi-fund manager ex-ante which fund is going to generate star performance. This finding shows that investors are better off investing in all the funds of the star performing multi-fund manager as opposed to only the current star fund.

My paper contributes to the vast literature on agency problems in the mutual fund industry. A very directly related work is that of Agarwal et al. (2018) who find that mutual fund families assign their skilled managers to the poorly performing funds or newly started funds. Their findings show that the funds that were already being managed by the multi-fund manager prior to the assignment of additional funds experience a deterioration in performance in the short-term, while the newly assigned funds to the multi-fund managers improve in performance. They interpret these findings as multi-fund managers focusing their effort and attention on the newly assigned fund. My study complements their work by revealing a different type of agency problem with assigning multiple mutual funds to the same manager.

Another very related literature branch is on cross-subsidization, e.g. Gaspar et al. (2006), which is the idea that the mutual fund families favour their relatively profitable funds at the cost of the lesser profitable funds by transferring performance from the latter to the former through, for example, cross-trading or preferential IPO allocation. Thus, cross-subsidization also distorts the return distribution among the funds similar to the investment coordination strategy. The key difference, however, is that it is known ex-ante by the managers and the mutual fund family which fund is going to achieve outperformance through cross-subsidization, while this is unknown in the investment coordination strategy.

Other related work in the literature is on the conflicts of interests that arise due to side-by-side management, that is, managers who manage both mutual funds and hedge funds simultaneously. These managers have an incentive to favour the hedge funds over the mutual funds in terms of generating performance, because the compensation structure of hedge funds is heavily based on performance, while, for mutual funds, performance receives relatively lower compensation rewards. Del Guercio et al. (2018) confirm that the mutual funds of side-by-side managers underperform and this underperformance is even more severe when cross-subsidization opportunities increase. My study contributes to this literature by showing there also exists conflicts of interests when managers manage multiple mutual funds in the mutual fund industry.

Another related literature is the branch that investigates the risk-taking behaviour of mutual fund managers. Massa and Patgiri (2008) show that mutual fund managers take on more risk when their compensation package incentivizes them to increase the assets under management of their fund. Shu et al. (2012) find that local religious beliefs affect the risk-taking behaviour of mutual fund managers. Ma and Tang (2019) show that mutual fund managers take on less excessive risk when they have their own stake in the fund consistent with the theory on how skin in the game aligns the best interests of managers with the investors. My paper complements this literature by documenting that mutual fund managers take on excessive risk when they manage multiple mutual funds simultaneously.

Lastly, my paper also contributes to the vast literature investigating whether mutual fund managers possess investment skill (Berk and Van Binsbergen, 2015; Carhart, 1997; Fama and French, 2010). I show that the lack of performance persistence in overperforming mutual funds is partly a mechanical outcome of multi-fund managers applying the investment coordinations strategy. My findings also suggests that investment skill is not only limited to picking out overperforming securities, but also pairing securities that are negatively correlated to each other.

The remainder of this paper is organized as follows. Section 2 provides a brief background of the literature relevant in developing the arguments for the multi-fund investment coordination strategy. Section 3 describes the data and presents basic descriptive statistics. Section 4 formally describes and conducts the tests for the existence of strategic investment coordination by multi-fund managers. Section 5 investigates the risk-taking behaviour of coordinating multi-fund managers. Section 6 explores the fund performance outcomes resulting from the strategic investment strategy. Section 7 concludes the paper.

2 Background Literature

There is an immense incentive in the mutual fund industry for mutual funds to generate outperformance with respect to their industry peers in the short-term. This incentive arises because mutual fund family profits mainly come from fund fees which are generally proportionate to their total assets managed (Massa and Patgiri, 2008), furthermore, there exists a convex relation between investor flows and yearly fund performance (Chevalier and Ellison, 1997; Sirri and Tufano, 1998). The convexity entails that the top performing mutual funds in the past year are rewarded with a disproportionately high amount of investment flows from investors. Moreover, these investment flows also spillover to other member funds in the same mutual fund family (Nanda et al., 2004). Thus, mutual fund families can substantially increase profits by producing star funds, that is, mutual funds with extreme outperformance.

Many studies document that mutual fund families behave in a way that optimizes the likelihood of producing star funds. Nanda et al. (2004) show that mutual fund families with lower ability to produce star funds increase the variation in returns across their mutual funds. This way the chances of generating outperformance is more spread out across the mutual funds in the family as opposed to all mutual funds relying on similar investments to perform well. Gaspar et al. (2006) find that mutual fund families cross-subsidize the best performing funds in the family through performance transfers at the cost of the worst performing funds. This cross-subsidization can be done through cross-trading stocks, preferential IPO allocation, or preferential transaction cost allocation (Ben-Rephael and Israelsen, 2017). Lastly, Ma et al. (2019) document that mutual fund managers generally have asymmetric performance based compensation contracts that reward managers with outperformance, but does not penalize underperformance. This introduces an option-like pay-off to the mutual fund managers that encourages them to achieve outperformance with very little downside risk.

Consequently, the asymmetric compensation contracts influence the investment behaviour of mutual fund managers. For instance, several studies find that mutual fund managers engage in so-called tournament behaviour, which entails that underperforming mutual fund managers in the first half of the year take on more risk in remainder of the year to gamble for extreme outperformance in order to catch up with the top performing mutual funds (Brown et al., 1996; Kempf and Ruenzi, 2008; Schwarz, 2011). This risk-taking behaviour is consistent with the option-like compensation structure of the mutual fund managers, but is not necessarily in align with the best interests of the mutual fund investors. The tournament behaviour can not only introduce undesirable excessive risk in the portfolio of the mutual fund investors, but can also be detrimental to the performance of the mutual funds (Huang et al., 2011). Mutual fund managers, however, have less incentives to take on excessive risk when they have larger concerns for their career (Kempf et al., 2009), as manager turnover is generally determined by poor performance (Khorana, 1996; Kostovetsky and Warner, 2015).

I hypothesize that the asymmetric compensation contract can also affect the investment behaviour of mutual fund managers in ways other than tournament behaviour. Namely, multi-fund managers can increase the probability that at least one of their funds will achieve outperformance by coordinating their investments, more specifically, multi-fund managers can distribute their investment bets among their funds in a strategic manner such that the bets have a low correlation between the funds. In the extreme case that the total portfolios of a multi-fund pair are perfectly negatively correlated with each other, then one portfolio will always generate a positive pay-off and the other portfolio will have the opposite negative pay-off or vice versa. The multi-fund manager will then receive a high compensation for the outperforming fund with the positive pay-off, while there will be no penalty for the underperformance of the other fund. This is a better outcome than having two average performing funds for which there is no bonus compensation because they are not the top outperforming mutual funds.

Furthermore, the coordinating multi-fund managers can also take on more risk in their funds for a couple reasons. First, the investment coordination strategy is more effective with more volatile and extreme performance outcomes, because the key feature of the investment coordination strategy is that it increase the probability of at least one favourable extreme outcome. So the likelihood of producing a star fund increases with higher levels of volatility among the multi-funds. This is akin to the family cross-fund return variation strategy to produce star funds found by Nanda et al. (2004), except the incentives and investment coordination strategy are at the manager level. Second, multi-fund managers have less career concerns because they have more bargaining power thanks to their outperforming funds that they are more likely to produce due to their investment coordination strategy. Massa et al. (2010) show that good performing mutual fund managers have more bargaining power to extract rents from the mutual fund family. Thus, coordinating multi-fund managers can use their bargaining power to prevent termination from their poor performing funds when the risky investments did not pay off.

3 Data

3.1 Sample Construction

My data sample is constructed from a combination of several sources. First, I use the CRSP Survivorship Bias Free Mutual Fund Database to obtain basic fund characteristics for U.S. domestic mutual funds. The database contains information on returns, total net assets (TNA), fees, investment styles, and various other fund characteristics at the fund share class level. I aggregate funds with multiple share classes into a single fund observation to avoid double counting. Specifically, the quantitative variables are aggregated as the value-weighted average over the different share classes. The sole exception is TNA which is aggregated as the sum of assets over the share classes. The oldest share class is chosen as the representative fund for the qualitative variables such as fund investment style or fund name. Following standard practice in the literature, I remove funds smaller than $15 million in TNA or younger than 3 years to mitigate, respectively, survivorship bias (Elton et al., 2001) and incubation bias (Evans, 2010).

Second, I obtain information on the underlying fund portfolio stock holdings from the Thomson Reuters S12 Mutual Fund Holding Database which I merge with the CRSP fund data via linking tables from MFLinks. I also augment the portfolio holding information with stock level data from the CRSP Stock Database. The holding database compiles only the stock holdings from mandatory SEC filings at a quarterly frequency. So in order to have a reliable representation of the fund portfolios, I remove funds with less than 15 stock holdings and less than 80% of their assets invested in stocks. Furthermore, I only use holdings for which the reporting date equals the vintage date in the database to have the most up-to-date information.

Lastly, I collect fund manager information from Morningstar Direct, as recent studies document that this database is currently the most accurate database for mutual fund manager data (Berk et al., 2017; Patel and Sarkissian, 2017). The database contains for each mutual fund a complete manager history along with a short biography for each manager. I manually extract manager characteristics, including age, education and gender, from the biographical descriptions. Furthermore, I also compute the tenure of the managers as the length of time that they have been managing equity mutual funds according to the history in the database. I eliminate fund observations for which the manager name comprises of a variation of "team", because I require the individual managers to be identifiable for my analyses.

The final sample consists of active equity mutual funds domestic in the U.S. covering the period from 2000 until 2018. I focus on funds with the following Lipper classification codes: LCCE, LCGE, LCVE, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, SCVE. These are equity funds that fit within a style categorization (large-cap, mid-cap, multi-cap, or small-cap) and investment style (value, growth, or core). I therefore do not consider balanced, bond, money market, and sector mutual funds. Lastly, I remove passive index funds identified by whether they have a variation of "index" in their names or those that have more than 500 stock holdings in their portfolio as these funds are likely to be index funds.

3.2 Multi-Fund Definition

I define a group of mutual funds as multi-funds when they are managed by the exact same managers from the same mutual fund family. So the funds either have the same single manager or the same identical manager team. This means that I rule out cases where a single manager in one fund is also a member of a team in another fund or funds with teams that have managers in common and also managers unique to certain teams.

There are a couple of reasons for these exclusions. The first reason is related to the incentives to strategically coordinate the investments of multi-funds. More specifically, if the team compositions are different for a group of multi-funds, then it can be difficult for a manager to take credit for the good performance of one fund with one team when another fund, that is managed by the same manager but has other team members, is performing poorly. It is important for managers to be able to take credit for their performance as this affects their incentives to generate performance and also their bargaining power (Massa et al., 2010), therefore, also affecting their incentives to strategically coordinate the investments of multi-funds.

The second reason is related to the ability of managers to strategically coordinate the investments of the multi-funds when the team compositions are different for each multi-fund. The coordination strategy only works with the collaboration of multiple funds and this is more difficult to accomplish when the managers are different for each fund, especially, since there is no strategic benefit for the managers that are not part of the group of multi-funds. Furthermore, Bär et al. (2010) show that the investment decisions of team-managed mutual funds are the result of a compromise between the team members, so it is generally unlikely that a single dominant member is able to dictate the investment decisions of all the funds.

3.3 Descriptive Statistics

To provide some context on the size and relevance of multi-fund managers in the mutual fund industry, I plot the total assets managed by multi-fund managers against the other remaining managers over time in Figure 1. The figure shows that mutual funds managed by multi-fund managers have been steadily growing in both absolute and relative market size over the last two decades, more specifically, the multi-fund market size has grown from \$270 billion in 2000 to \$1512 billion in 2018. These absolute numbers correspond to a threefold increase in the market share of multi-funds relative to the active equity mutual fund industry from 13% to 39%. It is therefore very much relevant to investigate the trading behaviour of multi-fund managers and the associated consequences for multi-fund investors, as a substantial amount of assets in the mutual fund industry are managed by multi-fund managers.

