Does Mutual Fund Size Matter?

The Relationship Between

Size and Performance

by

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Abstract

Berk and Green (2004) make a theoretical argument that performance persistence should not exist since new money flows into good-performing mutual funds and there are diseconomies of scale, or because successful funds capture excess returns by raising fees. We find that performance prediction continues when we examine samples of larger and larger funds and that past performance predicts future performance for holding periods up to three years. Funds that outperform index funds of the same risk can be identified. We find that expense ratios are lower for large funds, and decrease as funds get larger or perform well.

1. Introduction to Article

The predictability of mutual fund performance or, indeed, the performance of any money manager, has become an important topic in finance. There is a vast literature in finance dealing with models to measure portfolio performance. In addition, financial services (e.g., Morningstar) devote a huge amount of attention to developing and marketing performance statistics. While there are many reasons for measuring performance, the most important is to tell the investor something about future performance. The fact that the investing public believes that past performance contains useful information about the future can be seen by the size of the industry that has grown up to supply performance data to the public and, perhaps even more importantly, by the evidence that has been documented between performance and future cash flows. The strong relationship between performance and future cash flows has been documented by Ippolito (1992), Gruber (1996), Chevalier and Ellison (1997), and Sirri and Tufano (1998).

There is a vast literature that finds predictability in risk-adjusted performance over some time period when funds are ranked by risk-adjusted returns; see, e.g., Elton, Gruber and Blake (1996b), Gruber (1996), Carhart (1997), Busse and Irvin (2006), Elton, Gruber and Blake (2011), Fama and French (2011), and Frazzini and Lamont (2009). In addition, Cohen, Coval and Pastor (2005) find predictability in risk-adjusted returns when funds are ranked by the similarity of their portfolios to portfolios of successful managers, and Grinblatt and Titman (1993) find predictability in their measure when funds are ranked by their measure, and Cristopherson, Ferson and Turner (1999) find predictability in pension fund performance.[1]

Berk and Green (2004) make a compelling theoretical argument for why past performance should not predict future performance. They argue that a successful manager will capture excess return by charging more per dollar managed, thus increasing expense ratios, or, alternatively the fund will increase

[1] Predictability has not always been found when funds are ranked by return rather than by risk adjusted returns (see Carhart (1997) and Daniel, Grinblatt, Titman and Wermers (1997). Berk and Tonks (2007) acknowledge predictability for poor-performing funds but not for good-performing funds.

in size and, due to resulting diseconomies of scale such as greater transaction costs, organizational diseconomies, or the need to add poorer performing investments, excess returns will disappear and eliminate predictability.

In a later section we examine whether an increase in size or good performance leads to an increase in expenses. We find no evidence that would support this. Thus if predictability disappears, it is caused by diseconomies of scale as the fund grows. Several authors have considered this. Pollet and Wilson (2008) examine influences that could lead to diseconomies of scale. They hypothesize that management can put more money into existing stocks, therefore incurring higher transaction costs, or they can increase the number of stocks in the portfolio, thereby having to select securities with lower expected returns. They show management overwhelmingly reacts to an increase in size by increasing their ownership share in stocks already held in the portfolio rather than by increasing the number of investments. They find that a doubling of fund size increases the number of stocks in the fund by less than 10%. Since management does not react to increasing size by adding a large number of new investments, if performance deteriorates with size it has to be due to increased transaction costs due to a larger position in the securities they hold or organizational diseconomies. The relationship of trading costs and size of trade has been studied by a number of authors. Keim and Madhaven (1995) using Plexus data find that execution size increases transaction costs for institutional traders. However, as they point out, they cannot tell if the smaller order was a stand-alone order or simply a bigger order being executed as a series of small orders. Edelen, Evans and Kadlec (2007) use quarterly mutual fund trades and estimated transaction costs to infer trading costs and argue that trading costs are a major source of diseconomies of scale. A direct analysis of trading costs and size for mutual funds is presented in Christoffersen, Keim and Musto (2006), who studied Canadian mutual funds which are a market where trades have to be reported. They measure trading costs as the difference between a fund's net price and the value-weighted average price. This includes both transaction costs and price impact. They find that larger mutual funds have lower trading costs than smaller funds. However, the funds they study are smaller than many American funds.

