

Skill and Persistence in Mutual Fund Performance: A Manager-Level Assessment*

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April 2015

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JEL Classification: G11; G14; G23

Keywords: Mutual funds, mutual fund performance, portfolio management, fund manager performance, fund manager skill, skill versus luck.

* We thank Louis Ederington and Clemens Sialm for valuable discussions and assistance, and the Price College of Business for research support. We are responsible for any remaining errors.

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Abstract

Using individual portfolio managers as the unit of observation, we provide new evidence that some managers possess skill and persistently outperform over time. For managers who run multiple funds, our approach permits us to compare the performance of the same manager across different funds, and thus more robustly rule out luck as an alternative explanation of outperformance. We show that some managers who run multiple funds exhibit significant persistent cross-sectional outperformance. In particular, we find that the average persistence of benchmark adjusted returns and 4-factor alphas of managers in the CRSP database is higher than one would expect to observe if these managers had no skill, and they had zero benchmark adjusted returns and alphas that are uncorrelated in the cross section and through time. We also find that this cross-sectional persistence of performance persists up to six years. Taken together, our findings imply that, on average, performance of mutual fund managers is not simply due to chance or idiosyncratic events, but rather caused by persistent factors such as managerial skill. We also provide new evidence on managerial busyness by showing that performance drops significantly when managers run multiple funds, especially when these multiple funds have disparate objectives.

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1. Introduction

Mutual fund performance can be attributed to several factors including portfolio manager skill and luck, which are hard to distinguish from one another. This is true especially when the unit of observation is the mutual fund in the empirical tests. In this paper, we provide new evidence on the existence of mutual fund manager skill, using the portfolio manager as the unit of observation. In particular, we provide evidence that some mutual fund managers possess skill and consistently outperform, even when managing multiple funds, while others are unskilled and consistently perform poorly.

The mutual fund literature does not provide a definitive answer to the question of whether mutual fund managers have skill. A long list of studies find that mutual funds, and hence their managers, do not outperform their benchmarks or earn positive alphas that persist (see, for example, Jensen (1968), Gruber (1996), Carhart (1997), Fama and French (2010)). On the other hand, there are studies that document evidence of manager skill (see, for example, Grinblatt and Titman (1989, 1992, and 1993), Kacperczyk, Sialm, and Zheng (2005), Baker, Litov, Wachter, and Wurgler (2010)). A few recent studies explicitly test for luck in manager performance. Kosowski, Timmermann, Wermers, and White (2006) use a bootstrap technique to distinguish skilled managers from the lucky managers and conclude that the performance of the best and worst funds cannot be explained by luck alone and that some managers have the stock picking ability that allows them to more than cover the fund expenses. Barras, Scaillet, and Wermers (2010) control for luck in mutual fund performance and separate mutual funds as unskilled, zero-alpha, and skilled over the period 1975 to 2006. They conclude that about 75.4% percent of funds are zero-alpha and 24% of the funds are unskilled or negative alpha funds. This classification leaves only 0.6% of the fund population that can be classified as skilled, which is

statistically indistinguishable. In addition, similar to Kosowski et al. (2006), Fama and French (2010) use bootstrap simulations to show that when alpha is estimated using gross fund returns there is evidence of both superior and inferior performance in the extreme tails of the alpha estimates.

In the mutual fund literature, when testing managerial skill or persistence in performance, it is common practice to use the mutual fund as the unit of observation rather than the individual manager.¹ The main reason for this choice is that time series data on the identity of fund managers is not readily available.² But using the mutual fund as the unit of observation opens up the possibility of errors in performance measurement due to three reasons.

First, when the performance of individual funds is used to proxy for manager performance, it is implicitly assumed that the manager's identity is tied only to the single fund whose performance is being measured. If a fund generates positive abnormal returns and those returns persist, then one concludes that the manager(s) of that fund has skill. But what if that same manager simultaneously manages other funds, one or more of which generate negative abnormal returns?³ Under this scenario, it is erroneous to argue for the existence of managerial skill because the observed outperformance in one fund may simply be due to luck rather than managerial ability. However, since the existing studies use the mutual fund as the unit of observation, it is not possible, in those studies, to determine if managers consistently outperform their benchmarks or generate positive abnormal returns in all or most of the funds they manage. It is increasingly common for mutual fund managers to manage multiple funds, not only within

¹ See, for example, Grinblatt and Titman (1989), Gruber (1996), Carhart (1997), and Wermers (2010). Notable exceptions are the studies by Chevalier and Ellison (1999b) and Kacperczyk, Nieuwerburgh, and Veldkamp (2014) that we discuss later.

² While CRSP provides the names of managers (only last names when the fund has multiple managers), a unique identifier for those managers is not available.

³ In 2014, each portfolio manager ran an average of 2.32 funds.

the same objective class but also in different objective classes and even in different fund families. Therefore, it is important to account for multiple funds managed by the same manager, which can have a significant effect on the results of managerial skill and persistence studies. Indeed, the average number of funds managed by a manager has been increasing steadily over time, from 1.71 in 1992 to 2.32 in 2014.

Fund-based performance measurement also fails to account for the possibility that managers leave their funds, voluntarily or involuntarily, during the measurement period. This assumption is especially consequential when the persistence of managerial skill is tested. Khorana (2001) finds that mutual fund performance improves (deteriorates) when underperforming (overperforming) managers leave the fund. He also finds evidence that managers engage in risk shifting before replacement and that portfolio turnover decreases after the replacement. Khorana's findings imply that replacement of fund managers represents a significant performance-altering event for a fund, which might result from a change in managerial skill, risk taking behavior, fund expenses due to change in portfolio turnover, etc. Since using the mutual fund as the unit of observation would ignore this performance-changing event, one might incorrectly find that managers have no skill or any such skill does not persist.

Finally, it is assumed that there are no non-manager related factors that affect fund performance. Fund family characteristics also have an impact on fund performance beyond what managerial skill would contribute to it. Gaspar, Massa, and Matos (2006), for example, show that fund families pick favorites (high value funds) and subsidize them at the expense of low value funds by allocating more underpriced IPOs to the high value funds and through opposite trades (coordinated trades). To the extent that fund families can contribute to the performance of their funds beyond what the portfolio managers do, using the mutual fund as the unit of observation

and hence interpreting good fund performance as evidence for managerial skill might be inaccurate. Using the fund manager as the unit of observation can help mitigate these three problems presented above.

In this paper we use the fund manager as the unit of observation to examine whether the observed performance of mutual fund managers is a result of their skill or a result of luck. In order to separate skilled managers from lucky managers, we use the cross-sectional persistence of the performance of funds managed by the same manager during the same quarter. To measure the cross-sectional persistence of a manager's performance, we calculate the standard deviation of the performance ranks of that manager's funds in excess of the standard deviation obtained from a hypothetical sample of managers with no skill. We find that the cross-sectional persistence of manager performance is between 28 to 44 percent, significantly larger than what one would observe if managers had no skill, which suggests that the observed performance of managers cannot be explained by luck alone. We also find that this cross-sectional persistence continues for up to six years. We show that these findings cannot be explained by the possibility that managers invest in similar portfolios, which would mechanically create a cross sectional persistence in manager performance.

Although indirect, we then present evidence that, in addition to the level of manager performance, the cross-sectional persistence of manager performance demonstrates managerial ability, and performance alone cannot fully explain whether a manager has skill or not. In addition, we find that fund families who employ these fund managers take the cross sectional persistence of returns generated by their portfolio managers into account in their decisions to allocate fewer funds to their managers.

Our approach also enables us to study the effect of manager busyness, that is, whether the performance of managers is affected by the number and type of funds they manage. In particular, do managers who run multiple funds perform differently than managers who run a single fund? And do managers who run multiple funds that have the same investment objective and style perform differently from those who run multiple funds with different investment objectives and styles? We document a significant negative effect of managerial busyness. When we focus on the top-performing managers in each category, we observe a significant decline in the average performance of managers when they run more than one fund, which drops even further when those funds are from different objective classes. For example, for the top 10 managers who manage one fund, the average benchmark-adjusted gross return is 14.11%, which reduces by approximately 40 percent to 8.40% when the managers run two or more funds that are in the same objective class. When the funds belong to different objective classes, the average benchmark-adjusted return drops even further, to 5.92%.