[INSERT FIGURE 1 ABOUT HERE]

Table 1 presents several descriptive statistics of the full sample and the sub-sample of multi-funds. The full sample contains $102,466$ fund-quarter observations with approximately 30% belonging to multi-funds. The table indicates that multi-funds do not differ very much compared to the other funds along very basic fund characteristics, thus, suggesting that multi-funds are not very different from other funds except for their commonality in manager team compositions. The statistics do show that multi-funds tend to belong to bigger mutual fund families in terms of managed assets and number of funds. This is likely because larger mutual fund families assign multiple funds to managers for cost efficiency reasons. I will incorporate control variables and fixed effects to account for these discrepancies in mutual fund family characteristics between multi-funds and other funds in the empirical analyses.

[INSERT TABLE 1 ABOUT HERE]

4 Strategic Multi-Fund Investment Coordination

In this section, I test for strategic coordination of investments between multi-funds by examining their portfolio holdings. This choice over examining realized fund returns is often also made in other studies investigating mutual fund manager behaviour (Huang et al., 2011; Kacperczyk et al., 2005; Kempf et al., 2009), as this allows me to analyze the fund manager's intended investment strategy that is revealed by their portfolio holdings. Another empirical advantage relevant for my study is that I can disentangle the best ideas of multi-fund managers from their bets. Since multi-funds are managed by the exact same managers, there will naturally be a common overlap in stock holdings between the portfolios[1], which most likely represent the best ideas of the managers (Cohen et al., 2010; Jiang et al., 2014). There is very little to no room to strategically coordinate these best ideas between the multi-funds, except for preferential allocating them to certain funds, but this investment behaviour is not of interest for this study, so I try to account for this preferential treatment behaviour in the analyses. The more interesting part of the portfolios are the investments unique to each multi-fund, which I call the bets of the multi-fund managers, as these are most likely stocks for which the fund managers are unsure about their future performance. I investigate whether multi-fund managers distribute these bets among their funds in a strategic manner such that the bets are less correlated between the funds. This strategy would increase the probability that the bets will pay off for at least one multi-fund, thus, raising the likelihood of achieving extreme outperformance.

4.1 Methodology

I investigate whether multi-fund managers make uncorrelated bets between their funds by comparing the correlation of the portfolios between multi-fund pairs against matched fund pairs. See Figure 2 for an illustration of the empirical strategy. First, I form pairs of multi-funds that have the same managers and I determine, for each multi-fund pair, the stock holdings that the funds have in common and the stock holdings that are unique to each fund. That is, I decompose the portfolios of the pair of multi-funds i and j as follows:

$$\begin{aligned} \sum_{n \in C_{ij}} w_n^i + \sum_{n \in U_{ij}} w_n^i = 1 \\ \sum_{n \in C_{ji}} w_n^j + \sum_{n \in U_{ji}} w_n^j = 1, \end{aligned} \tag{1}$$

where C_{ij} represents the set of stocks that fund i in the pair with fund j have in common, and U_{ij} represents the set of unique stocks of fund i in relation to fund j. The portfolio weights of fund i is represented by w_n^i. Note that C_{ij} is the equivalent set to C_{ji} because both funds have the same stocks in common per definition.

[INSERT FIGURE 2 ABOUT HERE]

[1]In my sample, multi-funds with the same managers have on average 44% stock holdings in common.

Then for each multi-fund pair with fund i and fund j, I match only fund j with all funds in the same investment style and size quintile, and then decompose the portfolio of the matched fund M paired with fund i in the same manner as before.

$$\sum_{n \in C_{Mi}} w_n^M + \sum_{n \in U_{Mi}} w_n^M = 1 \tag{2}$$

The aim is to investigate whether the unique stocks (bets) in the portfolios of the multi-fund pair, i.e. U_{ij} and U_{ji}, have a lower correlation in comparison to the matched pair, i.e. U_{ij} and U_{Mi}. This could be done by simply comparing these sub-portfolios against each other, however, this direct comparison ignores how these sub-portfolios behave in relation to the total portfolios. For instance, it can be the case that the unique stocks only comprise a small part in weight of the total portfolio or there are diversification aspects left unaccounted for, such that the investment bets have very little impact on the final performance realization of the mutual fund. On the other hand, comparing the total portfolios directly against each other will bias the results heavily in favour of finding higher correlations between the multi-fund pairs, because there is generally a bigger overlap between multi-fund portfolios due to the nature of multi-funds being managed by the exact same managers.

I alleviate these issues by setting the common holdings for the matched fund M the same as fund j. More specifically, I construct the following hypothetical portfolio for matched fund M:

$$\sum_{n \in C_{ji}} w_n^j + \sum_{n \in U_{Mi}} w_n^{M*} = 1. \tag{3}$$

The first term is the same sub-portfolio with common stocks of fund j paired with fund i. And the second term is the sub-portfolio with the unique stocks of the matched fund M paired with fund i, where the weights w_n^{M*} are appropriately scaled such that the weights of the hypothetical portfolio still add to one.

$$w_n^{M*} = \frac{\sum_{k \in U_{ji}} w_k^j}{\sum_{k \in U_{Mi}} w_k^M} w_n^M \tag{4}$$

Thus, the only difference between the portfolio of fund j and this hypothetical portfolio of matched fund M is the sub-portfolios with bets. So when comparing the correlation between the portfolios of fund i and j against the correlation of fund i with this constructed hypothetical portfolio, I essentially only replace the bets of fund j with the bets of the matched fund M.

This way I eliminate the bias caused by the common holdings of multi-funds, while at the same time taking the size and diversification of the bets in relation to the total portfolio into account.

Then I construct hypothetical daily fund returns with the aforementioned portfolios that holds the stock weights constant over the quarter prior to the disclosure date of the portfolio holdings. Next, I measure the idiosyncratic correlation of the bets between the portfolios with the residuals of the hypothetical returns using the Carhart (1997) 4-factor model:

$$r_{i,t} - r_{f,t} = \alpha_j + \beta^1_{i,t}(r_{m,t} - r_{f,t}) + \beta^2_{i,t} SMB_t + \beta^3_{i,t} HML_t + \beta^4_{i,t} UMD_t + \varepsilon_{i,t}, \tag{5}$$

where the dependent variable is the hypothetical returns $r_{i,t}$ in excess of the risk-free rate $r_{f,t}$. The independent variables are the excess market returns $r_{m,t}$ over the risk-free rate, and the returns of three factor-mimicking portfolios[2], namely, the size factor SMB_t, the value factor HML_t, and the momentum factor UMD_t.

So I compute these idiosyncratic correlations for both the multi-fund pairs and matched pairs, where I use the the constructed hypothetical portfolios for the matched funds. Then I stack all these idiosyncratic correlations in one vector and estimate the following regression model:

$$IdioCorr_{i,j,t} = \alpha + \beta MultiFund_{i,j,t} + \Gamma' \boldsymbol{Controls}_{i,j,t} + \varepsilon_{i,j,t}, \tag{6}$$

where $IdioCorr_{i,j,t}$ is the idiosyncratic correlation between the hypothetical returns of fund i and fund j at quarter t. The $MultiFund_{i,j,t}$ dummy variable equals one if the fund pair is an actual multi-fund pair and zero if the fund pair is a matched pair. The control variables are a set of dummy variables indicating whether the pairs 1) have the same investment style; 2) belong to the same mutual fund family; 3) reside in the same city; 4) have a manager connection via another mutual fund, that is, managers from fund i and fund j also manage other different funds (excluding multi-funds) together. Lastly, the regression model includes time fixed effects and the standard errors are clustered by fund pairs.

4.2 Main Results

The regression estimation results in column 1 of Table 2 show that the idiosyncratic correlations between multi-fund pairs is significantly lower compared to the matched pairs with

[2] All these factor returns are obtained from Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html

a substantial magnitude of approximately 8.0%. This finding indicates that the commonality in manager team compositions between mutual funds influences the investment behaviour of these managers. This result in itself is to be expected. What is in contrary to known findings (Pool et al., 2015) is that the portfolios between multi-fund managers have lower idiosyncratic correlations, as opposed to higher which would have been consistent with managers making similar investments in all their funds in order to make efficient use of their information production. This lower correlation finding suggests that multi-fund managers take uncorrelated bets between their funds, which is consistent with the idea that multi-fund managers are strategically coordinating their investments among their funds in order to increase the likelihood of achieving extreme outperformance.

[INSERT TABLE 2 ABOUT HERE]

Furthermore, I still find the same result when investigating multi-funds for which there is a possible bias against my results. First, I examine a sub-sample consisting of only multi-funds that have the same investment style. These multi-fund managers concentrate their research on a limited investment opportunity set corresponding to their investment style and are therefore likely to have similar investments in all their funds for resource efficiency reasons as opposed to coordinating dissimilar investments across their funds. Second, I examine a sub-sample consisting of multi-funds with team sizes larger than three managers. It can be more difficult for managers to cooperate together when the team size becomes larger making it more difficult to coordinate investments between the funds. So there is a possible bias against strategic coordination of investments between the multi-funds in these sub-samples, however, the results in columns 2 and 3 still show statistically significant negative coefficient estimates for the $MultiFund$ variable with similar economic magnitudes.

The control variables all show the expected coefficient estimates. The $SameStyle$ estimate shows the largest economic effect size of 39.2%. This is not surprising, as mutual fund managers are confined to an investment opportunity set that fits within their corresponding fund style, e.g. a large-cap fund is unlikely to invest in small-cap stocks, so funds with the same investment styles will invest in very similar stocks and so their portfolios are more correlated with each other as a result. The $SameFamily$ estimate of 3.4% is consistent with Elton et al. (2007) who find that funds in the same mutual fund family have higher correlations with each other, most likely due to access to the same research resources and information from their internal analysts or manager colleagues. The $SameCity$ estimate is 5.5% and is in line with Hong et al. (2005) and Pool et al. (2015) who find that fund managers residing in close proximity from each other have larger overlaps in their portfolio holdings due to information sharing. Lastly, the $OtherFundConnection$ is positive with an effect size of 5.2% suggesting that managers with an indirect connection through another fund also share investment ideas with each other.

4.3 Placebo Test

To further establish that the coordination results are unique to multi-funds, which are groups of mutual funds with the exact same manager composition, I exploit cases where the manager compositions between mutual funds are similar to each other but not identical. First, I construct a placebo sample of these cases by altering the multi-fund definition slightly, namely, the placebo sample is constructed as the groups of mutual funds that have at least one manager in common, but also have at least one manager unique to the funds. These are therefore still mutual funds with a commonality in managers, though, the incentives or ability to strategically coordinate investments between the funds is reduced. This is because there are also managers who are not present in every fund team and these managers therefore do not benefit from the coordinating investments. Hence it will be difficult to coordinate investments between these mutual funds if there are managers present in the fund teams who are against the coordination strategy.

Then I only consider the cases that intersect the multi-fund sample and the placebo sample. This means that I analyze mutual funds that have both a multi-fund connection and placebo connection to other funds. So a mutual fund manager team manages multiple funds together, but there are also other mutual funds that the fund team manages though there is a slight difference in the team composition. The difference could be that certain managers are absent in these other funds or there is another unique manager added to the other fund team. To show that this slight difference in fund team compositions matters for their investment behaviour, I conduct the same analysis as before except I also use the $PlaceboPair$ variable to indicate fund pairs that have this placebo connection.

[INSERT TABLE 3 ABOUT HERE]

The results in Panel A of Table 3 show that the slight differences in manager team compositions affect their investment behaviour, namely, there is no indication of placebo fund pairs coordinating investments as indicated by the insignificant estimate of $PlaceboPair$, while there does exist strategic investment coordination between multi-funds as inferred from the significantly negative $MultiFund$ estimate. The same findings appear when dividing the sample into a sub-sample with placebo fund pairs where the difference in distinct managers between the fund pairs is less than three managers and another sub-sample with equal or more than three distinct managers. This placebo test affirms that the exact identical team composition between mutual funds matters in whether they can coordinate investments, thus, providing powerful evidence that such coordinating investment behaviour exists among multi-funds. Furthermore, these findings also suggest that this investment behaviour can be mitigated by simply changing the manager team compositions slightly for specific multi-funds.