Chan, Faff, Gallagher and Looi (2009) study 34 Australian funds which self-reported their transaction data. They find no significant impact of size on trading costs[2]. The relationship between trading costs and size of fund is unresolved. In addition, there has been very little direct evidence about the relationships between size, predictability of performance, and expense ratios. We will examine these extensively in this paper. Since we examine performance after all costs, including trading costs, the impact of trading costs will be included in our analysis.

How are we to reconcile the empirical evidence supporting predictability and the theoretical literature that implies that predictability can't exist? There are two possibilities. One is that the empirical evidence is wrong. The most frequent suggestion is that there is a common factor correlated across periods that is left out of the models. However, no one has identified the factor, and predictability results have been replicated across so many years and using so many different models it is hard to accept this explanation. The second explanation is that the mechanisms that Berk and Green (2004) believe cause funds to move to equilibrium don't exist, so there is predictability, or more likely that adjustment takes time, so that there is short-run predictability but predictability disappears over longer periods of time. The question remains as to how long the short run is. Is it long enough and are the effects large enough to be of practical as well as statistical significance?

We can logically support, in general, the case outlined by Berk and Green. A fund that performs well gets new cash flows and grows in size. Diseconomies of scale, whether caused by increased transaction costs, the acceptance of less profitable investments, organizational costs or other reasons mean that the skill embodied in past return disappears and returns are not predictable. Berk and Green have given us a useful framework for understanding the dynamics of performance in the mutual fund industry. If Berk and Green are correct but investors take time to reallocate funds or even to receive and process data, then growth in size takes place over time. Thus diseconomies of scale, to the extent they exist, will

[2] They do find that market impact is larger for larger funds. However, the larger funds trade in securities with lower bid ask spreads negating the higher impact. Whether this is a strategy to avoid transaction costs or that funds that are larger have large stock as their objective is unclear.

impact fund performance slowly over time. In this case predictability can exist although it should disappear over longer time periods. Furthermore, predictability should change as a function of fund size. If Berk and Green are right, then we should find no predictability among big funds for which diseconomies of scale are more likely to be important.

There are four papers that are directly related to our research. Chen, Hong, Wang and Kubik (2004) and Yan (2008) regress future alpha on a number of variables, including size and past return. They find a negative relationship between alpha and size and a positive relationship with past return. Thus, on average, they find future alpha is smaller for large funds but past return is associated with higher future alpha and predictability exists.[3] Reuter and Zitzewitz (2010) study the difference in performance between funds that have differing numbers of Morningstar stars but have almost identical Morningstar numerical rankings. Funds with more stars get greater inflows, and they study the difference in performance between funds with differing inflows but similar Morningstar numerical rankings. For the next six months, they find on average that the funds with greater inflows have slightly better performance, but they have slightly worse performance over 12, 18 and 24 months. They state that the difference is not enough to destroy predictability. Baker, Litov, Wachter and Wurgler (2004) study the performance of stocks that mutual funds buy and sell. They find that stocks that are bought have positive future alphas, while stocks that are sold have negative future alphas. They find that this persistence in correct decisions is stronger for larger funds. This is evidence of predictability that strengthens rather than weakens with size. None of these studies looks at whether predictability disappears for larger funds, which is the purpose of this study.[4]

This paper is divided into 5 sections. Section 2 contains a description of our sample. Section 3 describes our methodology. In this section we describe the models we will use to forecast alpha and to

[3] Using a different methodology, we find similar results, which are reported in a later section of this paper.

[4] There are two studies that look at the relationship between size and performance for a different financial intermediary (pension funds). Dyck and Pomorski (2011) find that performance increases with size, while Bauer, Cremers and Fredhen (2010) find that performance decreases with size.

evaluate the forecasting ability of past alpha. Section 4 presents our results. In this section we show that forecasting ability exists. While forecasting ability is impacted by size and cash flow, it exists within funds of different sizes and when both size and cash flow are incorporated into the analysis. Finally, Section 5 contains our conclusions.