Our paper is related to two other studies, by Chevalier and Ellison (1999b) and Kacperczyk, Nieuwerburgh, and Veldkamp (2014) that also relate manager characteristics to fund performance. Chevalier and Ellison (1999b) present a novel approach to measuring mutual fund manager skill by the average SAT score of the manager's undergraduate institution, and relate this skill measure, as well as other manager characteristics, to fund performance. Although Chevalier and Ellison (1999b) use manager characteristics such as SAT score, manager age, and tenure as the explanatory variables of their regressions and hence the unit of observation is the fund manager, they do not examine the consistency in the performance of each fund manager across all funds they manage. For example, their finding that funds with managers who attend selective schools on average outperform those who do not may indicate that managers have some

skill. However, there may be significant variation in the performance of funds managed by the same manager, which would cast doubt on the argument that their findings are "...suggestive that stock-picking ability does exist for a subgroup of managers." If some managers have stock-picking ability, then it is natural to expect that this ability should be reflected in the performance of all funds managed by the same manager. Second, although Chevalier and Ellison (1999b) examine manager termination, they do not follow the managers when they change funds either voluntarily or involuntarily to ascertain whether the documented performance differences persist.

Another study that examines manager skill at the fund manager level is Kacperczyk, Nieuwerburgh, and Veldkamp (2014). They undertake a thorough analysis of stock picking and market timing abilities of mutual fund managers, conditional on the business cycle, and show that managers exhibit different levels of stock picking and market timing skills in booms and recessions. In some of their tests, Kacperczyk, Nieuwerburgh, and Veldkamp (2014) use fund manager as the unit of observation and follow managers over time including when they change funds. They define market timing (stock picking) measure as the covariance of portfolio weights with the aggregate (firm-specific) component of stock returns. When the unit of observation is the manager, every month, they aggregate all the portfolios managed by the same manager, including the funds that are co-managed with other managers. Our study is different from that of Kacperczyk, Nieuwerburgh, and Veldkamp (2014) in that, instead of aggregating portfolios of managers, we estimate the performance of each fund managed by the same manager separately. This way, we are able to examine the persistence of manager performance in the cross-section. Analyzing the cross-sectional persistence of manager performance is important because, as stated above, if a manager truly has skill, then it should be reflected in the performance of all funds managed by that manager. In addition, unlike Kacperczyk, Nieuwerburgh, and Veldkamp's

(2014), our methodology allows us to control for fund objective and family characteristics. Aggregating portfolios managed by the same manager may hide important information related to objective and family characteristics of mutual funds. A fund manager may exhibit more skill in one objective class compared to another. In addition, a manager may be more successful in one fund family compared to another due to reasons other than skill as shown in Gaspar, Massa, and Matos (2006).

Our contribution to the literature is threefold. First, by using the individual managers as our unit of observation, we present new evidence regarding the existence of mutual fund manager skill. Second, we provide a second dimension to the measurement of skill. In particular, we show that average manager performance and the cross-sectional persistence of that performance must be used together to decide whether managers have skill or not. Third, we provide new evidence on managerial busyness by showing that performance drops significantly when managers run multiple funds, and even more when these multiple funds have disparate objectives.

The remainder of the paper proceeds as follows. In Section 2, we describe the data. In Section 3 we provide evidence on managerial skill and examine the cross-sectional persistence of manager performance as a measure of skill in addition to average manager performance. Section 4 concludes.

2. Data

We obtain data from the CRSP Survivor-Bias Free U.S. Mutual Fund Database from January 1992 to June 2014. We retrieve manager names and fund characteristics such as returns, total net assets under management (TNA), and expenses from CRSP and use the manager names

obtained from Morningstar Direct in addition to those from CRSP to assign unique identifiers to fund managers. Many mutual funds offer different share classes that represent claims on the same portfolio. We treat those multiple share class funds as a single fund and calculate asset value weighted averages of fund characteristics such as returns and expenses.

From our sample, we eliminate index funds and, as in Khorana (1996) and Chevalier and Ellison (1999a; 1999b), we restrict our sample to funds managed by a single manager. From 1992 to 2014, there are 20,973 mutual funds, of which 10,172 are single manager funds managed by 5,232 portfolio managers. Table 1 shows the number of funds and managers, in addition to the average, minimum and maximum number of funds per manager each year from 1992 to 2014. The number of funds managed by a single manager increased from 1.71 in 1992 to 2.32 in 2014. In the same period, the total number of managers decreased from 1,260 to 971, while the mean (median) fund size increased from \$387.9 (\$97.4) million to \$1,598.7 (\$218.7) million.

[Place Table 1 about here]

In order to be able to estimate the cross sectional persistence of manager performance, we eliminate those managers with only one fund under management. As presented in Table 2, this results in 8,950 funds in our sample from 1992 to 2014, compared to 20,973 funds in the CRSP database for the same period. The total assets under management averaged over 1992 to 2014 in our sample is about \$2.3 trillion, while it is \$8.3 trillion in the CRSP mutual fund database. The average fund in our sample is about 40% smaller than that in the CRSP database. The mean (median) size assets under management of the funds in our sample is \$979.55 (\$157.00) million, while it is \$1,656.29 (\$223.20) million. This difference is expected since very large funds are more likely to be managed by multiple managers. A comparison of the mean and median

expense ratios in addition to management fees shows that the two samples are very similar in terms of fund expenses and management fees.

[Place Table 2 about here]

In order to measure performance, we use benchmark adjusted return and Fama-French-Carhart 4-factor alpha. We follow Berk and Binsbergen (2013) and use eleven Vanguard index funds as the “alternative investment opportunity set” and define the benchmark adjusted return as the fund return minus the return of the closest portfolio created from the set of Vanguard index funds.

We use mutual fund holdings data from Thomson Reuters Mutual Fund Holdings Database, and construct a measure developed by Yadav (2010) in order to determine the degree to which two or more mutual funds managed by the same manager have common equity holdings. This measure is named “match” and it is defined between two portfolios A and B as the sum of the minimum weight of each stock in portfolios A and B.

$$Match = \sum_{i=1}^N \min(w_{i,A}, w_{i,B})$$

where $w_{i,A}$ and $w_{i,B}$ are the weights of stock i in portfolios A and B respectively and N is the total number of stocks in portfolios A and B. If portfolios A and B have no common stock holdings, *match* is equal to 0. If they are identical, then *match* is equal to 1. If a manager manages more than two funds, we define the *match* for a fund as the average *match* of that fund with other funds. For example, if a manager manages funds A, B, and C, then the *match* for fund A is the average of its match with funds B and C. While the best available, to our knowledge, this *match* measure is not without limitations. First, we can only compare the equity holdings of mutual funds, since Thomson Reuters Mutual Fund Holdings Database provides stock holdings

of funds only. Second, because we only have the stock holdings data, we are able to calculate *match* for a subsample of our main sample.

3 Results

3.1 Cross-sectional persistence

Using the fund manager as the unit of observation gives us the opportunity to conduct a novel test of the skill vs. luck argument. In particular, our data allows us to examine if portfolio managers can consistently generate positive abnormal returns across all funds they manage during the same time period. In other words, we test not only for time-series persistence of managerial skill, as done in the existing literature, but also for cross-sectional persistence.

In order to test for cross-sectional persistence, for each quarter and objective class, we sort the single manager funds into deciles based on their one-quarter lagged performance measures (benchmark adjusted returns and 4-factor alphas).⁴ We then assign these funds a ranking of 1 to 10 from the lowest to the highest performance decile. To assign the funds to the deciles, we conduct a separate sort for each of the 12 objective classes. Table 3 shows the number of managers who simultaneously manage funds from 1, 2, 3, 4, 5, and 6 objective classes each year from 1992 to 2014.

[Place Table 3 about here]

After each fund is assigned a decile rank, we calculate the standard deviation of the ranks in every quarter, for each manager who manages multiple funds. The minimum and maximum standard deviations are 0 and 6.36 respectively. In a given quarter, if a manager manages more

⁴ We created 12 broad objective classes: 1) Domestic equity sector fund; 2) Domestic equity fund; 3) Foreign equity fund; 4) Municipal fund; 5) Corporate bond fund; 6) U.S. Government bond fund; 7) Domestic money market fund; 8) Foreign money market fund; 9) Bond (other) fund; 10) Equity-bond mixed; 11) Mortgage fund; and 12) Currency fund.

than one fund and every single fund is in the same objective-adjusted performance decile, then the standard deviation of the decile ranks is equal to zero. On the other hand, if a manager manages two funds and one fund is in decile 1 and the other is in decile 10, then the standard deviation of the decile ranks is equal to 6.36, which is the maximum possible decile rank standard deviation. Finally, after finding the standard deviation of the decile ranks for each manager in each quarter, we compute the mean and median standard deviations across all managers and quarters.