4.4 Alternative Coordination Measures

Thus far, I have only examined the idiosyncratic correlation between the fund portfolios to capture the strategic coordination of idiosyncratic investment bets between multi-funds. This coordination strategy can, however, also be applied to other investment forms that are not necessarily idiosyncratic in nature. For instance, the multi-fund managers can take opposite positions across industries between their portfolios by overweighting various industries in one fund portfolio, while underweighting those industries in another fund portfolio. These multi-fund managers are then relying on the fact that certain industries will outperform other industries, though, they are uncertain about which exact industries are going to outperform. So by spreading out the overweightings and underweightings across their fund portfolios, it is more likely that at least one fund will overweight the outperforming industries, thus, increasing the likelihood that the fund will generate extreme outperformance. This is a better expected outcome compared to the situation where the multi-fund managers simply hold average industry weightings in all of their funds. I investigate this with the following measure calculating the absolute difference between industry weightings between fund portfolios:

$$IndustryDifference_{i,j,t} = \sum_{n=1}^{10} \mid W_{i,t,n} - W_{j,t,n} \mid, \tag{7}$$

where $W_{i,t,n}$ is the total portfolio weight in industry n of fund i at the end of quarter t. I use the same ten industry classifications as in Kacperczyk et al. (2005). This measure therefore simply looks at the difference in industry weightings between the portfolios of fund i and j.

[INSERT TABLE 4 ABOUT HERE]

The results in column 1 of Table 4 show there is a significantly large difference in industry compositions between the portfolios of multi-funds. The industry weighting difference of 15.8% is also economically meaningful suggesting that, on average, approximately one-seventh of the multi-fund portfolios are dedicated to strategically coordinating investments with respect to industries. Furthermore, the table also presents results for the portfolio weighting difference separately per industry revealing that the investment coordination strategy is applied to all industries. There is a clear inclination, however, to have opposite portfolio weightings in industries that are more volatile, e.g. finance or business equipment and services, as opposed to relatively safe industries, e.g. consumer durables and non-durables. This is because the investment coordination strategy is more effective and applicable for investments that have more extreme outcomes or for which there is a lot of uncertainty about the performance outcomes.

The same coordination strategy with industries can likewise be applied to factor styles, e.g. size factor, value factor, and momentum factor. There is an ongoing debate about whether mutual fund managers can time the market (Bollen and Busse, 2001; Elton et al., 2011; Henriksson, 1984; Treynor and Mazuy, 1966), let alone timing the standard return factors. Thus, similar as before, the multi-fund managers can spread their overweightings and underweightings in factor styles across their funds to increase the likelihood of generating a star fund. To investigate whether multi-fund managers also use this style coordination strategy, I use the following portfolio style difference measure:

$$StyleDifference_{i,j,t} = \sum_{n=1}^{4} \mid \hat{\beta}_{i,t,n} - \hat{\beta}_{j,t,n} \mid, \tag{8}$$

where $\hat{\beta}_{i,t,n}$ is factor loading n of fund i estimated using the hypothetical daily fund returns of the portfolio that holds the stock weights constant over the quarter prior to the disclosure date of the portfolio holdings at the end of quarter t. I use the same factors as in the Carhart (1997) 4-factor model. This measure therefore looks at the difference in factor loadings between the portfolios of fund i and j.

[INSERT TABLE 5 ABOUT HERE]

The results in column 1 of Table 5 confirm that multi-fund managers also take opposite positions between their funds when it comes to factor styles. The more important factor appears to be the size factor after examining the factor style differences individually. This finding suggests that multi-fund managers do not fully diversify their portfolios with respect to size, but rather take a more skewed position towards small-cap stocks in one fund and lean more towards large-cap stocks in another fund. This rather simple strategy reduces style timing concerns with respect to the size factor, as one fund will always have more exposure to the size factor when small-cap stocks are performing better than large-cap stocks or, conversely, less size factor exposure when the small-cap stocks are underperforming.

5 Multi-Fund Manager Risk-Taking

Having established that multi-fund managers strategically coordinate their investments between their funds, I now turn to investigating the investment behaviour of multi-fund managers in terms of risk-taking. If multi-fund managers are placing opposite bets between their funds, then they could also be taking on larger bets to increase the probability of generating extreme outperformance even more. For this purpose, I construct a multi-fund coordination measure at the manager level to compare multi-fund managers who are heavily following the investment coordination strategy versus those who do not. The coordination measure is as follows:

$$Coordination_{m,t} = \frac{1}{N^m} \sum_{i=1}^{N^m} \left(\overline{IdioCorr}_{i,t}^{Multi} - \overline{IdioCorr}_{i,t}^{Match} \right), \qquad (9)$$

where N^m is the total number of multi-funds managed by manager m at time t. The $\overline{IdioCorr}_{i,t}^{Multi}$ and $\overline{IdioCorr}_{i,t}^{Match}$ variables denote the average idiosyncratic correlation of, respectively, all relevant multi-fund pairs with fund i and all corresponding matched pairs. The $Coordination_{m,t}$ variable is set to zero if manager m is not a multi-fund manager. This coordination measure captures the essence of the matching methodology in the previous section into one variable. That is, I compare the idiosyncratic correlations between multi-fund pairs against benchmark matched pairs and aggregate this to the manager level by taking the average over all the multi-funds managed by the corresponding multi-fund manager. There is a higher indication of strategic investment coordination when the idiosyncratic volatility between multi-fund pairs is lower than the matched pairs. I therefore compare a group of multi-fund managers that are more likely to employ the coordination strategy versus the multi-fund manager group that does not with the following dummy variable:

$$CoordinationDummy_{m,t} = \begin{cases} 1, & \text{if } Coordination_{m,t} < 0 \\ 0 & \text{if } Coordination_{m,t} \leq 0 \end{cases} \tag{10}$$

5.1 Fund Return Volatility

I first investigate the risk-taking behaviour of multi-fund managers by testing whether the fund return volatilities are higher for coordinating multi-fund managers with the following regression model specification:

$$Volatility_{i,m,t} = \alpha + \beta CoordinationDummy_{i,m,t-1} + \Gamma' \boldsymbol{Controls}_{i,m,t-1} + \varepsilon_{i,m,t}, \tag{11}$$

where $Volatility_{i,m,t}$ is the fund return volatility of fund i at quarter t. The $CoordinationDummy_{i,m,t-1}$ variable indicates whether manager m corresponding to fund i at quarter $t-1$ is likely to engage in strategic multi-fund coordination. The set of controls are a host of fund, mutual fund family, and manager characteristics standard in the literature. The fund characteristics include the past performance, size, age, fees, and turnover. The mutual fund family characteristics include the size and number of funds of all active equity funds in the family. The manager characteristics include whether the fund is managed by a multi-fund manager, whether the fund is managed by a team, and the average tenure of all managers in the corresponding fund team. All size and age related variables are transformed by taking the natural logarithmic to reduce the effect of outliers. Lastly, time-by-style fixed effects are included in the regression model and the standard errors are clustered by fund.

[INSERT TABLE 6 ABOUT HERE]

The results shown in column 1 of Table 6 confirm that coordinating multi-fund managers take on more risk than other funds. The coefficient estimates of the coordination measures are statistically significant and the economic effect is quite sizable. More specifically, the coefficient estimate of the *CoordinationDummy* variable translates to approximately 0.30% higher yearly fund volatility for coordinating multi-funds in comparison to non-coordinating funds. To contrast this result, Massa and Patgiri (2008) find that mutual fund managers with a linear compensation contract have 0.54% higher yearly fund volatilities compared to managers with a concave compensation structure, and Ma and Tang (2019) find that mutual fund managers with an ownership stake in their own fund have 0.36% lower yearly fund volatilities. Thus, the effect size of the risk-taking behaviour of coordinating multi-funds is comparable, though slightly smaller, to other known determinants in the literature for mutual fund risk-taking. Furthermore, this finding is not driven by mutual fund family policies as the results stay significant with the inclusion of family fixed effects as shown in column 2.

I further investigate how coordinating multi-fund managers increase fund return volatility by decomposing it into systematic volatility and idiosyncratic volatility with the Carhart 4-factor model. The results presented in columns 3 until 6 in Table 6 show that coordinating multi-fund managers have higher fund return volatilities mainly due to taking on more idiosyncratic risk as opposed to systematic risk. This is consistent with coordinating multi-fund managers not only coordinating their bets, but also increasing the bet sizes to raise the probability of producing a star fund. This is more difficult to accomplish with systematic risk, as it is difficult for mutual fund managers to take short positions on the market with, for example, derivatives (Koski and Pontiff, 1999) and they are also constrained in levering up on the market (Boguth and Simutin, 2018). So it is generally unfeasible for multi-fund managers to take on opposite positions on the market, thus, there are no changes in systematic volatility for coordinating multi-funds.

5.2 Fund Activeness

I now investigate the activeness of coordinating multi-fund managers in terms of portfolio deviations from the benchmark and portfolio concentration. In the literature, fund activeness is generally associated with the ability of managers to select stocks or to time factors in order to outperform the benchmark or other peer funds (Cremers and Petajisto, 2009). In the context of coordinating multi-fund managers, however, I interpret fund activeness as way to measure the magnitude of the fund manager's investment bets. These bets are not necessarily derived from investment skill, but arise due to the rational coordination strategy of the multi-fund managers to produce star funds. For instance, higher levels of industry portfolio concentration would suggest that multi-fund managers do not have a well industry diversified portfolio for each fund, but they are betting on different industries across the funds. The same reasoning can be applied for higher factor style loadings or any other measure for fund activeness.

To investigate whether multi-fund funds are more active than other funds, I employ the same regression specification as before except with various fund active measures as the dependent variable. First, I use the industry concentration measure formulated by Kacperczyk et al.

(2005) and the style extremity measure used by Bär et al. (2010) to capture fund portfolio concentrations in terms of industry and style respectively. Second, I use active share[3] developed by Cremers and Petajisto (2009) as a measure to quantify the level of fund portfolio deviations from the benchmark. I also use another fund activeness measure proposed by Amihud and Goyenko (2013) which is computed as one minus the R-squared of the Carhart 4-factor model. Lastly, I use the absolute return gap (Kacperczyk et al., 2006) to measure the degree of trading activeness of fund managers.

[INSERT TABLE 7 ABOUT HERE]

The results presented in Table 7 show that coordinating multi-fund managers have significantly higher levels of fund activeness for all aforementioned measures. The industry and style concentration results are consistent with my previous coordination finding, as it shows that multi-fund managers not only take on opposite positions between funds but also invest more aggressively in the positions. This is to increase the probability that at least one fund will hold a position that has extremely positive pay-off, therefore, raising the likelihood that the fund will generate star performance. The other results show that multi-fund managers are more active in general and trade more aggressively than other funds, which is also consistent with aggressive betting or investing with the multi-fund coordination strategy.

5.3 Lottery Stocks

One very direct way of betting in stock markets is to invest in stocks with lottery-like properties. Agarwal et al. (2019) document that, on average, approximately 5% of mutual fund assets is invested in lottery-like stocks. This is somehwat surprising considering that lottery stocks are known to exhibit relatively poor performance (Bali et al., 2011; Barberis and Huang, 2008). Current documented explanations for this stylized fact include catering to investors who have a preference for lottery-like pay-offs (Akbas and Genc, 2016) and risk-shifting induced by incentives to catch up with overperforming peer funds (Agarwal et al., 2019). I propose an additional explanation that multi-fund managers invest in lottery-like stocks to exploit the extremely skewed pay-off distribution in their investment coordination strategy.

[INSERT TABLE 8 ABOUT HERE]

[3] I obtain this data from https://activeshare.nd.edu/data/

I find that coordinating multi-fund managers indeed hold more lottery-like stocks in their portfolios compared to other funds. These results are shown in Table 8 where I define lottery-like stocks as in Agarwal et al. (2019), namely, stocks in the top maximum daily return quintile in the prior quarter. I also use the average of the maximum five daily returns to define lottery-like stocks as robustness. The results indicate that coordinating multi-fund managers invest approximately 40 basis points of their portfolio more in lottery-like stocks compared to other funds. Thus, I add another explanation to the list of possible explanations as to why mutual fund managers hold lottery-like stocks, namely, multi-fund managers strategically allocate these lottery-like stocks as bets among their funds such that they always benefit from the extreme upsides of the lottery-like stocks.