2. Sample

Our sample is all mutual funds listed in CRSP that meet certain objectives and existed anytime from 1999-2009. 1999 was selected because 1999 is the first year that CRSP reports daily data for an entire year, and we need daily data to compute weekly returns. 2009 was the last complete year of data at the time this study was begun. The initial sample included all common stock funds.[5] From this group we excluded all international funds, index funds, sector funds, life cycle funds, flexible funds, and funds backing variable annuity products. We then calculated total assets by combining the assets of the different share classes that were part of the same portfolio.[6] We retained the return history for the longest existing share class and if tied, the biggest share class. Every year in which we prepared a forecast of performance we applied two exclusion rules. If a fund had less than $15 million in assets or existed less than three years, it was excluded from that year. We utilized these exclusion rules for two reasons. First, Evans (2010) shows that incubator funds come into the data set with a history, and only successful incubator funds are included in CRSP database. This introduces a bias. He shows eliminating the first three years of history eliminates this bias. Second, Elton, Gruber and Blake (2001) show that funds with less than $15 million in assets don't generally enter the database unless they are successful, and then they come in with a history, again introducing a bias. These two exclusion rules eliminate the known biases in the CRSP data. If a fund dropped below $15 million in assets in the evaluation year but was above $15 million in the year we prepared the forecast (the ranking year), it was retained. This means our results apply only to

[5] These common stock funds have Lipper objectives balanced,capital appreciation, equity income, growth, growth and income, income,mid-cap,micro-cap, and small cap. If there was no objective code, the funds were hand-classified by name and prospective.

[6] For many funds CRSP did not identify the group of funds with the same portfolio. These data were hand-collected. We measured asset size at the nearest date to year end.

funds over $15 million in total assets across all share classes and that have existed three years at the time they are ranked. In addition, any fund that had an R^2 less than 0.60 with a given index model in the ranking year was dropped from the sample. We used this rule since funds where the model poorly explains the return pattern are unlikely to have the estimate of past performance be a reliable predictor of future performance.[7] This left us with a final sample of between 3195 to 3238 funds and 17,651 and 17,743 fund years depending on the forecasting model used.

We can view our forecasts as a set of unbiased forecasts for a particular segment of the mutual fund industry. We only forecast for plain vanilla mutual funds which have at the time of the ranking three years of data, are over $15 million in size, and had at least 60% of their return explained by a set of recognized indexes. This does not bias our results, for all of the screening data is known at the time of the forecast. However, we can only certify our results for this large set of mutual funds, which represent a large percentage of the funds that exist over our sample period.

Table 1 reports our sample size each year and the percentage of funds in each size category. The number of funds grows each year with most of the growth occurring from 1999 (1,377 funds) and 2004 (1,894 funds). In the last four years there was only a small amount of growth, from 1894 to 1950 funds. 2008 was the market crash, and the TNA of funds became much smaller. However, examining the other years shows very little pattern, with the distribution of size very similar from year to year.

In addition to the CRSP data, we used return data on the return on the Fama-French factors, momentum return data from Ken French and bond index returns from Barclays.

3. Models and Methodology

All of the models we use for forecasting and evaluation are multi-index models of the form

[7] We would expect that the ability to forecast from historic data would be lower for funds that existed less than three years and had a poor fit to the index models employed. These funds are liable to be smaller than the funds in our sample and may shift strategies over time or invest in instruments whose performance is not captured by our model. About 2% of funds were eliminated because of R^2 less than .60.

$$R_i - R_f = \alpha_i + \sum_{j=1}^{N} \beta_{ij} I_j + \varepsilon_i$$

where

1. R_i is the return on the fund.
2. R_f is the return on the 30-day Treasury bill rate.
3. I_j is the excess return on an index. It is either the return on a single portfolio minus the return on the 30-day T-bill or the difference in return of two portfolios.
4. β_{ij} are sensitivity coefficients.
5. α_i is the measure of performance.
6. ε_i is the random error.

We examine results for four models. The first model is the standard Fama and French three-index model. Since the sample includes funds with substantial investment in bonds, our second model adds excess bond-index returns to the Fama French three-factor model. The third model is the Carhart model which adds a momentum factor to the Fama-French factors. Finally, the fourth model is the Carhart model with the addition of the bond index. Alphas were estimated each year using weekly data. Adjacent years were then paired into a ranking year and an evaluation year.