Table 4 Panel A shows that, using benchmark adjusted returns net of expenses as the performance measure, mean and median standard deviations are 1.7764 and 1.4769 respectively. Using 4-factor alphas calculated from net returns, they are 1.6823 and 1.4142. The mean and median standard deviations using gross returns (returns before fund expenses are subtracted) are similar to the ones found by using net returns. If the mean and median standard deviations obtained from our sample are smaller than those obtained from a hypothetical sample, in which managers have no skill (i.e., all managers manage funds with zero-mean performance that are uncorrelated within each manager and through time), then we infer that the observed performances of managers are not entirely due to luck. Therefore, we compare the standard deviations of the decile ranks obtained from our sample with the mean and median standard deviations obtained from a simulated data in which benchmark adjusted returns and alphas have zero means and are uncorrelated with those of the other funds managed by the same manager, and uncorrelated through time.⁵ The mean and median standard deviations using the simulated data range from 2.4595 to 2.5166, which one would expect to observe when managers have no skill and their performance rankings are purely the result of luck. The mean and median standard

⁵ We follow Carpenter and Lynch (1999), and simulate alphas that are cross-sectionally independent and heteroskedastic. Simulated benchmark adjusted returns are also cross-sectionally independent but homoskedastic. In addition, both the alphas and the benchmark adjusted returns have zero means and are independent across time.

deviations found using our sample are 28% to 44% smaller than those obtained from simulations.⁶ The results in Panel A show that there is a degree of cross-sectional consistency in manager performance within a given time period compared to when these performance measures are randomly drawn from a distribution with a zero mean. This implies that ex post performances of managers are not entirely due to luck, but managers possess some skill or some managers are skilled while others are not.⁷

[Place Table 4 about here]

A possible reason for the results above might be that multi-fund managers may manage funds with similar objectives and hence invest in similar portfolios for all the funds under their control. Therefore, it may be natural to find that, in a given quarter, when one fund ranks high (low) in terms of performance, the other funds managed by the same manager tend to rank high (low). We address this concern in two different ways.

First, we make a slight adjustment in our methodology by calculating, for each manager, the standard deviation of the performance deciles of funds that belong to different objective classes. In particular, we first eliminate all managers who manage funds within the same objective class only. Then, for each manager in each quarter, we find the mean performance ranks of funds that are in the same objective class and find the standard deviation of these mean rankings across different objective classes. For example, if a manager manages five funds, of which two are domestic equity and three are corporate bond funds, we find the average ranks of the two domestic equity and three corporate bond funds separately and find the standard deviation of the mean ranks of these two objective groups. Instead of using the fund style or objective classifications such as the Lipper objective code, as done in most studies, we create 12

⁶ The differences are statistically significant at the 1% level in both Panels A and C.

⁷ 12.4% (13.7%) of the manager-quarters have zero standard deviation when benchmark adjusted returns (alphas) are used.

broad objective classes: 1) Domestic equity sector fund; 2) Domestic equity fund; 3) Foreign equity fund; 4) Municipal fund; 5) Corporate bond fund; 6) U.S. Government bond fund; 7) Domestic money market fund; 8) Foreign money market fund; 9) Bond (other) fund; 10) Equity-bond mixed; 11) Mortgage fund; and 12) Currency fund. Table 3 shows the number of managers who simultaneously manage funds from multiple objectives in each year. In 2014, for example, 65.4% of all managers in our sample managed funds in the same objective class, 26.1% managed funds from two objective classes, and 6.7% managed funds from three different objective classes.

We use this broad objective classification in order to significantly mitigate the possibility that a manager with multiple funds, from different objectives, invests in the same portfolio. For example, it is very unlikely that a manager with a fund in the domestic equity and another one in the corporate fund objective class will invest in identical or similar portfolios. The results are presented in Table 4 Panel B. While the mean and median standard deviations are slightly larger compared to the figures in Panel A, they are 24% to 44% smaller than the simulation results. Therefore, the argument that fund managers may be constructing similar portfolios and hence their funds collectively perform well or poorly does not seem to explain the findings in Panel A of Table 4.

Second, we examine the relationship between the cross sectional persistence of mutual fund managers and the degree with which they hold common equity holdings in the funds they manage. In particular, every quarter, we estimate the *match* for each fund managed by the same manager, to determine the common stock holdings, and we calculate the mean match for each multi-fund manager. Then, we create deciles based on mean *match* and calculate mean and median standard deviations of performance decile rankings of the fund managers. Table 5 shows

that in all deciles, the mean and median standard deviations are less than those obtained from the simulated sample with zero skill managers. The mean (median) standard deviation in decile 1, for example, is 1.894 (1.414), while the mean (median) standard deviation for the simulated sample is 2.4821 (2.4595). Although, as expected, the cross sectional persistence of manager performance increases as the level of common holdings increase, Table 5 shows that, regardless of the level of *match*, the cross sectional persistence of manager performance is greater than what one would expect to observe when the managers truly have no skill. Therefore, our results are not simply an artifact of managers following similar investment strategies.

[Place Table 5 about here]

3.2 Cross-sectional performance persistence through time

In the previous section, we find that there is a degree of consistency in the manager performance within a given time period and thus argue that manager performance is not entirely due to luck. A natural question to ask is, does the consistency in manager performance persist through time? In other words, if the standard deviation of the performance rank of a manager is low in this quarter, does it tend to be low or high in the following quarters?

To answer this question, we sort managers into deciles by 1-quarter lagged standard deviations of their performance rankings. We compute the standard deviations of the performance rankings of managers as in Panel A of Table 4. Then, we keep these deciles for 1, 4, 8, 12, 16, 20, and 24 quarters and report the mean and median standard deviations of performance rankings for each holding period in Table 6. In Panels A, B, C, and D of Table 6, the performance measures are benchmark adjusted net return, alpha based on net return, benchmark adjusted gross return, and gross alpha respectively.

[Place Table 6 about here]

Table 6 shows that from one quarter to six years after sorting managers into standard deviation deciles, the mean and median standard deviations of performance rankings increase almost monotonically in decile rank. This means, low (high) performance-rank-standard deviation managers continue to be low (high) performance-rank-standard deviation managers. This persistence continues up to 6 years after the formation period, which shows that the consistency in manager performance within a time period is not constrained to that single time period but continues 6 years into the future.

Together, Table 4 Panel C and Table 6, show that, on average, good or poor manager performance is not simply due to chance or idiosyncratic events, but rather caused by factors, which tend to persist, such as managerial skill.

3.3 Relative performance and cross-sectional persistence as a measure of skill

In the previous section, we show that the mean and median cross-sectional persistence of manager performance is larger than that could be explained by luck alone. If a manager has a high average performance and a low performance volatility, then it is more likely that this high average performance is a result of skill rather than luck. In addition, if a manager has a low average performance and a low performance volatility, then it is more likely that this manager is unskilled rather than unlucky. A direct test of these arguments is not possible without a good measure of the inherent skills of managers and unfortunately such a measure does not exist. Therefore, we choose the next best alternative and test these arguments indirectly.

Suppose we accept the arguments that if a manager is skilled, then she will have high average performance and low performance volatility, and if a manager has low average

performance and low performance volatility, then she is unskilled. If these two arguments are correct, the following hypotheses should also be correct:

Hypothesis 1: If a manager is skilled in one period, she will more likely be skilled or less likely be unskilled in the next period. Thus, managers with high average performance and low performance volatility in one quarter are more likely to have high average performance and low performance volatility in the next quarter. In addition, managers with high average performance and low performance volatility in one quarter are less likely to have low average performance and low performance volatility in the next quarter.

Hypothesis 2: If a manager is unskilled in this period, she will less likely be skilled or more likely be unskilled in the next period. Thus, managers with low average performance and low performance volatility in one quarter are more likely to have low average performance and low performance volatility in the next quarter. In addition, managers with low average performance and low performance volatility in one quarter are less likely to have high average performance and low performance volatility in the next quarter.

To test these two hypotheses, we create a 4 x 4 contingency table as presented in Table 7. In this table, high rank is defined as average performance decile rank of 8 or above and low rank is defined as average performance decile rank of 3 or below. Low (High) Stdev means the standard deviation of rankings is less (greater) than the one obtained from the simulated data for managers with zero and non-persistent alpha. In Table 7 Panel A, the rows indicate performance and persistence groups in this quarter and the columns show the performance and persistence groups in the next quarter. In Panel B, the columns indicate the performance and persistence groups after four quarters. Table 7 Panel A shows that 89.11% of the managers, who have high performance (*High Rank*) and high cross-sectional persistence (*Low Stdev*) in this quarter,

continue to have high performance and high cross-sectional persistence. Only 10.38% have high performance and low cross-sectional persistence in the next quarter, and less than 0.5% have low rank. In addition, Panel B shows that 75.68% of the managers with high performance and high cross-sectional persistence in one quarter continue to have high performance and high cross-sectional persistence after four quarters. Therefore, managers with high performance rank and high cross-sectional persistence in one period are more likely to have high performance rank and high cross-sectional persistence in the next period.