6 Multi-Fund Outcomes

In this section, I examine the benefits of applying the investment coordination strategy by multi-fund managers for both the manager and the mutual fund family. The main benefit for multi-fund managers is that they are more likely to produce star funds which is rewarded with bonus compensation (Ma et al., 2019). And mutual fund families enjoy a substantial increase in profits, as star funds attract tremendous investment flows not only to themselves but also to other member funds in the family (Nanda et al., 2004). The investment coordination strategy therefore aligns with the interests of the multi-fund manager and the mutual fund family.

The investment coordination strategy does introduce potential agency problems to the multi-fund investors. This agency problem arises because the investment coordination strategy maximizes the likelihood of generating star performance for at least one fund by making uncorrelated investment bets with undiversified portfolios, however, this also implies that the bets do not pay off for some funds resulting in underperformance. The investors of these underperforming funds would have been better off with fully diversified portfolios with respect to the investment bets. An issue is that investors are greatly attracted to the star fund of the coordinating multi-fund manager, however, it is possible that the star fund will experience underperformance in the following period, because the star performance was achieved through the investment coordination strategy as opposed to superior investment skill. And the investment coordination strategy does not guarantee persistence in star performance as the coordinating multi-fund managers do not know ex-ante which investment bets are going to pay off.

6.1 Star Fund Production

First, I investigate whether coordinating multi-fund managers are more likely to produce star funds in each year. The reason for examining star fund production at the yearly frequency is because several studies argue that mutual fund investors use calendar year returns as one of the more important fund evaluation measures, subsequently, mutual fund managers alter their investment behaviour according to the calendar year period (Brown et al., 1996; Chaudhuri et al., 2017). I define star funds as the top 5% mutual funds with the highest investment style adjusted fund returns in the past year among all fund peers. As a robustness check, I use an alternate star fund definition by comparing fund performance only among fund peers with the same investment style. I conduct the following logistic regression model:

$$Pr(StarFund_{i,m,y} = 1) = \alpha + \beta CoordinationDummy_{i,m,y-1} + \Gamma' Controls_{i,m,y-1} + \varepsilon_{i,m,y}, \quad (12)$$

where $StarFund_{i,m,y}$ is a dummy variable indicating whether fund i is a star fund in year y and $CoordinationDummy_{i,m,y-1}$ is a dummy variable indicating whether manager m corresponding to fund i is more likely to engage in strategic multi-fund coordination at quarter $t-1$. The set of controls variables is similar as in previous sections. Lastly, time fixed effects are included in the regression model and the standard errors are clustered by fund.

[INSERT TABLE 9 ABOUT HERE]

The results of Table 9 show that coordinating multi-fund managers are more likely to produce star funds compared to both other non-coordinating multi-fund managers and single fund managers. The estimated coefficient of the dummy coordination variable translates to higher odds of approximately 1.44, so coordinating multi-fund managers are 44% more likely to produce star funds than all other mutual fund managers. This is an economically large effect and therefore indicates that multi-fund managers can effectively raise the likelihood of producing a star fund by applying the investment coordination strategy.

6.2 Investment Flow Spillover

Next, I examine the investment flow benefits to the mutual fund family when a multi-fund manager produces a star fund. Nanda et al. (2004) already find that star performance results in spillover investment flows to other member funds of the same mutual fund family, possibly, due to increased publicity or exposure of the family. However, I argue these spillover effects are stronger for multi-funds, that is, when a multi-fund manager produces a star fund, this will result in strong investment flow spillovers to other funds managed by the same manager. This is because investment skill is directly linked to the manager, thus, investors could perceive that all funds managed by a star manager will perform better in the future. Consequently, the investors will invest not only in the star fund, but also in other funds managed by the star manager.

I investigate the multi-fund spillover effects with the following regression model:

$$Flows_{i,m,t} = \alpha + \beta MultiFundStar_{i,m,y-1} + \Gamma' \boldsymbol{Controls}_{i,m,t-1} + \varepsilon_{i,m,t}, \tag{13}$$

where $Flows_{i,m,t}$ is the total net investment flows to fund i over quarter t. The $MultiStarFund_{i,m,y-1}$ dummy variable equals one if fund i is not a star fund at the end of year $y-1$, but the corresponding manager m does manage another fund that is a star fund. The set of controls variables is similar as in previous sections with an additional dummy variables indicating star funds and star families. Lastly, time-by-style and family fixed effects are included in the regression model and the standard errors are clustered by fund.

[INSERT TABLE 10 ABOUT HERE]

The results in Table 10 show there are significant star performance spillover effects to the funds managed by the same star manager. The $MultiFundStar$ estimate suggests that the investment flow spillovers are approximately 4.5% to 6.3% on an annual basis depending on the fixed effects specification. The insignificant $FamilyStar$ estimate indicates there are no spillover benefits of a star fund to other member funds in the corresponding mutual fund family. This result is in contrast to Nanda et al. (2004) who do find these significant spillover effects, though, this could be explained by a slightly different model specification and different sample frequency. Nevertheless, these findings could imply that mutual fund families assign multiple funds to managers in order to benefit from the potential spillover investment flows resulting from star performance generated by the multi-fund manager.

6.3 Star Switching

Finally, I explore whether the investment coordination strategy produces star fund outcomes that are random. More specifically, the multi-fund managers are uncertain about which investment bets are going to pay-off, hence, why they distribute these bets among their funds with the expectation that the bets will pay off for at least one fund. This implies that multi-fund managers do not know which fund will achieve extreme outperformance ex-ante, in other words, the star fund outcome is random. Another way of framing this is that there is no performance persistence of the star funds produced by multi-fund managers. I therefore investigate the lack of performance persistence of multi-funds with the following logistic regression:

$$\begin{aligned} Pr(High_{i,m,y} = 1) = \alpha + &\beta_1 CoordinationDummy_{i,m,y-1} + \beta_2 High_{i,m,y-1} \\ &+ \beta_3 CoordinationDummy_{i,m,y-1} \times High_{i,m,y-1} \\ &+ \Gamma' Controls_{i,m,y-1} + \varepsilon_{i,m,y}, \end{aligned} \tag{14}$$

where $High_{i,m,y}$ indicates whether fund i is the highest performing fund in terms of style-adjusted fund returns among all funds managed by manager m in year y. The set of controls variables is similar as in previous sections. Lastly, time fixed effects are included in the regression model and the standard errors are clustered by fund. Note that this regression is estimated using a sample of only multi-funds as opposed to the full sample. The results are shown in Panel A of Table 11.

[INSERT TABLE 11 ABOUT HERE]

The results show a positive significant coefficient estimate of $High$ indicating that the likelihood of being the best performing fund among the funds managed by the same corresponding manager is higher when the fund was already the better performing fund in the previous year, i.e. there is performance persistence in general. However, the negative coefficient of the interaction effect between $CoordinationDummy$ and $High$ indicates that this performance persistence is completely eliminated when the better performing fund is managed by a multi-fund manager who applies the investment coordination strategy.

I obtain similar findings with conditional logistic regressions shown in Panel B. These regressions analyze the probability of fund i being the highest performing fund of multi-fund manager m in year y conditional on the performance rankings in the previous year. The results indicate that the probability that a fund stays the best performing fund of a multi-fund manager in consecutive years is lower when the manager applies the investment coordination strategy. These findings therefore provide evidence that the investment coordination strategy produces star fund outcomes that are not persistent, thus, investors are possibly missattributing the star performance of coordinating multi-fund manager to superior investment skill.

7 Conclusion

I study the investment behaviour of mutual fund managers that manage multiple mutual fund simultaneously. Consistent with incentives in the mutual fund industry to produce star funds, I find that multi-fund managers engage in an investment coordination strategy that maximizes the probability that at least one fund will generate extreme outperformance. The investment coordination strategy entails that the multi-fund managers take large investment bets in their funds, but they distribute these bets among their funds such that the bets have a low correlation between the funds. The multi-fund managers therefore take on excessive risk in the individual funds, because the fund portfolios could have been more diversified if the investment bets were spread out more evenly among the funds as opposed to each fund having distinct concentrated bets. However, this strategic investment distribution increases the probability that at least one fund has large investment bets that will pay off, thus, raising the likelihood that the fund generates star performance.

This investment coordination strategy coincides with the interests of the multi-fund manager and mutual fund family, as both receive more compensation or more profit by producing star funds, but both also do not get heavily penalized from producing underperforming funds. However, not only is the investment coordination strategy in conflict with the interests of the investors, because it does not maximize the returns of each fund individually, it also introduces potentially unwanted excessive risk in the portfolios of the investors. These problems can be easily alleviated by investing in all the funds managed by the same multi-fund manager, but it is the fiduciary responsibility of mutual fund managers to act in the best interest of the investors for each individual fund. This study therefore provides insights on new agency problems arising from mutual fund managers managing multiple funds simultaneously and also documents how the organizational structure at the manager level can affect manager investment behaviours.

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Figure 1: The Market Size of Multi-Funds

This figure plots the total assets managed by U.S. active equity mutual funds over the period from 2000 until 2018. The figure also highlights the total assets managed by multi-funds which are defined as groups of funds that are managed by the exact same managers from the same mutual fund family.

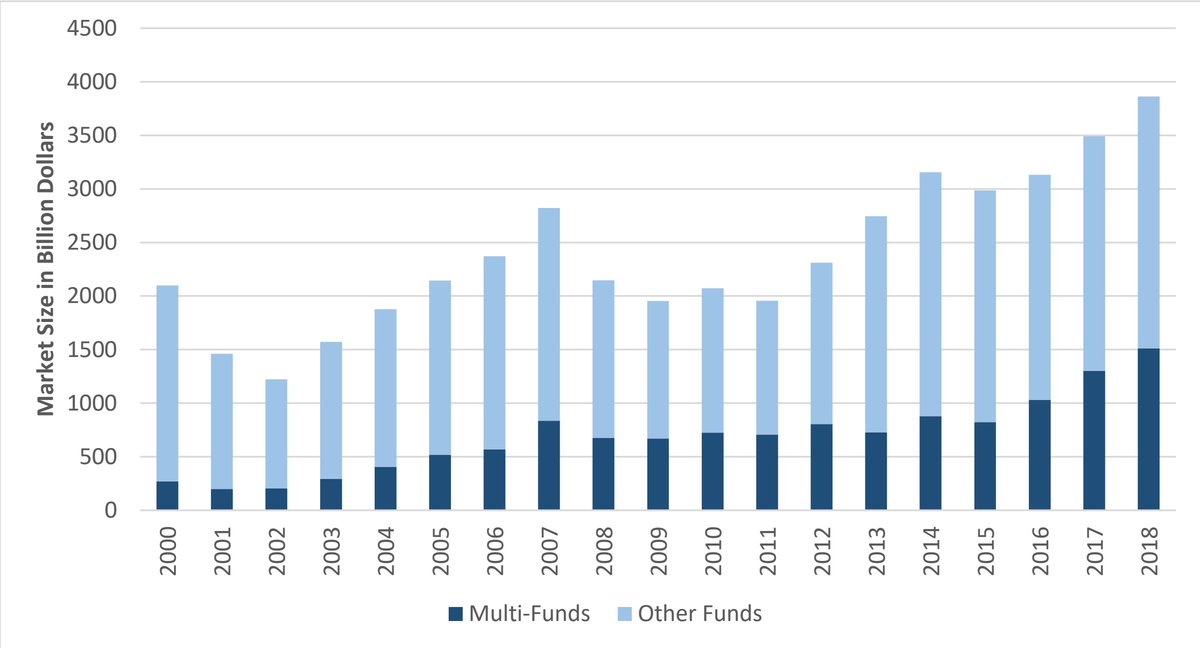

Figure 2: Empirical Strategy

This figure illustrates the construction of the portfolios of multi-fund pairs and matched fund pairs. The w_i^n variable denotes the portfolio weight of fund i in stock n. The superscript $*$ denotes scaled weights such that the total portfolio weights add to one. The C_{ij} variable denotes the set of stocks that fund i has in common with fund j. The U_{ij} variable denotes the set of unique stocks of fund i in relation to fund j.