For example, if 1999 was a ranking year, 2000 was the evaluation year; if 2000 was the ranking year, then 2001 was the evaluation year. If the fund merged or liquidated in the ranking year it was eliminated from the sample for both the ranking and evaluation years. If the fund merged or liquidated in the evaluation year, the alpha was computed using available data if it existed for at least 45 weeks in the evaluation year, or alpha was set at the average alpha over all funds if the fund existed for less than 45 weeks. Note that setting alpha equal to the average alpha biases the results. Elton, Gruber and Blake (1996a) have shown that funds that disappear tend to have large negative alphas before disappearance.

Thus, using an average alpha for funds that merge or liquidate increases the alpha in the evaluation period for funds with low alphas in the ranking period and reduces the likelihood of finding predictability. Note also that any fund that merges or liquidates would be included when it disappears in an evaluation year but is excluded if it disappears in a ranking year. As explained earlier, we eliminated any fund from the ranking year if R^2 with the ranking model was less than .60. In each ranking year we divided funds into ten groups based on alpha.[8] For each of these groups we then computed the average size of the fund at the beginning of the evaluation year and the average alpha in the evaluation year.

Berk and Green (2004) argue that there is no predictability. A less extreme version of their argument would be that any predictability that exists would disappear as funds get larger. We explore this in a number of ways. First we divide the sample into two groups by size and compare the predictability of the group of large- and small-size funds. Since fund size might differ across fund objectives, we first sorted by size within each objective. Then we divided the funds in each objective in half by size. We then combined separately the top and bottom half by size across all objectives. Second, we examine predictability for funds that exceed some size levels. We choose \$500 million, \$1 billion, \$3 billion and \$8 billion as our size cutoffs. The \$500 million was chosen because it is roughly twice the size of medium-sized funds in our sample. \$1 billion was chosen because discussions with firms that measure trading costs of mutual funds indicated a belief that trading costs start to rise when a fund reached \$1 billion in size. \$3 billion and \$8 billion were included to see if any results change for very large funds.

4. Results

In this section we present the results of our analysis. We initially look at predictability by dividing the funds into 10 deciles. We first rank into deciles by size and look at the impact of size on future performance and then we rank by past performance for funds of different size and examine the relationship between past and future performance. Second, we look at how expense ratios change with

[8] We also replicated our results for alpha over residual risk. The results are so similar that we do not report them.

size and performance. Third, we use regression analysis to explore how future alpha is related to past alpha and a set of variables that have been hypothesized as related to future performance.

4.1 Predictability and Size

Table 2 shows the average alpha in the evaluation year when funds are divided into deciles by size (Panel A) and when funds are divided into deciles by prior period alpha using either of two models (Panels B and C) of Table 2. The evaluation alpha is the alpha from the five-index model (Carhart model plus a bond index). The division into size deciles is done by ranking by size within each objective code and dividing funds in each objective code into ten deciles by size and then combining deciles across all objective codes. The first decile contains funds whose average size is 1.6% of the mean size within each objective, while for the 10th decile the ratio is 7 times the average size in each fund's objective. The alpha shown in the table is a weekly alpha. The –0.013 average alpha for all funds shown in Table 2 translates into roughly -70 basis points per year.[9] This is consistent with previous results, e.g., Elton, Gruber and Blake (1996b), Gruber (1996), Zheng (1999), and Bollen and Busse (2001).

While the objective of this paper is to examine whether predictability disappears for large funds, it is worth noting the general relationship between performance and size. Examining Table 2 reveals that the magnitude of the evaluation alpha shows a positive correlation with size that is not quite significant at the 5% level. Thus, if anything, larger funds seem to have a higher alpha.

The second and third groups of columns show the evaluation alpha when funds are ranked into deciles by the Carhart model (Panel B) or the Carhart model plus a bond index (Panel C). When ranking is done by prior years' alpha, there is a strong relationship between prior alpha and the evaluation alpha

[9] Many authors test the difference between top and bottom deciles. These differences are highly significant for Table 2, Panels B and C, and for Tables 3 and 4. We emphasize whether we find significant predictability in the top deciles, since mutual funds can not be sold short.