[Place Table 7 about here]

In addition, 89.17% of the managers, who have low performance and high cross-sectional persistence in this quarter, continue to have low performance and high cross-sectional persistence in the next quarter. As before, only 10.38% have low rank and low cross-sectional persistence, and less than 0.5% have high rank in the next quarter. The percentage of low performance and high cross-sectional persistence managers becomes 75.77 in Panel B.

We hypothesize that if high cross-sectional persistency in good or poor performance is a sign of skill or a lack of skill rather than luck, then one would expect a high cross-sectional performance persistency to remain high over time. Overall, the results presented Table 7 support hypotheses 1 and 2. In light of the evidence provided in Table 7, we argue that without the cross-sectional persistence of a manager's performance, the level of her performance alone is an incomplete or perhaps a misleading indicator of her skill.

3.4 Time-series persistence

There are several tests of time-series persistence of mutual fund returns in the mutual fund literature. Hendricks, Patel, and Zeckhauser (1993), Elton, Gruber, and Blake (1996),

Carhart (1997), Bollen and Busse (2004) are just a few of them. As common in the literature, these studies use the mutual fund as the unit of observation. In this section, we examine the time-series persistence of mutual fund manager performance rather than mutual fund performance.

3.4.1 Persistence of manager performance rankings across time

To examine the time series persistence in fund manager performance, we first extend our analyses in Panels A and B of Table 4. As in Panels A and B, we sort the single manager funds into deciles based on their one-year lagged performance measures and assign them a ranking of 1 to 10 from the lowest to the highest performance. Then, different from these two panels, for each fund, we calculate the standard deviation of these rankings through time and find the mean and median standard deviations across all funds. We repeat the same steps for our simulated sample to make comparisons. Table 4 Panel C shows that the mean and median standard deviations are 11% to 45% smaller than those obtained from simulations, which implies that managerial skill persists over time.

3.4.2 Persistence of manager performance across deciles

In this section, we test for manager performance persistence by constructing performance deciles as in Hendricks, Patel, and Zeckhauser (1993) and Carhart (1997). We start by computing the asset-value-weighted averages of the performance measures for each manager in each quarter. Then, on January 1st of each year, we sort mutual fund managers into deciles according to their 1-year lagged asset-value-weighted average performances. We keep these deciles for 1, 4, 8, and 12 quarters and calculate mean and median manager performance in each decile and report them in Table 8. The performance measures in Panels A, B, C, and D, are benchmark

adjusted net return, alpha based on net return, benchmark adjusted gross return, and gross alpha respectively.

[Place Table 8 about here]

In all Panels of Table 8 and for all time periods the differences in the performance measures between decile 1 and decile 10 are significant at the 1% level. This is true even after controlling for individual stock momentum using 4-factor alphas. Results in Table 8 support the hypothesis that performance of mutual fund managers persist across time.

3.4.3 Test of persistence of manager performance using regression

As an additional test for persistence of manager performance, we examine whether the performance of a single-manager fund in quarter t (Fund A_t) is related to the lagged 1-quarter performance of the same fund (Fund A_{t-1}) and the lagged 1-quarter performance of another fund (Fund B_{t-1}) managed by the same manager. A manager can manage more than two funds in the same period. Therefore, we define Fund A and Fund B as follows. Suppose that in a given quarter a manager has N funds. These funds are numbered from 1 to N . First, fund 1 is defined as Fund A and fund 2 is Fund B. This is the first observation for our manager in that quarter. Then, while fund 1 is still Fund A, fund 3 is defined as Fund B, creating a new observation for that manager in the same quarter. This process continues until fund N is defined as Fund B, which creates a total of $N - 1$ observations for that manager in that quarter. Second, fund 2 is defined as Fund A. While fund 2 is still Fund A, funds 1, and funds 3 to N are defined as Fund B separately, creating a total of $N - 1$ new observations. This process is repeated until all funds from 1 to N become the dependent variable.

The regression results are reported in Table 9. In Panel A, benchmark adjusted returns and 4-factor alphas are calculated using mutual fund returns net of expenses. In Panel B, benchmark adjusted returns and 4-factor alphas are calculated using gross returns. We estimate standard errors clustered by manager and year and report p-values in parentheses.

[Place Table 9 about here]

In the models without the lagged performance of Fund A (columns 2 and 4 of Table 9), the coefficient estimates of Fund B_{t-1} are positive and significant at the 1% level. This indicates that managers are responsible for persistence. In columns 3 and 5 of Table 9, we present the results with the performance of Fund A_{t-1} added as an explanatory variable. After including Fund A_{t-1} the coefficient estimates of Fund B_{t-1} are still positive and significant at the 1% level. This further suggests that managerial skill causes mutual fund performance to persist.

3.5 Determinants of increases and decreases in the number of funds managed

To the extent that skilled mutual fund managers can be identified by investors or fund families, these skilled managers should be better compensated than those that are unskilled or simply lucky. For most mutual fund managers, compensation is a function of the value of assets under management (AUM) and there may be a direct link between compensation and AUM for some managers. For a portfolio manager, increases or decreases in AUM can happen in two different ways. First, because of inflows to or outflows from existing funds, size of funds managed by a manager may change. Second, a manager may be given more funds to manage or may lose funds that are currently under management of that manager. Inflows to a fund are controlled by investors rather than fund families. In other words, a fund family cannot reward a skilled manager with greater inflows. On the other hand, only fund families can reward skilled

managers by giving them more funds to manage. In this section, we examine the decision by the fund families to increase or decrease the number of funds managed by their managers and show that both the average performance and the cross-sectional persistence of performance affect manager compensation in the form of increases or decreases in the number of funds managed.

We use a multinomial logit (MNL) model with three events: 1) no change in the number of funds managed, 2) increase in the number of funds managed, and 3) decrease in the number of funds managed. We report standard errors adjusted for clustering on fund family and time. The results are presented in Table 10. In our regression models, *Performance* is the asset-weighted average of the benchmark adjusted gross returns of a manager averaged over the last 4 or 8 quarters. *Stdev* is the standard deviation of the performance rankings of a manager's funds, averaged over the past 4 and 8 quarters. *High Return*Stdev* is equal to *Stdev* multiplied by *High Return*, where *High Return* is a dummy variable, which takes the value 1 if the *Performance* of a manager is greater than the asset-weighted average of the benchmark adjusted returns of funds in the same objective classification, and zero otherwise. *Inflow* is the average quarterly asset growth rate net of holding period returns. *Size* is the natural logarithm of the one quarter lagged total assets under management. *Number of funds managed* is the number of funds managed by each manager. *Number of objective classes* is the number of unique objective classes that a portfolio manager manages funds from. *Objective performance* is the value-weighted average holding period returns of an objective class in each period calculated after excluding the fund for which this variable is calculated. *Objective inflow* is the value-weighted average fund inflows of an objective class in each period calculated after excluding the fund for which this variable is calculated. We include year dummies in all models.

[Place Table 10 about here]

Table 10 shows that the performance of a manager, averaged across all funds she manages over the past 4 and 8 quarters, is inversely related with the likelihood of a decrease in the number of funds that manager manages. For example, for the decrease category, the multinomial logit coefficient estimate of *Performance* when it is averaged over the last 4 quarters is -0.0518, which is statistically significant at the 1% level. This means, a 1% increase in the past performance of a manager is associated with a 5% decrease in the predicted odds of a decrease in the number of funds managed by that manager. When *Performance* is measured over the past 8 quarters, the odds ratio falls from 0.95 to 0.88, which means the decrease in the predicted odds becomes 12% in response to a 1% increase in a manager's performance.

Table 10 shows that the cross sectional persistence of a manager's performance also plays an important role in the likelihood of a fund family reducing the number of funds assigned to a manager. In particular, for the decrease category, the coefficient estimate of *Stdev* when it is averaged over the last 4 quarters is 0.2802, which is statistically significant at the 1% level. The odds ratio for *Stdev* is 1.32, which shows that a 1 unit increase in *Stdev*, is expected to increase the odds of a decrease in the number of funds managed by a manager by 32%. This implies that fund families penalize managers for inconsistent performance, which may further imply that they see a high variation in a manager's performance as a sign of lack of skill. The coefficient estimate of *Performance*Stdev*, which is 0.0859 and statistically significant at the 5% level for the decrease category, further supports this argument. For managers who perform better than others in the same objective classification, the odds of a decrease in the number of funds managed increases by an additional 9% for 1 unit increase in *Stdev*.

Overall, Table 10 shows that, fund families allocate fewer funds to managers with inconsistent performance and hence they take the cross sectional persistence in performance into

account when they decide on allocating their mutual funds to portfolio managers. We argue that fund families consider a low persistence in performance as a sign of lack of skill.