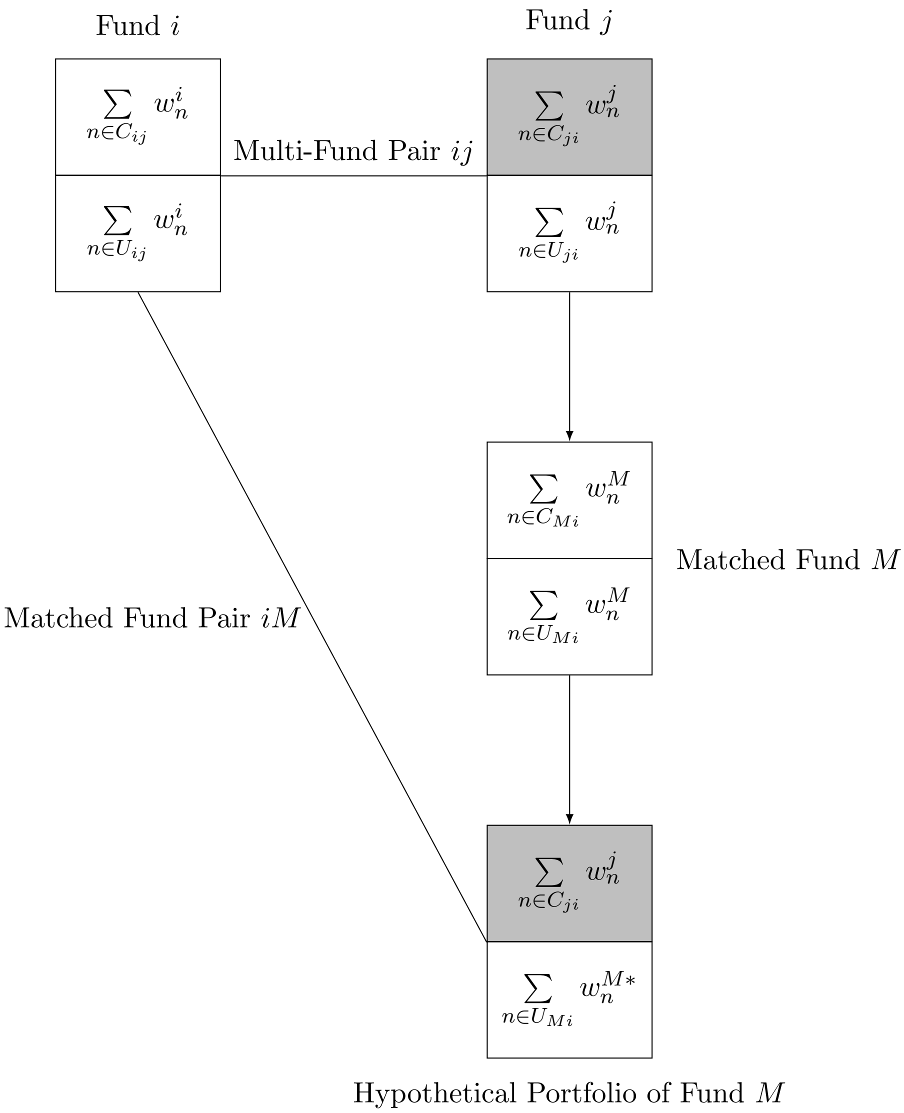

Table 1: Summary Statistics

This table presents summary characteristics of several fund, family, and manager characteristics for U.S. active equity mutual funds over the period from 2000 until 2018. The fund characteristics include fund returns, fund volatility, turnover ratio, expense ratio, size, and age. The family characteristics include the size and number of all active equity funds in the family. The manager characteristics include whether the fund is managed by a team and the average tenure of all managers in the corresponding fund. The shown statistics include the mean, standard deviation, 1st, 25th, 50th, 75th, and 99th percentiles. All these statistics and variables are computed at a quarterly frequency. Panel A reports the statistics for the full sample. Panel B reports the statistics for a sub-sample of multi-funds, which are defined as groups of mutual funds with identical manager team compositions.

	Full Sample							
	mean	SD	1th prctile	25th prctile	median	75th prctile	99th prctile	# obs
Returns (%)	2.17	9.37	-25.16	-1.77	3.07	7.31	22.90	102,466
Risk (%)	9.05	5.04	3.38	5.91	7.66	10.34	32.27	102,466
Turnover Ratio (%)	87.85	281.10	3.00	33.00	61.00	101.00	383.84	102,466
Expense Ratio (%)	1.33	3.62	0.25	0.94	1.15	1.38	2.26	102,466
TNA (millions)	1,764	6,445	18	106	348	1,207	24,084	102,466
Age (years)	15.7	11.0	3.4	7.8	12.8	19.7	51.9	102,466
Family TNA (millions)	34,447	85,734	23	1,191	6,671	24,976	477,868	102,466
Funds in Family	13.7	13.9	1.0	4.0	9.0	19.0	72.0	102,466
Team	0.68	0.47	0.00	0.00	1.00	1.00	1.00	102,466
Manager Tenure (years)	9.0	5.2	0.7	5.2	8.2	11.8	25.3	102,466
	Multi-Fund Sample							
	mean	SD	1th prctile	25th prctile	median	75th prctile	99th prctile	# obs
Returns (%)	2.30	9.08	-25.19	-1.45	3.26	7.39	21.72	32,320
Risk (%)	9.03	5.09	3.38	5.91	7.65	10.25	32.61	32,320
Turnover Ratio (%)	85.58	82.42	3.00	36.00	66.00	110.00	383.00	32,320
Expense Ratio (%)	1.13	0.43	0.18	0.91	1.12	1.34	2.17	32,320
TNA (millions)	1,589	4,598	19	121	398	1,300	17,779	32,320
Age (years)	15.8	10.7	3.5	8.2	13.3	19.9	51.4	32,320
Family TNA (millions)	46,417	100,962	82	2,607	11,834	33,027	501,628	32,320
Funds in Family	17.2	15.7	2.0	6.0	13.0	23.0	74.0	32,320
Team	0.67	0.47	0.00	0.00	1.00	1.00	1.00	32,320
Manager Tenure (years)	9.2	5.2	0.7	5.4	8.3	12.1	25.5	32,320

Table 2: Coordination Results

This table presents OLS regression results of the following model equation estimated using a sample of U.S. active equity mutual funds from 2000 until 2018:

$$IdioCorr_{i,j,t} = \alpha + \beta MultiFund_{i,j,t} + \Gamma' \boldsymbol{Controls}_{i,j,t} + \varepsilon_{i,j,t},$$

where $IdioCorr_{i,j,t}$ is the idiosyncratic correlation between the portfolios of fund i and fund j at quarter t. These idiosyncratic correlations are computed with the residuals of the Carhart (1997) 4-factor model for all fund pairs. The $MultiFund_{i,j,t}$ variable equals one if the fund pair i and j is a multi-fund pair and zero if the fund pair is a matched pair. The multi-funds are defined as groups of funds that are managed by the exact same managers from the same mutual fund family. The matched funds are funds with same investment style and in the same size decile as fund j. $Controls_{i,j,t}$ represents a host of relevant control variables. *SameStyle* indicates whether both funds in the pair have the same investment style. *SameFamily* indicates whether both funds in the pair are in the same mutual fund family. *SameCity* indicates whether both funds in the pair are located in the same city. *OtherTeamConnection* indicates whether managers from both funds in the pair manage another non multi-fund together. The standard errors are clustered by fund pairs and are shown in parentheses. Column 1 shows results for the full sample. Column 2 shows results for a sub-sample where both funds in the pairs have the same investment style. Column 3 shows results for a sub-sample where the team size of the multi-funds is larger than three managers.

	(1) Full Sample	(2) Same Style Sample	(3) Team > 3 Sample
$MultiFund$	-8.034***	-6.263***	-10.041***
	(1.286)	(1.337)	(3.320)
$SameStyle$	39.237***		44.984***
	(1.772)		(4.128)
$SameFamily$	3.375**	1.243	0.409
	(1.392)	(1.181)	(3.732)
$SameCity$	5.482***	2.666**	9.758***
	(1.272)	(1.156)	(2.587)
$OtherTeamConnection$	5.179***	4.433**	7.225
	(1.618)	(1.774)	(4.511)
Observations	235,816	68,069	51,901
Adjusted R2	0.287	0.048	0.331
Time Fixed Effects	Y	Y	Y

***, ** and * show significance at the 1%, 5% and 10% level respectively.

Table 3: Coordination Results with Placebos

This table presents OLS regression results of the following model equation estimated using a sample of U.S. active equity mutual funds from 2000 until 2018:

$$IdioCorr_{i,j,t} = \alpha + \beta MultiFund_{i,j,t} + \gamma PlaceboPair_{i,j,t} + \Gamma' \boldsymbol{Controls}_{i,j,t} + \varepsilon_{i,j,t},$$

where $IdioCorr_{i,j,t}$ is the idiosyncratic correlation between the portfolios of fund i and fund j at quarter t. These idiosyncratic correlations are computed with the residuals of the Carhart (1997) 4-factor model for all fund pairs. The $MultiFund_{i,j,t}$ variable equals one if the fund pair i and j is a multi-fund pair and zero if the fund pair is a matched pair. The multi-funds are defined as groups of funds that are managed by the exact same managers from the same mutual fund family. There is also a $PlaceboPair_{i,j,t}$ variable indicating whether the fund pair i and j are a placebo pair, which is defined when the manager teams of fund i and j have both managers in common and also at least one manager unique to the funds. The matched funds are funds with same investment style and in the same size decile as fund j. $Controls_{i,j,t}$ represents a host of relevant control variables. $SameStyle$ indicates whether both funds in the pair have the same investment style. $SameFamily$ indicates whether both funds in the pair are in the same mutual fund family. $SameCity$ indicates whether both funds in the pair are located in the same city. $OtherTeamConnection$ indicates whether managers from both funds in the pair manage another non multi-fund together. The standard errors are clustered by fund pairs and are shown in parentheses. Columns 1 and 2 show results for the sub-sample with manager teams that manage both multi-funds and placebo funds. Columns 3 and 4 show results for a similar sub-sample, except the placebo fund pairs have less than three distinct managers not in common, while columns 5 and 6 show results for a similar sub-sample with equal or more than three distinct managers.

	All Placebos		Manager Difference < 3		Manager Difference ≥ 3	
	(1)	(2)	(3)	(4)	(5)	(6)
$MultiFund$	-6.685***		-7.894**		-3.458**	
	(1.813)		(3.319)		(1.632)	
$PlaceboPair$		-0.889		1.452		0.577
		(2.620)		(3.078)		(2.386)
$SameStyle$	38.678***	30.716***	32.908***	29.697***	36.527***	32.259***
	(2.321)	(2.908)	(3.299)	(2.606)	(3.170)	(5.037)
$SameFamily$	3.146*	5.521**	2.502	2.275	5.190***	4.164*
	(1.749)	(2.557)	(3.621)	(3.119)	(1.527)	(2.123)
$SameCity$	3.476**	-3.432***	4.713	-1.822	-0.790	-3.250***
	(1.765)	(1.199)	(3.191)	(1.491)	(1.268)	(0.954)
$OtherTeamConnection$	4.328**	-0.564	2.882	0.143	2.113	0.881
	(1.697)	(2.161)	(3.334)	(2.322)	(1.702)	(2.487)
Observations	81,470	96,351	55,541	76,051	46,696	39,854
Adjusted R2	0.351	0.141	0.223	0.166	0.408	0.158
Time Fixed Effects	Y	Y	Y	Y	Y	Y