(future alpha).[10] With both models the rank correlation is significant at better than 0.01 level. The evaluation alpha is positive for the top two deciles and for the top decile is substantial, about 1.5% per year.[11] The other decile that is notable is the bottom decile where the negative evaluation alpha is large. The lowest decile has much higher fees, which is in part the cause of the much lower performance. Note also that the worst-performing funds are the smallest in size. Poor performance of the bottom decile has been found by many others.[12]

We examine the statistical significance of the alpha in the top decile using simulation. We randomly divide our funds each year into 10 groups. We then compute the evaluation alpha for each group. We repeated this 1,000 times and looked at the evaluation alpha in group 10. In this and subsequent tables for decile 10 the frequency of evaluation alpha being as large as what we find was well less than one in a hundred. Thus it is very unlikely to see values like those we find by chance. The other issue that needs to be addressed is whether these results could be obtained because of an error in the model that causes alpha to be correlated across periods since we rank and evaluate using the same model. To analyze this we used the model that worked best – the five-index model – to rank funds, but we compute evaluation alphas using a wide variety of alternatives, namely the market model, the Fama-French Model, the Fama-French Model plus a bond index, the Carhart model, the Carhart model plus a bond index, the Carhart model plus a bond index where betas are estimated both using the Dimson Marsh (1979) correction for non-synchronous trading, and the conditional beta model (1999) (conditional on the dividend price ratio and T-bills) of Christopherson, Ferson & Turner.[13] The results are shown in Table 3. The top decile has a positive and statistically significant alpha at the 0.01 level, regardless of the model

[10] We also ranked by alpha over residual risk. The results didn't differ in any meaningful way. This was true in all subsequent tables and will not be discussed again. Likewise, the relationship was similar for the Fama-French three-factor model and the four-factor Fama-French plus bond model. From this point forward we only employ the Carhart model plus a bond index. While the results for all models are similar, this model represents the richest description of the data.

[11] Within each type of fund (e.g., growth, small cap) the top decile had better performance than the average fund of that type.

[12] See Elton, Gruber and Blake (1996b), Gruber (1996), and Zheng (1999).

[13] For the Dimson and Marsh adjustment we used one week lead and lag. For the Christopherson, Ferson and Turner adjustment we used the lagged T-bill rate and the dividend price ratio of Boudoukh, et al (2007). This data was provided by Roberts.

we use to compute evaluation alphas. The pattern of alphas across deciles is the same. The rank correlations across rank alpha deciles are significant at the 0.01 level, regardless of the model we use to compute evaluation alphas. The lowest-ranked decile is the poorest performing no matter which model we use. Finally, using simulation to examine whether the top decile is significantly different from zero shows that the numbers reported could occur by chance less than once in a hundred times. In what follows we will only report results using the five-index model, although we have computed results for all of the multi-index models discussed earlier. The results for the different models are very similar. Not only do we find statistical significance for the pattern of evaluation alphas, but we also find that decile 10 has an annual positive alpha of 99 to 192 basis points per year, depending on the model used in the evaluation Examining evaluation alphas using the Dimson and Marsh correction and the alphas using conditional betas suggests that persistence in mutual fund alphas are not caused by stale prices or due to persistent bias in alphas or betas.

The principal focus of this article is the effect of size on predictability. Can funds become so large that their performance deteriorates and we can no longer find funds with positive alpha? Table 4 presents the results of this analysis. For the first two sets of columns we split our sample in half by size. The lower half has funds that averaged about $100 million in size, and in the upper half the funds averaged about $2.9 billion. We find predictability in both samples with a rank correlation that is significant at better than the .001 level. The larger funds have an average alpha of about 27 basis points per year better than the smaller funds.