3.6 Manager busyness and performance

In the previous sections, we provide evidence that the performance of managers who run multiple funds exhibit significant cross-sectional persistence. Additionally, our findings in the prior section suggests that fund families allocate more funds to successful managers, and *vice versa*. Nonetheless, a question that naturally arises is whether the performance of managers is affected by the number and type of funds they manage. In particular, do managers who run multiple funds perform differently than managers who run a single fund? And do managers who run multiple funds that have the same investment objective and style perform differently from those who run multiple funds with different investment objectives and styles?

We answer this question by comparing the performance of top-performing managers who manage 1) one fund only; 2) two or more funds from the same objective class; and 3) two or more funds from different objective classes. In addition to classifying managers based on the number and type of funds they manage, we create three sub-samples by drawing annually from the lists of: 1) top 10 managers; 2) top 100 managers; and 3) top 10 percent of all managers; and using this data in conjunction with the list of all managers in the sample from 1992 to 2014. We then calculate the average quarterly performance for each group and present the results in Table 11. The performance measures used are benchmark-adjusted returns and 4-factor alphas estimated from gross fund returns (after expenses are added).

[Place Table 11 about here]

Table 11 documents a significant decline in the average performance of managers when they run more than one fund. The performance drops further when those funds are from different objective classes. The differences in performance are statistically significant at 1% level in all groups with two exceptions that are in the all managers sample. For the top 10 managers who manage one fund, for example, the average benchmark adjusted gross return is 14.11%, which reduces by approximately 40 percent to 8.40% when the managers run two or more funds that are in the same objective class. When the funds belong to different objective classes, the average benchmark adjusted return reduces to 5.92%, which is a 30 percent decline from 8.40%. A similar pattern is observed for the other samples except the all-managers sample, which implies that such a pattern is more pronounced for managers who outperform.

Table 12 contains the names of the managers who consistently enter the top 100 managers list. In particular, it presents the names of all managers who are ranked within top 100 for at least 5 years over our 22-year sample period. One manager enters this list for 11 years over the 22-year sample period, which is the highest number of years a manager stays in this list. The second-ranked manager enters the list for 9 years. There are a total of 52 managers who stay on this top 100 performing managers list for at least 5 years.

[Place Table 12 about here]

4 Conclusion

When historical performance of mutual funds is examined, it is not easy to distinguish luck from skill, especially when the unit of measurement is the mutual fund rather than the fund manager. In this paper, using mutual fund data at the fund manager level, we present evidence that some fund managers are skilled while others are not. In particular, we show that the average

persistence of benchmark adjusted returns and 4-factor alphas of managers in the CRSP database is higher than what one would expect to observe if these managers had no skill and they had zero benchmark-adjusted returns, and alphas that are uncorrelated in the cross section and through time. We also find that this cross-sectional persistence of performance persists up to 6 years.

Together, these findings imply that, on average, performance of mutual fund managers is not simply due to chance or idiosyncratic events, but rather caused by persistent factors such as managerial skill. Our findings suggest that fund families, which have an informational advantage over mutual fund investors about portfolio managers' skill levels, may use the cross-sectional persistence of managers' performance in their decision making processes when they decide whether they will increase or reduce the number of funds allocated to their managers or not. Nonetheless, our findings also suggest that increasing the number of funds run by a manager comes at the cost of a decline in performance, especially when the funds have disparate objectives.

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Table 1. Summary statistics of mutual funds and managers

This table reports the summary statistics of mutual funds and fund managers. The sample period is from January 1992 to June 2014. In each year, the number of funds, number of managers, and number of funds per manager (average, minimum, and maximum) are presented. In addition, the average, median, and total values of the net assets under management are reported.

Year	# funds	# managers	Avg. # funds per manager	Min # funds per manager	Max # funds per manager	Avg. TNA (in millions)	Median TNA (in millions)	Sum TNA (in millions)
1992	2,151	1,260	1.71	1	20	387.9	97.4	816,157.3
1993	2,576	1,470	1.75	1	22	436.4	101.0	1,107,939.9
1994	2,791	1,546	1.81	1	19	427.4	91.0	1,180,890.0
1995	2,805	1,551	1.81	1	19	557.7	112.4	1,557,551.1
1996	2,732	1,523	1.79	1	19	654.0	130.5	1,780,080.5
1997	2,832	1,605	1.76	1	19	723.1	130.0	2,035,485.9
1998	3,035	1,636	1.86	1	19	800.8	123.4	2,407,904.1
1999	3,006	1,570	1.91	1	19	1,007.5	138.8	3,011,350.4
2000	3,048	1,550	1.97	1	19	958.5	140.3	2,908,979.3
2001	2,895	1,419	2.04	1	19	875.7	135.3	2,522,814.5
2002	2,772	1,357	2.04	1	19	839.2	129.6	2,313,617.6
2003	2,630	1,275	2.06	1	20	975.9	167.9	2,555,005.5
2004	2,469	1,175	2.10	1	20	1,019.7	164.2	2,510,520.7
2005	2,470	1,147	2.15	1	20	1,086.7	184.3	2,676,494.1
2006	2,418	1,096	2.21	1	22	1,271.6	218.0	3,060,827.2
2007	2,414	1,063	2.27	1	22	1,371.2	208.6	3,299,080.4
2008	2,415	1,046	2.31	1	26	923.6	131.6	2,214,823.7
2009	2,202	999	2.20	1	28	1,333.5	195.3	2,889,778.7
2010	2,107	961	2.19	1	24	1,488.5	234.1	3,113,950.6
2011	2,189	991	2.21	1	24	1,424.8	212.6	3,108,931.4
2012	2,172	986	2.20	1	24	1,529.4	217.3	3,306,655.1
2013	2,224	986	2.26	1	26	1,600.2	220.1	3,542,899.8
2014	2,253	971	2.32	1	28	1,598.7	218.7	3,585,937.3

Table 2. Summary statistics

This table presents a comparison of the summary statistics of the sample used in this study and the CRSP universe in terms of the number of funds, total size of the funds, and mean and median values of the value of total net assets under management, expense ratios, and management fees. Number of funds is the total number of mutual funds from 1992 to 2014. Total size of funds is the average of the total net assets of all funds in each year. Number of families is the total number of fund families from 1992 to 2014. Fund size, expense ratio, and management fees are the mean and median values of total net assets, expense ratio, and management fees of all funds from 1992 to 2014.

	Sample		CRSP Universe	
Number of funds	8,950		20,973	
Total size of funds (\$ million)	2,307,931		8,298,690	
Number of families	847		1,798	
	Mean	Median	Mean	Median
Fund size (\$ million)	979.55	157.00	1,656.29	223.20
Expense ratio (%)	1.05	0.0098	1.09	1.03
Management fee (%)	0.50	0.54	0.20	0.52

Table 3. Multi-fund manager counts and objective classification

This table reports the total number of mutual fund managers with multiple funds under management and the number of managers, who manage funds from 1, 2, 3, 4, and 6 objective classes each year from 1992 to 2014. A mutual fund can belong to one of twelve broad objective classes: 1) Domestic equity sector fund; 2) Domestic equity fund; 3) Foreign equity fund; 4) Municipal fund; 5) Corporate bond fund; 6) U.S. Government bond fund; 7) Domestic money market fund; 8) Foreign money market fund; 9) Bond (other) fund; 10) Equity-bond mixed; 11) Mortgage fund; and 12) Currency fund.

Year	Total number of managers	Number of objective classes					
		1	2	3	4	5	6
1992	562	358	173	20	10	1	0
1993	692	438	210	32	12	0	0
1994	780	518	210	45	6	1	0
1995	857	587	217	48	4	0	1
1996	853	591	227	32	2	0	1
1997	905	663	206	30	4	1	1
1998	990	739	209	32	8	2	0
1999	1,018	749	221	40	8	0	0
2000	1,018	748	227	34	8	0	1
2001	1,017	773	209	30	5	0	0
2002	957	731	185	37	4	0	0
2003	866	656	160	45	3	2	0
2004	826	631	153	35	6	1	0
2005	816	616	160	31	9	0	0
2006	793	599	157	34	2	1	0
2007	778	593	138	40	5	2	0
2008	770	572	154	36	7	0	1
2009	721	527	151	35	7	0	1
2010	685	503	140	35	5	2	0
2011	689	492	156	34	3	3	1
2012	679	472	163	32	8	1	3
2013	701	484	167	35	12	3	0
2014	625	409	163	42	7	4	0

Table 4. Cross-sectional performance persistence

This table presents mean and median standard deviations of performance decile rankings of mutual fund managers, who manage more than one fund and are the only managers in the funds they manage. In Panel A, for each year and objective class, single manager funds are sorted into deciles based on their one-year lagged performance measures, which are benchmark adjusted returns and 4-factor alphas. Funds are assigned a ranking of 1 to 10 from the lowest to the highest performance decile. Then, each year, standard deviation of the decile ranks of each manager is calculated and the overall mean and median of those standard deviations are found. In addition, mean and median standard deviations are also obtained from simulated data, in which benchmark adjusted returns and alphas have zero means and are uncorrelated with the funds managed by the same manager and through time. In Panel B, managers who manage funds within the same objective class only are eliminated. Then, for each manager in each year, the mean performance ranks of funds in the same objective class are calculated and the standard deviations of these mean rankings across different objective classes are found. For example, if a manager manages five funds, of which two are domestic equity and three are corporate bond funds, we find the average rank of the two domestic equity and three corporate bond funds separately and find the standard deviation of the mean ranks of these two objective groups. Panel C shows the time series persistence in manager performance. As in Panels A and B, single manager funds are sorted into deciles based on their one-year lagged performance measures and a ranking of 1 to 10 from the lowest to the highest performance is assigned. Then, for each fund, the standard deviation of these rankings through time is calculated and the mean and median standard deviations across all funds are found.