***, ** and * show significance at the 1%, 5% and 10% level respectively.

Table 4: Coordination Results with Industries

This table presents OLS regression results of the following model equation estimated using a sample of U.S. active equity mutual funds from 2000 until 2018:

$$IndustryDifference_{i,j,t} = \alpha + \beta MultiFund_{i,j,t} + \Gamma' \boldsymbol{Controls}_{i,j,t} + \varepsilon_{i,j,t},$$

where $IndustryDifference_{i,j,t}$ is the total absolute difference in industry weights between the portfolios of fund i and fund j at quarter t. The industry classifications are the same as in Kacperczyk et al. (2005). The $MultiFund_{i,j,t}$ variable equals one if the fund pair i and j is a multi-fund pair and zero if the fund pair is a matched pair. The multi-funds are defined as groups of funds that are managed by the exact same managers from the same mutual fund family. The matched funds are funds with same investment style and in the same size decile as fund j. $Controls_{i,j,t}$ represents a host of relevant control variables. *SameStyle* indicates whether both funds in the pair have the same investment style. *SameFamily* indicates whether both funds in the pair are in the same mutual fund family. *SameCity* indicates whether both funds in the pair are located in the same city. *OtherTeamConnection* indicates whether managers from both funds in the pair manage another non multi-fund together. The standard errors are clustered by fund pairs and are shown in parentheses. Column 1 shows results for the total portfolio weight difference of all ten industries. Columns 2 until 11 shows results for the portfolio weight difference for all ten industries individually. The industries are classified as follows: 1) Consumer non-durables; 2) Consumer durables; 3) Healthcare; 4) Manufacturing; 5) Energy; 6) Utilities; 7) Telecom; 8) Business equipment and services; 9) Wholesale and retail; 10) Finance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	All Industries	Industry 1	Industry 2	Industry 3	Industry 4	Industry 5	Industry 6	Industry 7	Industry 8	Industry 9	Industry 10
MultiFund	15.834***	0.971***	0.696***	1.349***	1.738***	1.303***	0.776***	0.699***	3.013***	1.650***	3.640***
	(1.044)	(0.104)	(0.060)	(0.105)	(0.157)	(0.125)	(0.095)	(0.104)	(0.249)	(0.150)	(0.307)
SameStyle	-18.160***	-1.382***	-1.063***	-1.717***	-2.383***	-1.365***	-0.944***	-0.998***	-3.238***	-2.147***	-2.922***
	(1.028)	(0.087)	(0.071)	(0.100)	(0.159)	(0.084)	(0.070)	(0.074)	(0.203)	(0.169)	(0.201)
SameFamily	-4.725***	-0.304***	-0.189***	-0.262***	-0.766***	-0.285***	-0.255***	-0.170***	-1.141***	-0.453***	-0.900***
	(0.756)	(0.091)	(0.052)	(0.078)	(0.128)	(0.078)	(0.079)	(0.054)	(0.216)	(0.114)	(0.172)
SameCity	-3.985***	-0.338***	-0.328***	-0.500***	-0.555***	-0.266***	-0.039	-0.235***	-0.474***	-0.642***	-0.610***
	(0.731)	(0.061)	(0.049)	(0.067)	(0.120)	(0.051)	(0.061)	(0.053)	(0.174)	(0.111)	(0.176)
OtherTeamConnection	-3.631***	-0.405***	-0.275***	-0.407***	-0.457***	-0.263***	-0.125	-0.164**	-0.545***	-0.247	-0.742***
	(0.860)	(0.072)	(0.058)	(0.105)	(0.149)	(0.093)	(0.077)	(0.076)	(0.191)	(0.180)	(0.179)
Observations	235,888	235,888	235,888	235,888	235,888	235,888	235,888	235,888	235,888	235,888	235,888
Adjusted R2	0.223	0.085	0.092	0.102	0.092	0.119	0.063	0.086	0.100	0.090	0.093
Time Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

***, ** and * show significance at the 1%, 5% and 10% level respectively.

Table 5: Coordination Results with Factor Styles

This table presents OLS regression results of the following model equation estimated using a sample of U.S. active equity mutual funds from 2000 until 2018:

$$StyleDifference_{i,j,t} = \alpha + \beta MultiFund_{i,j,t} + \Gamma' \boldsymbol{Controls}_{i,j,t} + \varepsilon_{i,j,t},$$

where $StyleDifference_{i,j,t}$ is the total absolute factor loading difference between the portfolios of fund i and fund j at quarter t. The factors are the same as the Carhart (1997) 4-factor model. The $MultiFund_{i,j,t}$ variable equals one if the fund pair i and j is a multi-fund pair and zero if the fund pair is a matched pair. The multi-funds are defined as groups of funds that are managed by the exact same managers from the same mutual fund family. The matched funds are funds with same investment style and in the same size decile as fund j. $Controls_{i,j,t}$ represents a host of relevant control variables. *SameStyle* indicates whether both funds in the pair have the same investment style. *SameFamily* indicates whether both funds in the pair are in the same mutual fund family. *SameCity* indicates whether both funds in the pair are located in the same city. *OtherTeamConnection* indicates whether managers from both funds in the pair manage another non multi-fund together. The standard errors are clustered by fund pairs and are shown in parentheses. Column 1 shows results for the total portfolio factor loading difference of all four factors. Columns 2 until 5 shows results for the portfolio factor loading difference for, respectively, the market factor, size factor, value factor, and momentum factor.

	(1) All Factors	(2) Market	(3) Size	(4) Value	(5) Momentum
$MultiFund$	0.153***	0.014***	0.109***	0.020***	0.010**
	(0.017)	(0.002)	(0.011)	(0.005)	(0.004)
$SameStyle$	-0.548***	-0.035***	-0.304***	-0.137***	-0.072***
	(0.022)	(0.002)	(0.015)	(0.006)	(0.004)
$SameFamily$	-0.057***	-0.006***	-0.035***	-0.010*	-0.005*
	(0.017)	(0.002)	(0.011)	(0.006)	(0.003)
$SameCity$	-0.089***	-0.009***	-0.049***	-0.013**	-0.018***
	(0.018)	(0.002)	(0.013)	(0.005)	(0.003)
$OtherTeamConnection$	-0.023	-0.002	-0.004	-0.012**	-0.005
	(0.019)	(0.002)	(0.013)	(0.005)	(0.003)
Observations	235,816	235,816	235,816	235,816	235,816
Adjusted R-squared	0.296	0.171	0.218	0.175	0.155
Time Fixed	Y	Y	Y	Y	Y

***, ** and * show significance at the 1%, 5% and 10% level respectively.

Table 6: Fund Return Volatility

This table presents OLS regression results of the following model equation estimated using a sample of U.S. active equity mutual funds from 2000 until 2018:

$$Volatility_{i,m,t} = \alpha + \beta CoordinationDummy_{i,m,t-1} + \Gamma' \boldsymbol{Controls}_{i,m,t-1} + \varepsilon_{i,m,t},$$

where $Volatility_{i,m,t}$ is the fund return volatility of fund i over quarter t. The table also reports results with systematic volatility and idiosyncratic volatility obtained from the Carhart (1997) 4-factor model. The $CoordinationDummy_{i,m,t-1}$ variable indicates whether manager m corresponding to fund i at quarter $t-1$ is likely to engage in strategic multi-fund coordination. $Controls_{i,j,t}$ represents a host of relevant fund, mutual fund family, and manager control variables. The fund controls include the past performance, size, age, fees, and turnover. The mutual fund family controls include the size and number of funds of all active equity funds in the family. The manager control include whether the fund is managed by a multi-fund manager, whether the fund is managed by a team, and the average tenure of all managers in the corresponding fund team. All size and age related variables are transformed by taking the natural logarithmic to reduce the effect of outliers. The standard errors are clustered by fund and are shown in parentheses. The column headers indicate the volatility measure used as the dependent variable in the regression model.

	Volatility		Systematic Volatility		Idiosyncratic Volatility	
	(1)	(2)	(3)	(4)	(5)	(6)
CoordinationDummy	0.152***	0.114***	-0.009	0.009	0.185***	0.085***
	(0.045)	(0.036)	(0.029)	(0.025)	(0.026)	(0.019)
MultiFund	-0.011	-0.020	-0.001	-0.003	-0.003	-0.006
	(0.031)	(0.030)	(0.023)	(0.019)	(0.023)	(0.018)
PastPerformance	-0.025***	-0.025***	-0.007***	-0.008***	-0.003*	-0.002
	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
Turnover	0.177***	0.149***	0.121***	0.084***	0.023	0.019
	(0.024)	(0.020)	(0.017)	(0.013)	(0.017)	(0.013)
ExpenseRatio	-0.008***	-0.002	-0.008***	-0.003	0.000	-0.001
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
FundTNA	-0.009	-0.017	-0.005	-0.015*	-0.020**	-0.014**
	(0.014)	(0.011)	(0.010)	(0.008)	(0.009)	(0.007)
FundAge	-0.039	0.015	0.004	0.051***	-0.047**	-0.058***
	(0.029)	(0.028)	(0.020)	(0.019)	(0.019)	(0.017)
FamilyTNA	-0.010	0.158***	-0.013	0.071***	-0.014	0.026*
	(0.018)	(0.030)	(0.015)	(0.017)	(0.013)	(0.015)
FamilyFunds	0.061*	-0.080*	0.130***	-0.017	-0.128***	-0.019
	(0.035)	(0.045)	(0.026)	(0.028)	(0.025)	(0.024)
Team	-0.043	-0.048	0.044*	0.008	-0.137***	-0.100***
	(0.036)	(0.032)	(0.026)	(0.021)	(0.023)	(0.019)
ManagerTenure	0.020	-0.001	-0.038*	-0.013	0.112***	0.034**
	(0.032)	(0.028)	(0.022)	(0.017)	(0.021)	(0.016)
Observations	102,466	102,466	102,466	102,466	102,466	102,466
Adjusted R2	0.918	0.931	0.951	0.960	0.542	0.660
Time x Style Fixed	Y	Y	Y	Y	Y	Y
Family Fixed	N	Y	N	Y	N	Y

***, ** and * show significance at the 1%, 5% and 10% level respectively.

Table 7: Fund Activeness

This table presents OLS regression results of the following model equation estimated using a sample of U.S. active equity mutual funds from 2000 until 2018:

$$Activeness_{i,m,t} = \alpha + \beta CoordinationDummy_{i,m,t-1} + \Gamma' \boldsymbol{Controls}_{i,m,t-1} + \varepsilon_{i,m,t},$$

where $Activeness_{i,m,t}$ is an activeness of fund i over quarter t. The activeness measures include portfolio industry concentration (Kacperczyk et al., 2005), style extremity (Bär et al., 2010), active share (Cremers and Petajisto, 2009), one minus the R-squared of the Carhart (1997) 4-factor model (Amihud and Goyenko, 2013), and absolute return gap (Kacperczyk et al., 2006). The $CoordinationDummy_{i,m,t-1}$ variable indicates whether manager m corresponding to fund i at quarter $t-1$ is likely to engage in strategic multi-fund coordination. $Controls_{i,j,t}$ represents a host of relevant fund, mutual fund family, and manager control variables. The fund controls include the past performance, size, age, fees, and turnover. The mutual fund family controls include the size and number of funds of all active equity funds in the family. The manager control include whether the fund is managed by a multi-fund manager, whether the fund is managed by a team, and the average tenure of all managers in the corresponding fund team. All size and age related variables are transformed by taking the natural logarithmic to reduce the effect of outliers. The standard errors are clustered by fund and are shown in parentheses. The column headers indicate the activeness measure used as the dependent variable in the regression model.