Size, at least at this very coarse level, doesn't seem to destroy predictability. In the remaining columns we analyze predictability when we sequentially restrict the sample to include only funds larger than $500 million, $1 billion, $3 billion and $8 billion. These exclusion rules cut out a substantial number of funds. Dropping funds below $500 million in size retains only 37% of the funds, dropping funds below $1 billion retains 23% , dropping funds below $3 billion retains 9.6% and dropping funds below $8 billion retains only 3.5% of the funds. In each case the top decile ranking by prior periods' alpha has a positive alpha in the evaluation period. The alphas for decile 10 range from 78 basis points per year to over 1.5% per year depending on the minimum size fund included. Also note that in all but one case decile 9 also has a positive alpha. Using simulations to analyze significance shows that all of the alphas in decile 10 are statistically significantly different from zero at the 1% level.

The rank correlation across deciles is always significant at the 5% level, and for minimums of a billion dollars or less it is significant at the 1% level. The bottom decile is always the worst performer in the evaluation period no matter what the minimum size. Also, in each case the worst-performing funds are smaller on average. Note finally the large average size ranging from \$3.75 billion when we impose a minimum size of \$500 million to about \$21.8 billion when we impose a size of \$8 billion. There is a steady decline in evaluation alpha in the top decile as we move from a minimum cutoff of \$500 million to \$3 billion, but it increases again with an \$8 billion minimum. The \$8 billion cutoff is a much smaller sample, and its difference from 0.015 (the evaluation alpha for \$3 billion) is not statistically significant, so there may be a decline in the performance of the top decile as we increase the minimum size of a fund. However, even with very large minimums we find predictability, and the top decile has significant positive alphas both statistically and economically.

We examined several other issues with the top decile. First, is there any relationship between size and evaluation alpha within the top decile? To examine this for the entire market we divided the top decile in the rank period into five groups by size and looked at the evaluation alpha for each of the five groups. There was no pattern. Next we asked ourselves if closet index funds were in the top decile in the ranking period. We defined closet index funds as funds with a R^2 greater than 0.985 for the ranking period. 4.7% of our sample met this criterion. In 7 of the 10 years none of these funds were in decile 10 in the rank year, and in two other years there was only one. In total, 0.6% of the funds in the top decile had R^2 greater than 0.985. We find predictability in alpha regardless of size.

Another issue is does predictability disappear for the funds that grow the fastest. To examine this in each rank year we divided funds into groups based on past growth in that year, and assets. We find that the alpha in the next year is perfectly aligned with past growth, with the average alpha for the smallest quartile to the largest being -.028, -.070, -.011, -.003. The fastest-growing funds have higher average alphas in the year following the growth year. In addition, within each growth quartile funds were divided into ten groups according to the alpha in that year. When we look at the alphas that were realized, we find no difference in predictive power. The correlation coefficient between past and future alphas across deciles for each group is above .85, and all of the correlation coefficients are statistically significant at better than the .01 level.

4.2 Expenses

One of the arguments made for why we should not find predictability in performance is that high performance funds will grow and become large and that larger funds will have higher expenses, thus eroding performance. A second argument only indirectly related to size is that good performance will cause management to capture this performance by raising the fees charged to investors. Both of these will be examined in this section. While dollar expenses and dollar management fees are higher for large firms, we now show that expense ratios and percent management fees go down with size. We examine this both cross-sectionally and in time series. We then examine what happens to fees over time for the funds ranked highest by alpha.

In Table 5 we examine over our entire sample the relationship between size, expense ratios and management fees and administrative costs. It is clear from this table that larger funds have both lower expense ratios and lower percent management fees than smaller funds. Examining the second and third row shows that the principal difference between the largest 50% of funds in size and the smallest 50% is the portion of expenses that are associated with non-management fees (administrative costs). The top 50% of funds in asset size compared to the bottom 50% have expense ratios that are 15% lower in total expenses, with percent management fees that are that are 4% lower and administrative costs that are 29%

lower. The last four rows of Table 5 show what happens to expenses as we restrict our sample to all funds over $500 million, $1 billion, $3 billion and $8 billion. As we use higher and higher cutoff rates, expenses, percentage management fees and percentage administrative costs continue to drop by 24% for total expenses, 27% for management fees, and 19% for administrative costs. Another possible way to examine expense ratios is to look at what happens to expenses as size increases within an objective code. Table 2, column 3 of Section A shows what happens to expenses within an objective code when we divide each objective code into deciles by size. The expense ratio declines from 1.37% for the smallest decile to 0.93% for the largest, a drop of 32% in total expenses. Clearly, larger funds have lower expense ratios and lower management fees.