		Benchmark adjusted		Alpha	
		Mean	Median	Mean	Median
Panel A					
Sample period	Net of Expenses	1.7764	1.4769	1.6823	1.4142
	Gross	1.7787	1.4142	1.6884	1.4142
Simulated sample		2.4821	2.4595	2.5008	2.5166
Panel B					
Sample period	Net of Expenses	1.8789	1.5275	1.8118	1.4142
	Gross	1.8880	1.5275	1.8246	1.4142
Simulated sample		2.4821	2.4595	2.5008	2.5166
Panel C					
Sample period		2.3936	2.5166	1.6004	1.5275
Simulated sample		2.6137	2.7112	2.5917	2.6458

Table 5. Common equity holdings of funds and cross-sectional persistence

This table presents the cross sectional persistence of mutual fund managers in relation to the degree with which they hold common equity holdings in the funds they manage. In particular, the table shows the mean and median standard deviations of performance decile rankings for each manager decile formed based on the common stock holdings measure named match. Match (m) measures the degree to which two or more mutual funds managed by the same manager have common equity holdings. It is defined between two portfolios A and B as the sum of the minimum weight of each stock in portfolios A and B.

$$Match = \sum_{i=1}^N \min(w_{i,A}, w_{i,B})$$

where $w_{i,A}$ and $w_{i,B}$ are the weights of stock i in portfolios A and B respectively and N is the total number of stocks in portfolios A and B. If portfolios A and B have no common stock holdings, *match* is equal to 0. If they are identical, then match is equal to 1. If a manager manages more than two funds, we define the *match* for a fund as the average *match* of that fund with other funds. For example, if a manager manages funds A, B, and C, then the *match* for fund A is the average of its match with funds B and C.

Decile	Match (m)	Standard Deviation (Mean)	Standard Deviation (Median)
1	$m \leq 0.05$	1.894	1.414
2	$0.05 < m \leq 0.12$	2.055	1.528
3	$0.12 < m \leq 0.19$	1.876	1.414
4	$0.19 < m \leq 0.27$	1.872	1.414
5	$0.27 < m \leq 0.36$	1.668	1.414
6	$0.36 < m \leq 0.46$	1.551	1.414
7	$0.46 < m \leq 0.58$	1.407	1.095
8	$0.58 < m \leq 0.74$	1.382	1.155
9	$0.74 < m \leq 0.90$	1.043	0.707
10	$0.90 < match$	0.760	0.707

Table 6. Persistence of the cross-sectional variation in performance deciles of managers

This table presents the time-series persistence of the cross sectional variation in the performance deciles of managers. Each quarter, managers are sorted into deciles by 1-quarter lagged standard deviations of their performance rankings. These deciles are kept for 1, 4, 8, 12, 16, 20, and 24 quarters and mean and median standard deviations of performance rankings are reported for each holding period. In Panels A, B, C, and D, the performance measures are benchmark adjusted net return, alpha based on net return, benchmark adjusted gross return, and gross alpha respectively. In order to calculate the standard deviations of the performance rankings of managers, in each quarter and objective class, single manager funds are sorted into deciles based on their one-quarter lagged performance measures. Funds are assigned a ranking of 1 to 10 from the lowest to the highest performance decile. Then, each quarter, standard deviation of the decile ranks of each manager is calculated.

Decile	(t, t+1)	(t, t+4)	(t, t+8)	(t, t+12)	(t, t+16)	(t, t+20)	(t, t+24)	(t, t+1)	(t, t+4)	(t, t+8)	(t, t+12)	(t, t+16)	(t, t+20)	(t, t+24)
	Mean							Median						
Panel A: Benchmark adjusted returns net of expenses														
1	1.32	1.32	1.34	1.35	1.35	1.36	1.36	0.71	1.10	1.19	1.22	1.24	1.24	1.24
2	1.29	1.32	1.34	1.36	1.37	1.38	1.38	0.82	1.16	1.20	1.24	1.26	1.27	1.28
3	1.28	1.29	1.30	1.31	1.32	1.32	1.32	0.71	1.06	1.15	1.18	1.20	1.20	1.21
4	1.56	1.58	1.58	1.59	1.59	1.59	1.60	1.36	1.45	1.48	1.50	1.51	1.52	1.52
5	1.57	1.56	1.57	1.57	1.58	1.58	1.58	1.41	1.41	1.48	1.49	1.50	1.51	1.53
6	1.87	1.81	1.81	1.81	1.80	1.80	1.80	1.73	1.76	1.77	1.77	1.77	1.76	1.76
7	1.89	1.87	1.87	1.87	1.87	1.86	1.86	1.79	1.85	1.86	1.86	1.86	1.85	1.85
8	2.10	2.09	2.07	2.06	2.06	2.05	2.04	2.12	2.11	2.08	2.06	2.06	2.06	2.05
9	2.28	2.26	2.22	2.20	2.19	2.19	2.19	2.27	2.29	2.21	2.20	2.19	2.19	2.19
10	2.50	2.46	2.40	2.37	2.35	2.34	2.34	2.52	2.47	2.39	2.36	2.33	2.32	2.33
Panel B: 4-factor alphas net of expenses														
1	0.83	0.95	1.01	1.04	1.04	1.04	1.05	0.58	0.58	0.71	0.71	0.71	0.71	0.72
2	0.77	0.92	1.01	1.06	1.08	1.09	1.10	0.71	0.71	0.80	0.87	0.88	0.91	0.93
3	0.77	0.88	0.95	0.97	0.98	0.99	0.99	0.71	0.71	0.71	0.73	0.75	0.75	0.76
4	1.20	1.31	1.36	1.38	1.39	1.39	1.39	1.13	1.16	1.21	1.24	1.25	1.25	1.24
5	1.29	1.36	1.39	1.41	1.42	1.42	1.43	1.29	1.25	1.30	1.33	1.34	1.36	1.38
6	1.60	1.64	1.66	1.66	1.66	1.66	1.66	1.53	1.58	1.61	1.61	1.63	1.63	1.62
7	1.93	1.89	1.87	1.85	1.84	1.83	1.83	2.00	1.90	1.86	1.85	1.85	1.83	1.83
8	2.36	2.22	2.13	2.09	2.07	2.06	2.06	2.38	2.25	2.12	2.12	2.08	2.07	2.05
9	2.89	2.64	2.49	2.42	2.39	2.38	2.37	2.89	2.71	2.53	2.47	2.42	2.38	2.38
10	3.83	3.38	3.08	2.95	2.90	2.87	2.85	3.79	3.49	3.11	2.92	2.83	2.83	2.80