	(1)	(2)	(3)	(4)	(5)
	Industry	Style			
	Concentration	Extremity	Active Share	1 - R2	Return Gap
$CoordinationDummy$	0.438***	6.480***	2.975***	0.790***	0.147**
	(0.141)	(1.792)	(0.584)	(0.174)	(0.063)
$MultiFund$	0.225*	4.908***	-1.530***	0.187	-0.016
	(0.132)	(1.303)	(0.584)	(0.168)	(0.048)
$PastPerformance$	-0.002	-0.175*	0.075***	-0.002	-0.020*
	(0.009)	(0.104)	(0.012)	(0.013)	(0.011)
$Turnover$	-0.663***	0.248	0.163	-0.279**	0.053
	(0.121)	(1.111)	(0.347)	(0.111)	(0.036)
$ExpenseRatio$	0.320*	0.026	0.067	0.015	0.156
	(0.174)	(0.127)	(0.152)	(0.019)	(0.099)
$FundTNA$	0.038	-0.390	-0.449**	-0.107*	-0.036*
	(0.060)	(0.569)	(0.189)	(0.059)	(0.021)
$FundAge$	-0.232*	-3.016**	0.059	-0.432***	-0.005
	(0.120)	(1.172)	(0.402)	(0.128)	(0.044)
$FamilyTNA$	0.018	-0.298	0.145	-0.068	0.039
	(0.082)	(0.779)	(0.255)	(0.102)	(0.028)
$FamilyFunds$	-0.597***	-9.780***	-2.604***	-1.117***	-0.227***
	(0.161)	(1.619)	(0.443)	(0.201)	(0.051)
$Team$	-0.170	-9.384***	-0.549	-1.035***	-0.076
	(0.142)	(1.469)	(0.387)	(0.172)	(0.048)
$ManagerTenure$	0.481***	5.389***	2.193***	0.671***	0.093**
	(0.136)	(1.470)	(0.381)	(0.138)	(0.043)
Observations	50,291	102,466	77,912	102,466	51,033
Adjusted R2	0.309	0.045	0.462	0.339	0.319
Time x Style Fixed	Y	Y	Y	Y	Y

***, ** and * show significance at the 1%, 5% and 10% level respectively.

Table 8: Lottery Stock Holdings

This table presents OLS regression results of the following model equation estimated using a sample of U.S. active equity mutual funds from 2000 until 2018:

$$LotteryHolding_{i,m,t} = \alpha + \beta CoordinationDummy_{i,m,t-1} + \Gamma' \boldsymbol{Controls}_{i,m,t-1} + \varepsilon_{i,m,t},$$

where $LotteryHolding_{i,m,t}$ is the total lottery-like stock portfolio weight of fund i at quarter t. The lottery-like stocks are identified as stocks in either the top maximum daily return (MAX) decile or the top average maximum five daily return ($MAX5$) decile in the prior quarter. The $CoordinationDummy_{i,m,t-1}$ variable indicates whether manager m corresponding to fund i at quarter $t-1$ is likely to engage in strategic multi-fund coordination. $Controls_{i,j,t}$ represents a host of relevant fund, mutual fund family, and manager control variables. The fund controls include the past performance, size, age, fees, and turnover. The mutual fund family controls include the size and number of funds of all active equity funds in the family. The manager control include whether the fund is managed by a multi-fund manager, whether the fund is managed by a team, and the average tenure of all managers in the corresponding fund team. All size and age related variables are transformed by taking the natural logarithmic to reduce the effect of outliers. The standard errors are clustered by fund and are shown in parentheses. The column headers indicate the lottery-like stock definition used to measure the fund lottery-like stock portfolio weights that is used as the dependent variable in the regression model.

	(1)	(2)
	MAX	MAX5
$CoordinationDummy$	0.406***	0.385***
	(0.101)	(0.111)
$MultiFund$	-0.223**	-0.181*
	(0.093)	(0.102)
$PastPerformance$	0.019**	0.036***
	(0.009)	(0.010)
$Turnover$	1.185***	1.634***
	(0.172)	(0.207)
$ExpenseRatio$	0.152	0.116
	(0.106)	(0.110)
$FundTNA$	-0.035	-0.036
	(0.038)	(0.041)
$FundAge$	0.072	0.081
	(0.074)	(0.080)
$FamilyTNA$	0.041	0.034
	(0.049)	(0.053)
$FamilyFunds$	-0.116	-0.084
	(0.093)	(0.104)
$Team$	-0.213**	-0.289***
	(0.087)	(0.096)
$ManagerTenure$	0.111	0.109
	(0.074)	(0.084)
Observations	50,291	50,291
Adjusted R2	0.440	0.490
Time Style Fixed	Y	Y

***, ** and * show significance at the 1%, 5% and 10% level respectively.

Table 9: Star Fund Production

This table presents logistic regression results of the following model equation estimated using a sample of U.S. active equity funds from 2000 until 2018:

$$Pr(StarFund_{i,m,y} = 1) = \alpha + \beta CoordinationDummy_{i,m,y-1} + \Gamma' Controls_{i,m,y-1} + \varepsilon_{i,m,y},$$

where $StarFund_{i,m,t}$ indicates whether fund i is a fund with star performance at year y. Star funds are the top 5% mutual funds with the highest investment style-adjusted fund returns in the past year among all fund peers (Star) or among their peers with the same investment style (Star by Style). The $CoordinationDummy_{i,m,t-1}$ variable indicates whether manager m corresponding to fund i at quarter $t-1$ is likely to engage in strategic multi-fund coordination. $Controls_{i,j,t}$ represents a host of relevant fund, mutual fund family, and manager control variables. The fund controls include the past performance, size, age, fees, and turnover. The mutual fund family controls include the size and number of funds of all active equity funds in the family. The manager control include whether the fund is managed by a multi-fund manager, whether the fund is managed by a team, and the average tenure of all managers in the corresponding fund team. All size and age related variables are transformed by taking the natural logarithmic to reduce the effect of outliers. The standard errors are clustered by fund and are shown in parentheses. The column headers indicate the star fund definition used as the dependent variable in the regression model.

	(1)	(2)
	Star	Star by Style
$CoordinationDummy$	0.381***	0.328***
	(0.127)	(0.123)
$MultiFund$	0.090	0.156*
	(0.087)	(0.082)
$PastPerformance$	0.013***	0.008*
	(0.004)	(0.004)
$Turnover$	0.236**	0.046
	(0.107)	(0.111)
$ExpenseRatio$	-0.016**	0.003
	(0.006)	(0.011)
$FundTNA$	-0.038	-0.055*
	(0.034)	(0.031)
$FundAge$	-0.123*	0.039
	(0.070)	(0.063)
$FamilyTNA$	0.060	0.087**
	(0.040)	(0.038)
$FamilyFunds$	-0.311***	-0.334***
	(0.071)	(0.066)
$Team$	-0.271***	-0.296***
	(0.075)	(0.070)
$ManagerTenure$	0.042	0.014
	(0.067)	(0.062)
Observations	21,906	21,906
Psuedo R2	0.014	0.012
Time Fixed	Y	Y

***, ** and * show significance at the 1%, 5% and 10% level respectively.

Table 10: Star Multi-Fund Spillover

This table presents OLS regression results of the following model equation estimated using a sample of U.S. active equity mutual funds from 2000 until 2018:

$$Flows_{i,m,t} = \alpha + \beta MultiFundStar_{i,m,y-1} + \Gamma' \boldsymbol{Controls}_{i,m,t-1} + \varepsilon_{i,m,t},$$

where $Flows_{i,m,t}$ is the total net investment flows to fund i over quarter t. The $MultiStarFund_{i,m,y-1}$ dummy variable equals one if fund i is not a star fund at the end of year $y-1$, but the corresponding manager m does manage another fund that is a star fund. $Controls_{i,j,t}$ represents a host of relevant fund, mutual fund family, and manager control variables. The fund controls include the past performance, size, age, fees, turnover, and a star fund indicator. The mutual fund family controls include the size and number of funds of all active equity funds in the family, and a dummy variables indicating whether there exists a star fund in the family of fund i but the fund itself is not a star fund. The manager control include whether the fund is managed by a multi-fund manager, whether the fund is managed by a team, and the average tenure of all managers in the corresponding fund team. All size and age related variables are transformed by taking the natural logarithmic to reduce the effect of outliers. The standard errors are clustered by fund and are shown in parentheses.

	(1)	(2)	(3)	(4)
$MultiFundStar$	1.251***	1.563***	1.118***	1.502***
	(0.410)	(0.395)	(0.404)	(0.390)
$StarFund$	4.726***	4.752***	4.467***	4.557***
	(0.329)	(0.323)	(0.317)	(0.312)
$FamilyStar$	0.003	0.030	0.063	0.096
	(0.119)	(0.123)	(0.118)	(0.121)
$MultiFund$	-0.216*	-0.303**	-0.133	-0.193
	(0.126)	(0.144)	(0.123)	(0.140)
$PastPerformance$	0.103***	0.105***	0.490***	0.473***
	(0.004)	(0.004)	(0.018)	(0.018)
$Turnover$	-0.209***	-0.097	-0.327***	-0.179**
	(0.065)	(0.075)	(0.068)	(0.077)
$ExpenseRatio$	-0.010	0.024	-0.001	0.020
	(0.010)	(0.015)	(0.011)	(0.017)
$FundTNA$	-0.051	0.003	-0.131***	-0.109**
	(0.047)	(0.047)	(0.047)	(0.047)
$FundAge$	-2.174***	-2.469***	-1.846***	-1.934***
	(0.109)	(0.124)	(0.105)	(0.123)
$FamilyTNA$	0.535***	-0.535***	0.516***	-0.251*
	(0.067)	(0.139)	(0.067)	(0.145)
$FamilyFunds$	-1.076***	-0.581**	-0.895***	0.101
	(0.116)	(0.233)	(0.117)	(0.241)
$Team$	-0.21*	-0.170	0.089	0.130
	(0.123)	(0.153)	(0.124)	(0.152)
$ManagerTenure$	-0.103	-0.123	0.196*	0.197*
	(0.104)	(0.117)	(0.104)	(0.116)
Observations	102,229	102,229	102,229	102,229
Adjusted R2	0.040	0.073	0.087	0.118
Time Style Fixed	N	N	Y	Y
Family Fixed	N	Y	N	Y

***, ** and * show significance at the 1%, 5% and 10% level respectively.

Table 11: Multi-Fund Star Switching

This table presents logistic regression results of the following model equation estimated using a sample of U.S. active equity funds from 2000 until 2018:

$$Pr(High_{i,m,y} = 1) = \alpha + \beta_1 CoordinationDummy_{i,m,y-1} + \beta_2 High_{i,m,y-1} + \beta_3 CoordinationDummy_{i,m,y-1} \times High_{i,m,y-1} + \Gamma' Controls_{i,m,y-1} + \varepsilon_{i,m,y},$$

where $High_{i,m,t}$ indicates whether fund i is the fund with the highest style-adjusted performance among all funds managed by manager m at year y. The $CoordinationDummy_{i,m,t-1}$ variable indicates whether manager m corresponding to fund i at quarter $t-1$ is likely to engage in strategic multi-fund coordination. $Controls_{i,j,t}$ represents a host of relevant fund, mutual fund family, and manager control variables. Panel A reports the results of this logistic regression. Panel B reports the estimation results of the following conditional logistic regression model:

$$Pr(High_{i,m,y} = 1 | High_{i,m,y-1}) = \alpha + \beta_1 CoordinationDummy_{i,m,y-1} + \Gamma' Controls_{i,m,y-1} + \varepsilon_{i,m,y}.$$

In the table, $Low_{i,m,y}$ is used to indicate when $High_{i,m,y}$ equals zero. The fund controls include the past performance, size, age, fees, and turnover. The mutual fund family controls include the size and number of funds of all active equity funds in the family. The manager control include whether the fund is managed by a multi-fund manager, whether the fund is managed by a team, and the average tenure of all managers in the corresponding fund team. All size and age related variables are transformed by taking the natural logarithmic to reduce the effect of outliers. The standard errors are clustered by fund and are shown in parentheses.

	Panel A	Panel B			
	(1)	(2)	(3)	(4)	(5)
		$High_{y-1}$	$High_{y-1}$	Low_{y-1}	Low_{y-1}
	$High_y$	$High_y$	Low_y	$High_y$	Low_y
$CoordinationDummy$	0.121	-0.206*	0.101	0.071	0.007
	(0.103)	(0.116)	(0.074)	(0.070)	(0.096)
$High_{y-1}$	0.481***				
	(0.066)				
$CoordinationDummy \times$	-0.407**				
$High_{y-1}$	(0.161)				
$PastPerformance$	-0.007**	0.021***	-0.027***	0.035***	-0.025***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
$Turnover$	0.209**	0.299**	0.047	0.020	-0.276**
	(0.091)	(0.134)	(0.084)	(0.081)	(0.132)
$ExpenseRatio$	-0.252***	-0.389***	-0.051	0.049	0.248*
	(0.092)	(0.134)	(0.076)	(0.077)	(0.127)
$FundTNA$	-0.010	0.004	-0.020	0.013	0.002
	(0.026)	(0.041)	(0.023)	(0.022)	(0.035)
$FundAge$	-0.002	-0.018	0.018	0.016	-0.005
	(0.049)	(0.075)	(0.043)	(0.042)	(0.064)
$FamilyTNA$	-0.012	-0.046	0.017	-0.032	0.036
	(0.036)	(0.056)	(0.032)	(0.031)	(0.049)
$FamilyFunds$	-0.074	0.094	-0.183***	-0.079	0.149*
	(0.064)	(0.103)	(0.057)	(0.054)	(0.086)
$Team$	-0.049	-0.198**	0.119**	0.116**	-0.022
	(0.067)	(0.100)	(0.056)	(0.055)	(0.089)
$ManagerTenure$	0.168***	0.100	0.170***	0.135***	-0.293***
	(0.059)	(0.092)	(0.052)	(0.050)	(0.072)
Observations	6,784	6,784	6,784	6,784	6,784
Psuedo R2	0.0137	0.0144	0.0164	0.0207	0.0215
Time Fixed	Y	Y	Y	Y	Y

***, ** and * show significance at the 1%, 5% and 10% level respectively.

APPENDIX

Appendix A Strategic Multi-Fund Coordination Robustness

In this section, I perform the analysis testing for the existence of the investment coordination strategy among multi-fund managers with an alternative matching procedure. Namely, I match the multi-funds to mutual funds with the same investment style and closest in terms of size. An issue with this matching procedure is that there are very little matching fund observations in the same family as the multi-fund. This introduces multicollinearity problems between $MultiFund$ and $SameFamily$, because multi-fund pairs belong to the same mutual fund family by definition, thus, making $MultiFund$ and $SameFamily$ almost identical variables. I alleviate this multicollinearity problem by simply removing $SameFamily$ from the analysis. The investment coordination strategy results remain qualitatively unchanged as shown in Table A1.