In Table 6 we examine the relationship between change in expenses and change in size for each fund over time (953 separate regressions). The table presents the number of times that the relationship between change in expenses and change in size was statistically significant at the 5% level and the number where the coefficient on size was positive or negative. Across the 953 funds in our analysis the expense ratio was significantly negatively related to size (at the 5% level) fo78 of the funds while it was significantly positively related to size for only 15.[14] Change in management fees shows a small tendency to decrease with size, while administrative costs show a very strong negative relationship to size. Whether we examine the relationship between expenses and size for all funds or individually for each fund over time, it is clear that expenses go down with size, not up, and the components of expenses outside of management fees have the biggest impact.

Another issue to examine is what happens to expenses after funds have superior performance. To examine this we computed the change in expense ratio for each of the three years after a fund appears in each decile. The results appear in Table 7. The table shows the change in expense ratio for the following year, and for each of the subsequent two years. Expense ratios decrease for the better-performing funds,

[14] We require at least 9 years of data containing expense ratios, which reduces the sample size.

while they increase for the worst-performing funds. This is the opposite of what is required for expense ratio changes to destroy performance.

Thus, whether we look at the change in expense ratios as a function of the change in size, the firms' expense ratios at different size levels, or how expenses change with performance, expense ratios do not reduce predictability. Furthermore since expense ratios decrease with size, other costs that can potentially increase with size must increase enough to cause overall costs to increase.

4.3 Evaluation alphas and fund characteristics

We have examined the ability of past alpha to identify the portfolio of funds that will have high alphas in the future. The approach so far has identified groups of funds (deciles) that will do well, and we have shown that past alpha is useful in placing funds in deciles and that these behave as they should have if past alphas have predictive power. We have also examined the robustness of predictive power for funds of different sizes. In this section we present the results of a regression of evaluation alpha on a set of variables that have been hypothesized by us or by others as affecting the future alpha.[15]

The dependent variable we examine is the average weekly evaluation alpha in any year. We explain this alpha using the following set of variables:

1. The average weekly alpha for a fund in the prior year (ranking alpha)
2. The percent cash flow to the fund in the preceding year. Cash flow is defined as the total net assets at the end of a year minus the beginning total net assets times one plus the rate of return on the fund, all divided by the beginning total net assets (TNA).
3. The size of the fund. This is measured as the log of TNA of the fund at the end of the prior year.
4. The expense ratio of the fund in the prior year.
5. The turnover ratio in the prior year.

[15] See Chen, Hong, Huang and Kubik (2004). Chan, Faff, Gallagher and Looi (2009), Gervais, Lynch and Musto (2005), Pollet and Wilson (2008).

6. Family size in the prior year. Family size is measured by the aggregate of the TNA of all the funds in a fund family minus the TNA across all share classes of the fund being examined.[16]

In addition, the regression includes a dummy variable to account for each type of fund in the sample and each year of the sample period. In order to interpret the importance of each variable in explaining future alphas, in addition to examining the regression coefficient on each variable and its *t* value, we also examine the regression coefficient for each variable times the standard deviation of that variable. This measures how much a one standard deviation change in a variable adds or subtracts from the evaluation alpha. While the *t* value measures statistical significance, the regression coefficient times the standard deviation is a measure of economic significance. The results are shown in Table 8.

We will primarily discuss the second regression presented in Table 8. While the regression coefficients in both the regressions are similar, we find that the inclusion of a family size variable adds virtually no value to our analysis. While the coefficient on family size is positive, indicating that funds from large families tend to have higher alphas, the coefficient is small, not statistically significant at any reasonable level, and of little economic significance.

We will now discuss the impact of each variable that is common to the two regressions in more detail. By far the most significant variable is past alpha. The *t* value associated with its regression coefficient is twice the *t* value associated with any other variable. Past alpha not only shows statistical significance, but its economic importance can be judged by the fact that a one standard deviation change in past alpha is associated with a 0.0187 weekly (or approximately 0.96 yearly) increase in percent future alpha. Clearly, past alpha has both a statistically and economically significant impact on future alpha.