Table 6 - continued

Decile	(t, t+1)	(t, t+4)	(t, t+8)	(t, t+12)	(t, t+16)	(t, t+20)	(t, t+24)	(t, t+1)	(t, t+4)	(t, t+8)	(t, t+12)	(t, t+16)	(t, t+20)	(t, t+24)
	Mean							Median						
Panel C: Benchmark adjusted gross returns														
1	1.33	1.33	1.34	1.35	1.36	1.36	1.36	0.71	1.09	1.19	1.24	1.24	1.24	1.25
2	1.32	1.35	1.36	1.37	1.38	1.38	1.38	0.96	1.22	1.24	1.26	1.28	1.29	1.29
3	1.27	1.30	1.32	1.34	1.34	1.34	1.35	0.71	1.08	1.19	1.24	1.24	1.24	1.24
4	1.55	1.57	1.58	1.57	1.57	1.58	1.58	1.38	1.43	1.50	1.50	1.51	1.51	1.50
5	1.59	1.58	1.59	1.59	1.59	1.59	1.59	1.41	1.44	1.50	1.52	1.51	1.51	1.50
6	1.85	1.81	1.80	1.80	1.80	1.80	1.79	1.73	1.76	1.75	1.73	1.73	1.73	1.72
7	1.89	1.87	1.87	1.87	1.86	1.86	1.86	1.76	1.79	1.85	1.84	1.84	1.84	1.84
8	2.09	2.07	2.06	2.05	2.04	2.04	2.03	2.12	2.08	2.05	2.04	2.04	2.03	2.03
9	2.29	2.28	2.24	2.22	2.21	2.21	2.20	2.26	2.30	2.24	2.23	2.22	2.20	2.21
10	2.49	2.44	2.39	2.37	2.35	2.34	2.34	2.38	2.47	2.38	2.36	2.32	2.32	2.32
Panel D: 4-factor alphas estimated from gross returns														
1	0.80	0.92	0.98	0.99	1.00	1.00	1.00	0.50	0.53	0.69	0.71	0.71	0.71	0.71
2	0.78	0.97	1.06	1.10	1.11	1.12	1.13	0.71	0.72	0.88	0.90	0.91	0.94	0.94
3	0.77	0.89	0.97	1.00	1.01	1.02	1.01	0.71	0.71	0.72	0.77	0.80	0.81	0.81
4	1.18	1.28	1.34	1.36	1.37	1.37	1.37	1.13	1.15	1.18	1.18	1.21	1.21	1.22
5	1.30	1.35	1.38	1.39	1.40	1.41	1.41	1.29	1.24	1.27	1.30	1.31	1.33	1.34
6	1.64	1.65	1.66	1.67	1.66	1.65	1.65	1.53	1.59	1.60	1.60	1.59	1.59	1.58
7	1.95	1.90	1.86	1.84	1.83	1.82	1.81	2.06	1.87	1.79	1.78	1.77	1.77	1.77
8	2.40	2.26	2.17	2.13	2.11	2.10	2.09	2.50	2.30	2.16	2.12	2.11	2.09	2.08
9	2.90	2.64	2.50	2.44	2.41	2.40	2.39	2.95	2.75	2.55	2.46	2.42	2.41	2.40
10	3.89	3.44	3.15	3.02	2.96	2.93	2.91	4.00	3.54	3.20	3.01	2.91	2.86	2.83

Table 7. Transition matrix of average performance and cross-sectional persistence rank

This table presents the transition matrix of managers' average performance and cross-sectional persistence rankings from quarter Q to quarters Q + 1 and Q + 4. Managers with average performance decile rank of 8 or above are classified as High Rank, and managers with average performance decile rank of 3 or below are classified as Low Rank. Managers with negative excess standard deviations are classified as Low Stdev and those with positive excess standard deviations are classified as High Stdev. Excess standard deviation is defined as the difference between the standard deviation of performance rankings of a manager's funds in a given quarter obtained from the actual sample and the simulated data with unskilled managers.

		Next Quarter				
		High Rank & Low Stdev	High Rank & High Stdev	Low Rank & High Stdev	Low Rank & Low Stdev	Total
This Quarter		Panel A: Q + 1				
High Rank & Low Stdev	89.11%	10.38%	0.26%	0.26%		771
High Rank & High Stdev	28.72%	70.61%	0.68%	0.00%		296
Low Rank & High Stdev	0.40%	1.98%	67.98%	29.64%		253
Low Rank & Low Stdev	0.30%	0.15%	10.38%	89.17%		665
This Quarter		Panel B: Q + 4				
High Rank & Low Stdev	75.68%	16.54%	2.53%	5.25%		514
High Rank & High Stdev	45.14%	43.43%	3.43%	8.00%		175
Low Rank & High Stdev	8.45%	3.52%	38.73%	49.30%		142
Low Rank & Low Stdev	5.93%	2.32%	15.98%	75.77%		388

Table 8. Persistence of average manager performance across deciles

This table presents the 1-, 4-, 8-, and 12-quarter persistence of average quarterly performance of managers. In each quarter, the asset-value-weighted averages of the performance measures for each manager are calculated and on January 1st of each year, mutual fund managers are sorted into deciles according to their 1-year lagged asset value weighted average performances. These deciles are kept for 1, 4, 8, and 12 quarters and then mean and median manager performance in each decile is calculated. In Panels A, B, C, and D, the performance measures are benchmark adjusted net return, alpha based on net return, benchmark adjusted gross return, and gross alpha respectively.

Decile	(t, t+1)	(t, t+4)	(t, t+8)	(t, t+12)	(t, t+1)	(t, t+4)	(t, t+8)	(t, t+12)
	Mean (%)				Median (%)			
Panel A: Benchmark adjusted returns net of expenses								
1	-0.50	-0.50	-0.42	-0.43	-0.47	-0.36	-0.27	-0.23
2	-0.39	-0.32	-0.28	-0.28	-0.49	-0.38	-0.33	-0.36
3	-0.32	-0.27	-0.28	-0.28	-0.32	-0.29	-0.28	-0.29
4	-0.18	-0.19	-0.18	-0.18	-0.12	-0.14	-0.15	-0.14
5	-0.21	-0.21	-0.18	-0.16	-0.14	-0.14	-0.14	-0.13
6	-0.17	-0.13	-0.14	-0.12	-0.09	-0.09	-0.09	-0.09
7	-0.18	-0.08	-0.07	-0.10	-0.04	-0.01	-0.03	-0.03
8	-0.06	-0.02	-0.07	-0.12	-0.02	0.03	-0.00	-0.02
9	0.21	0.14	0.01	-0.07	0.09	0.13	0.01	-0.02
10	1.44	1.01	0.76	0.60	0.77	0.43	0.21	0.08
Panel B: 4-factor alphas net of expenses								
1	-0.96	-0.56	-0.40	-0.37	-0.78	-0.37	-0.28	-0.26
2	-0.93	-0.81	-0.69	-0.59	-0.88	-0.78	-0.65	-0.57
3	-0.55	-0.48	-0.40	-0.34	-0.48	-0.42	-0.38	-0.35
4	-0.34	-0.31	-0.27	-0.24	-0.32	-0.29	-0.27	-0.25
5	-0.20	-0.20	-0.19	-0.17	-0.14	-0.14	-0.14	-0.13
6	-0.07	-0.11	-0.12	-0.10	-0.06	-0.09	-0.10	-0.09
7	0.11	0.06	0.04	0.02	0.01	-0.04	-0.06	-0.06
8	0.32	0.23	0.15	0.10	0.12	0.04	0.01	0.00
9	0.60	0.44	0.28	0.16	0.55	0.34	0.17	0.10
10	1.82	1.49	1.09	0.78	1.55	1.23	0.87	0.62

Table 8 - continued

Decile	(t, t+1)	(t, t+4)	(t, t+8)	(t, t+12)	(t,t+1)	(t, t+4)	(t, t+8)	(t,t+12)
	Mean (%)				Median (%)			
Panel C: Benchmark adjusted gross returns								
1	-0.13	-0.10	-0.03	-0.03	-0.14	-0.04	0.05	0.07
2	-0.04	0.03	0.06	0.05	-0.21	-0.11	-0.08	-0.09
3	0.01	0.01	0.03	0.02	-0.05	-0.04	-0.02	-0.00
4	0.03	0.04	0.05	0.06	0.06	0.05	0.05	0.07
5	0.00	0.02	0.06	0.08	0.04	0.05	0.06	0.07
6	0.05	0.09	0.10	0.10	0.08	0.09	0.10	0.10
7	0.04	0.17	0.15	0.14	0.12	0.16	0.14	0.13
8	0.20	0.25	0.20	0.15	0.15	0.19	0.18	0.17
9	0.56	0.45	0.32	0.24	0.38	0.41	0.24	0.23
10	1.86	1.38	1.11	0.94	1.16	0.76	0.55	0.37
Panel D: 4-factor gross alphas								
1	-0.60	-0.22	-0.05	-0.02	-0.45	-0.12	-0.00	0.02
2	-0.61	-0.49	-0.36	-0.27	-0.55	-0.44	-0.31	-0.26
3	-0.30	-0.23	-0.15	-0.10	-0.25	-0.20	-0.17	-0.14
4	-0.11	-0.08	-0.04	-0.01	-0.05	-0.02	-0.01	0.00
5	0.03	0.03	0.05	0.07	0.06	0.06	0.07	0.07
6	0.17	0.12	0.11	0.12	0.13	0.10	0.09	0.09
7	0.36	0.30	0.27	0.25	0.18	0.14	0.13	0.13
8	0.58	0.49	0.40	0.34	0.43	0.28	0.19	0.17
9	0.91	0.74	0.58	0.46	0.85	0.69	0.52	0.42
10	2.18	1.85	1.45	1.14	1.90	1.58	1.23	0.95