Table A1: Coordination Results with Nearest Neighbour Matching

This table presents OLS regression results of the following model equation estimated using a sample of U.S. active equity mutual funds from 2000 until 2018:

$$IdioCorr_{i,j,t} = \alpha + \beta MultiFund_{i,j,t} + \Gamma' \boldsymbol{Controls}_{i,j,t} + \varepsilon_{i,j,t},$$

where $IdioCorr_{i,j,t}$ is the idiosyncratic correlation between the portfolios of fund i and fund j at quarter t. These idiosyncratic correlations are computed with the residuals of the Carhart (1997) 4-factor model using weekly returns for all fund pairs. The $MultiFund_{i,j,t}$ variable equals one if the fund pair i and j is a multi-fund pair and zero if the fund pair is a matched pair. The multi-funds are defined as groups of funds that are managed by the exact same managers from the same mutual fund family. The matched funds are funds with same investment style and closest in terms of size as fund j. $Controls_{i,j,t}$ represents a host of relevant control variables. *SameStyle* indicates whether both funds in the pair have the same investment style. *SameFamily* indicates whether both funds in the pair are in the same mutual fund family. *SameCity* indicates whether both funds in the pair are located in the same city. *OtherTeamConnection* indicates whether managers from both funds in the pair manage another non multi-fund together. The standard errors are clustered by fund pairs and are shown in parentheses. Column 1 shows results for the full sample. Column 2 shows results for a sub-sample where both funds in the pairs have the same investment style. Column 3 shows results for a sub-sample where the team size of the multi-funds is larger than three managers.

	(1)	(2)	(3)
	Full Sample	Same Style Sample	Team > 3 Sample
$MultiFund$	-4.607***	-5.344***	-9.637***
	(1.508)	(1.552)	(2.688)
$SameStyle$	37.641***		41.731***
	(1.620)		(3.760)
$SameCity$	7.307***	5.672***	12.261***
	(1.607)	(1.805)	(2.898)
$OtherTeamConnection$	8.335***	6.994**	-1.856
	(2.286)	(2.743)	(7.486)
Observations	30,458	7,159	6,638
Adjusted R2	0.252	0.051	0.302
Time Fixed Effects	Y	Y	Y

***, ** and * show significance at the 1%, 5% and 10% level respectively.

Appendix B Multi-Fund Manager Risk-Taking Robustness

In this section, I perform a couple robustness checks for the analysis testing the risk-taking behaviour of coordinating multi-fund managers. First, I use the *Coordination* measure instead of the *CoordinationDummy* as the main independent variable of interest. The *Coordination* measure evaluates to what extend multi-fund managers are employing the investment coordination strategy, but it is a noisy measure due to the way it is constructed. Nevertheless, the coordinating multi-fund risk-taking results in Table B1 are qualitatively the same as the main results. Note that lower values of *Coordination* imply that multi-fund managers are more likely to coordinate investments, hence, why the signs are flipped compared to the main results.

Next, I use an alternative fund risk measure that proxies the intended risk-taking of the manager. Namely, I use the hypothetical daily fund returns that holds the fund portfolio stock weights constant over the quarter prior to the disclosure date of the portfolio holdings to construct the same risk measures as the main analysis. These risk measures therefore proxy the risk level that the manager wants to take in the fund using all available information about the most recently disclosed portfolio holdings and past stock returns. The results in Table B2 are again qualitatively the same as the main results. Note that the number of observations are substantially lower compared to the main analysis due to relatively less data about portfolio holdings of mutual funds compared to mutual fund return data.

Table B1: Fund Return Volatility with Coordination Measure

This table presents OLS regression results of the following model equation estimated using a sample of U.S. active equity mutual funds from 2000 until 2018:

$$Volatility_{i,m,t} = \alpha + \beta Coordination_{i,m,t-1} + \Gamma' \boldsymbol{Controls}_{i,m,t-1} + \varepsilon_{i,m,t},$$

where $Volatility_{i,m,t}$ is the fund return volatility of fund i over quarter t. The table also reports results with systematic volatility and idiosyncratic volatility obtained from the Carhart (1997) 4-factor model. The $Coordination_{i,m,t-1}$ variable measures whether manager m corresponding to fund i at quarter $t-1$ is likely to engage in strategic multi-fund coordination. $Controls_{i,j,t}$ represents a host of relevant fund, mutual fund family, and manager control variables. The fund controls include the past performance, size, age, fees, and turnover. The mutual fund family controls include the size and number of funds of all active equity funds in the family. The manager control include whether the fund is managed by a multi-fund manager, whether the fund is managed by a team, and the average tenure of all managers in the corresponding fund team. All size and age related variables are transformed by taking the natural logarithmic to reduce the effect of outliers. The standard errors are clustered by fund and are shown in parentheses. The column headers indicate the volatility measure used as the dependent variable in the regression model.

	Volatility		Systematic Volatility		Idiosyncratic Volatility	
	(1)	(2)	(3)	(4)	(5)	(6)
$Coordination$	-0.418*	-0.453**	0.488***	0.107	-0.684***	-0.347***
	(0.228)	(0.181)	(0.169)	(0.143)	(0.148)	(0.099)
$MultiFund$	0.021	0.006	-0.006	-0.002	0.038*	0.013
	(0.032)	(0.031)	(0.023)	(0.020)	(0.023)	(0.018)
$PastPerformance$	-0.025***	-0.025***	-0.007***	-0.008***	-0.003*	-0.002
	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
$Turnover$	0.177***	0.149***	0.121***	0.084***	0.023	0.018
	(0.024)	(0.020)	(0.017)	(0.013)	(0.017)	(0.013)
$ExpenseRatio$	-0.008***	-0.002	-0.008***	-0.003	0.000	-0.001
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
$FundTNA$	-0.010	-0.018	-0.005	-0.015*	-0.021**	-0.014**
	(0.014)	(0.011)	(0.010)	(0.008)	(0.009)	(0.007)
$FundAge$	-0.036	0.016	0.003	0.052***	-0.045**	-0.057***
	(0.029)	(0.028)	(0.020)	(0.019)	(0.019)	(0.017)
$FamilyTNA$	-0.011	0.157***	-0.013	0.071***	-0.015	0.025*
	(0.018)	(0.030)	(0.015)	(0.017)	(0.013)	(0.015)
$FamilyFunds$	0.063*	-0.080*	0.131***	-0.017	-0.126***	-0.019
	(0.035)	(0.045)	(0.026)	(0.028)	(0.025)	(0.024)
$Team$	-0.041	-0.046	0.043*	0.008	-0.134***	-0.099***
	(0.036)	(0.031)	(0.026)	(0.021)	(0.023)	(0.019)
$ManagerTenure$	0.021	-0.001	-0.038*	-0.013	0.114***	0.034**
	(0.032)	(0.028)	(0.022)	(0.017)	(0.021)	(0.016)
Observations	102,466	102,466	102,466	102,466	102,466	102,466
Adjusted R2	0.918	0.931	0.951	0.960	0.542	0.660
Time x Style Fixed	Y	Y	Y	Y	Y	Y
Family Fixed	N	Y	N	Y	N	Y

***, ** and * show significance at the 1%, 5% and 10% level respectively.

Table B2: Intended Fund Volatility

This table presents OLS regression results of the following model equation estimated using a sample of U.S. active equity mutual funds from 2000 until 2018:

$$IntendedVolatility_{i,m,t} = \alpha + \beta Coordination_{i,m,t-1} + \Gamma' \boldsymbol{Controls}_{i,m,t-1} + \varepsilon_{i,m,t},$$

where $IntendedVolatility_{i,m,t}$ is the volatility of hypothetical daily fund returns that holds the portfolio stock weights constant of fund i over the quarter prior to the disclosure date of the portfolio holdings at the end of quarter t. The table also reports results with systematic volatility and idiosyncratic volatility obtained from the Carhart (1997) 4-factor model. The $Coordination_{i,m,t-1}$ variable measures whether manager m corresponding to fund i at quarter $t-1$ is likely to engage in strategic multi-fund coordination. $Controls_{i,j,t}$ represents a host of relevant fund, mutual fund family, and manager control variables. The fund controls include the past performance, size, age, fees, and turnover. The mutual fund family controls include the size and number of funds of all active equity funds in the family. The manager control include whether the fund is managed by a multi-fund manager, whether the fund is managed by a team, and the average tenure of all managers in the corresponding fund team. All size and age related variables are transformed by taking the natural logarithmic to reduce the effect of outliers. The standard errors are clustered by fund and are shown in parentheses. The column headers indicate the volatility measure used as the dependent variable in the regression model.

	Volatility		Systematic Volatility		Idiosyncratic Volatility	
	(1)	(2)	(3)	(4)	(5)	(6)
$CoordinationDummy$	0.169***	0.085**	-0.029	-0.026	0.162***	0.064***
	(0.049)	(0.040)	(0.024)	(0.024)	(0.026)	(0.019)
$MultiFund$	-0.052	-0.032	-0.023	-0.016	0.026	0.011
	(0.032)	(0.032)	(0.018)	(0.017)	(0.022)	(0.019)
$PastPerformance$	-0.003	-0.002	0.004	0.004	-0.000	0.000
	(0.005)	(0.005)	(0.003)	(0.003)	(0.002)	(0.002)
$Turnover$	0.160***	0.147***	0.119***	0.098***	0.004	0.008
	(0.027)	(0.024)	(0.013)	(0.012)	(0.019)	(0.014)
$ExpenseRatio$	0.057	0.226***	-0.001	0.069**	0.080*	0.228***
	(0.043)	(0.056)	(0.008)	(0.032)	(0.048)	(0.036)
$FundTNA$	0.013	0.019	0.009	0.009	0.006	0.010
	(0.015)	(0.014)	(0.008)	(0.007)	(0.010)	(0.008)
$FundAge$	-0.073**	-0.023	-0.014	0.008	-0.076***	-0.059***
	(0.034)	(0.035)	(0.017)	(0.016)	(0.022)	(0.020)
$FamilyTNA$	0.028	0.183***	0.020*	0.074***	-0.005	0.034*
	(0.020)	(0.037)	(0.011)	(0.016)	(0.014)	(0.018)
$FamilyFunds$	-0.083**	-0.150***	-0.012	-0.052*	-0.145***	-0.018
	(0.039)	(0.056)	(0.019)	(0.029)	(0.025)	(0.028)
$Team$	-0.101***	-0.054	-0.040**	-0.022	-0.088***	-0.071***
	(0.038)	(0.037)	(0.018)	(0.017)	(0.024)	(0.021)
$ManagerTenure$	0.092***	0.026	0.023	0.017	0.110***	0.034*
	(0.035)	(0.032)	(0.018)	(0.016)	(0.024)	(0.019)
Observations	50,267	50,267	50,267	50,267	50,267	50,267
Adjusted R2	0.929	0.941	0.970	0.973	0.640	0.747
Time x Style Fixed	Y	Y	Y	Y	Y	Y
Family Fixed	N	Y	N	Y	N	Y

***, ** and * show significance at the 1%, 5% and 10% level respectively.