Table 9. Fund performance regressed on the lagged performance of the other fund

This table presents the relationship between the performance of a single-manager fund in quarter t (Fund A_t) with the lagged 1-quarter performance of the same fund and (Fund A_{t-1}) and the lagged 1-quarter performance of another fund (Fund B_{t-1}) managed by the same manager. Since a manager can manage more than two funds in the same year, Fund A and Fund B are defined as follows. Suppose that in a given year a manager has N funds. These funds are numbered from 1 to N . First, fund 1 is defined as Fund A and fund 2 is Fund B. Then, while fund 1 is still Fund A, fund 3 becomes Fund B, creating a new observation for the regression. This process continues until fund N is defined as Fund B, which creates a total of $N - 1$ observations for that manager in that year. Second, fund 2 is defined as Fund A. While fund 2 is still Fund A, funds 1, and funds 3 to N are defined as Fund B separately, creating a total of $N - 1$ new observations. This process is repeated until all funds from 1 to N become the dependent variable. Standard errors are clustered by manager and year. P-values are reported in parentheses. The notation *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Benchmark adjusted return		4-factor alpha	
	Fund A_t	Fund A_t	Fund A_t	Fund A_t
Panel A: Net of expenses				
Intercept	-0.002*** (<.0001)	-0.002*** (<.0001)	-0.001*** (<.0001)	-0.000*** (<.0001)
Fund A_{t-1}		0.042 (0.143)		0.926*** (<.0001)
Fund B_{t-1}	0.056*** (<.0001)	0.042*** (0.001)	0.332*** (<.0001)	0.015*** (<.0001)
Num. of Obs.	330640	329457	276136	274514
Adjusted R^2	0.002781	0.004465	0.1340	0.8861
Panel B: Gross				
Intercept	0.001* (0.065)	0.001* (0.076)	0.001*** (<.0001)	-0.000 (0.405)
Fund A_{t-1}		0.040 (0.168)		0.924*** (<.0001)
Fund B_{t-1}	0.051*** (<.0001)	0.038*** (0.002)	0.320*** (<.0001)	0.014*** (<.0001)
Num. of Obs.	319998	318807	270429	268831
Adjusted R^2	0.002384	0.003912	0.1249	0.8832

Table 10. Multinomial logit regressions: The effect of cross-sectional performance persistence on the increase and decrease in the number of funds assigned to the managers

This table presents results from a multinomial logit model with 3 events: no change, increase, and decrease in the number of funds managed. Standard errors are adjusted for clustering on fund family and time. Performance is the asset-weighted average of the benchmark adjusted gross returns of a manager averaged over the last N quarters (in models 1 and 2, N is equal to 4 and 8 respectively). Stdev is the standard deviation of a manager’s performance rank averaged over the last N quarters. High Return*Stdev is equal to Stdev multiplied by High Return, where High Return is a dummy variable, which takes the value 1 if the Performance of a manager is greater than the asset-weighted average of the benchmark adjusted returns of funds in the same objective classification, and zero otherwise. Inflow is the average quarterly asset growth rate net of holding period returns over the past N quarters. Size is the natural logarithm of the 1-quarter lagged total assets under management. Number of funds managed is the number of funds managed by each manager. Number of objective classes is the number of unique objective classes that a portfolio manager manages funds from. Objective performance is the value-weighted average holding period returns of an objective class in each period calculated after excluding the fund for which this variable is calculated. Objective inflow is the value-weighted average fund inflows of an objective class in each period calculated after excluding the fund for which this variable is calculated. The notation *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Model 1 (t = 4 quarters)				Model 2 (t = 8 quarters)			
	Increase		Decrease		Increase		Decrease	
	Coefficient	Odds	Coefficient	Odds	Coefficient	Odds	Coefficient	Odds
Intercept	-3.9824	***	-3.6972	***	-4.1234	***	-3.8316	***
Performance (q – t)	0.0284		-0.0518	***	0.0674	**	-0.1227	***
Stdev (q – t)	-0.0276		0.2802	***	0.0060		0.3184	***
High Return*Stdev (q – t)	0.0822	**	0.0373		0.0790		0.0859	**
Inflow (q – t)	0.0003		-0.0009		0.0031	**	-0.0005	
Size (q – 1)	-0.0412	***	0.1719	***	-0.0263		0.1744	***
Number of funds managed	0.1820	***	-0.2401	***	0.1716	***	-0.1868	***
Number of objective classes	0.1903	***	0.0766	***	0.1975	***	0.0902	***
Objective performance (q – t)	0.0343	***	0.0173	**	0.0519	***	0.0043	
Objective inflow (q – t)	-0.0031		-0.0160	***	0.0012		-0.0264	***
Number of observations	33,944				25,386			
Pseudo R-squared	0.0832				0.0820			

Table 11. Performances of managers grouped by the number of related and unrelated funds under management

This table contains a comparison of the average quarterly performance of managers, who manage: 1) only one fund; 2) two or more related funds (same objective class); and 3) two or more unrelated funds (different objective class). The performance measures are benchmark adjusted return and 4-factor alpha estimated from gross fund returns (after expenses are added). The table shows the average performance of managers for 4 samples: 1) Top 10 managers; 2) Top 100 managers; 3) Top 10 percent of the managers; and 4) All managers in the sample from 1992 to 2014. Sorting of managers into different groups such as top 10, top 100, and top 10 percent is done separately in each quarter. A mutual fund can belong to one of twelve broad objective classes: 1) Domestic equity sector fund; 2) Domestic equity fund; 3) Foreign equity fund; 4) Municipal fund; 5) Corporate bond fund; 6) U.S. Government bond fund; 7) Domestic money market fund; 8) Foreign money market fund; 9) Bond (other) fund; 10) Equity-bond mixed; 11) Mortgage fund; and 12) Currency fund. The notation *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

		1	2	3	1 - 2	2 - 3
Top 10 managers	Net Return (%)	14.11	8.40	5.92	5.71***	2.48***
	Alpha (%)	4.72	3.45	2.52	1.26***	0.93***
Top 100 managers	Net Return (%)	5.68	2.95	1.59	2.74***	1.36***
	Alpha (%)	2.08	1.34	0.85	0.74***	0.49***
Top 10% of managers	Net Return (%)	5.57	5.07	4.72	0.50***	0.35***
	Alpha (%)	2.06	1.97	1.79	0.09***	0.18***
All managers	Net Return (%)	0.26	0.19	0.23	0.07***	-0.04
	Alpha (%)	0.13	0.14	0.25	-0.01	-0.11***

Table 12. Managers who place persistently in the annual list of top 100 managers

This table contains the names of the single- and multi-fund managers, who were ranked in the top 100 managers list for at least five years from 1992 to 2014. Each year, single-manager mutual funds are ranked by their gross benchmark adjusted returns in descending order to determine the top 100 managers. The names of the managers that enter this top 100 list in at least five years are reported along with the number of years they stay in the list. The list is first sorted by the number of years and then by alphabetical order.

	Manager Name	Number of years in top 100
1	Robert B Bruce	11
2	David H. Ellison	9
3	Michael A. Del Balso	8
4	Robert D. Goldfarb	8
5	Ron Baron	8
6	Van Robert Hoisington	8
7	Cliff Greenberg	7
8	David L. Cohen	7
9	Huachen Chen	7
10	Manu Daftary	7
11	Mark Johnson	7
12	Shanguan Li	7
13	Brett Barner	6
14	Geoffrey P. Dybas	6
15	James D Oelschlager	6
16	John Bogle Jr	6
17	John Carle	6
18	Michael B Orkin	6
19	Robert Brody	6
20	Rob Scharar	6
21	Ryan I. Jacob	6
22	Steve Buller	6
23	Will Danoff	6
24	Anthony Rizza	5
25	Bill Miller	5
26	Brian E. Stack	5
27	Dan Fuss	5
28	Daniel J. Vrabac	5
29	Edward W. Turville	5

Table 11 - continued

30	F. James Hutchinson	5
31	G Paul Matthews	5
32	Gary A. Tanaka	5
33	Gary L Pilgrim	5
34	Gerald Perritt	5
35	Irving Levine	5
36	James B. Miles	5
37	James K Schmidt	5
38	John S. Segner	5
39	Jonathan M. Zang	5
40	Kenichi Mizushita	5
41	Mark P. Snyderman	5
42	Michael W. Weilheimer	5
43	Rajiv Jain	5
44	Richard E. Lane	5
45	Robert M. Shearer	5
46	Sam Lieber	5
47	Stephen Dalton	5
48	Steve Wymer	5
49	Thomas B Winmill	5
50	Thomas Fitzgerald	5
51	William J Landes	5
52	Laura Linehan	5