The next two variables in order of importance are turnover ratio and expense ratio. Both are negatively related to future alpha. Both are statistically significant at the 0.01 level, and one standard

[16] Family size is included because a number of authors have hypothesized and/or tested its importance. As examples, Gervais, Lynch and Musto (2001) find large family size helps performance, while Chan, Faff, Gallagher and Looi (2009) find family size doesn't affect costs, and Bhojraj, Cho, Yehuda (2010) find fund family helps performance before 2000 but not after 2000.

deviation of each changes future weekly alpha by respectively –0.00926 and –0.00715. Both of these variables represent aspects of investor expense. Whether the expenses are in the form of direct expenses or higher costs through increased trading, expenses are negatively related to future alpha. If we did not include these variables as control variables, the association between past and future alphas could simply be caused by persistence in expense ratios and trading costs over time.

The next most significant variable is cash flow. Funds with large cash flows tend to have lower future alphas than past alphas would suggest. This result is statistically significant and economically significant, though its economic importance is only 17% of the impact of past alpha. This lends some credence to one interpretation of Berk and Green (2004). Large inflows have a negative effect on future performance. However, the impact of cash flows compared to past alpha in predicting future alpha makes it clear that this influence will take some time, certainly much longer than one year to destroy predictability.

The final variable to discuss is fund size. While the relationship between evaluation alpha and fund size is negative, we find no statistically significant or economically significant impact of fund size on performance. When we examined the relationship between evaluation alpha and fund size in Table 4, we found a weak and not statistically significant relationship. The lack of a relationship in Table 8 comes about because of controlling for additional variables (e.g., expense ratios) which are correlated with size.

4.4 Performance Over Time

One of the questions that needs to be examined is whether ranking by one-year alpha predicts performance for holding periods longer than one year. This simply involves repeating the analysis performed above with the dependent variable computed first as the evaluation alpha computed over one year, then the annual average of the cumulative evaluation alphas computed over the first and second evaluation years, and finally the annual average of the cumulative evaluation alphas computed over the first, second and third evaluation years.[17]

The results as presented in Table 9 are clear.[18] As we move from explaining one-year forecasts to two-year forecasts to three-year forecasts, the following results occur:

1. First and foremost, the regressions are statistically significant and they all show forecasting ability.
2. The coefficient of determination goes down from 0.21 to 0.15 to 0.12.
3. The importance of past alphas in explaining future alphas decreases. However, even for the case of a three-year forecast, past alpha is still statistically significant at the 0.01 level and a one standard deviation change in past alpha has an impact on the three-year alpha of 23 basis points per year.
4. The importance of both expense ratio and turnover ratio increases as we forecast for longer horizons. The *t* value of each of these variables increases, as does the impact of a one-standard-deviation change in each of these variables.
5. The impact of cash flow does not change in importance, and remains statistically significant.
6. Portfolio size is not significant in any case.
7. The importance of family size increases with longer horizons. It is not significant in the one-year case, but becomes statistically significant for the two- and three-year case.

These regressions show an interesting story. The predictive power of past alpha decreases as we forecast for longer holding periods. However, the predictive power of past alpha still exists at a statistical and economic level for periods as long as three years in the future.

[17] The one-year results are somewhat different from those presented in Table 8 because a number of fund-years of data had to be dropped so that a common set of data could be used when evaluation alphas were compared over different time spans.

[18] All regression results presented in the tables were computed with both year and fund objective dummy variables included. These variables were included to remove year effects and fund type effects from the results. The coefficients on the dummy variables are not reported in the interest of space.

While the importance of past alpha as a predictor decreases, the importance of expense ratio and turnover ratios stay relatively constant in magnitude but increase in statistical significance. We suspect this is due to the fact that expense ratios and turnover tend to more stable over time than management performance.

Size does not seem to be an important determinant of future performance over any horizon examined and is never statistically significant. On the other hand, cash flow is negatively related in performance and is significant over all horizons.

The largest surprise is family size. The size and significance of its impact grows larger for longer forecasts. While a larger family seems to have little impact over one year, it seems to help over longer periods. Perhaps as the impact of past performance diminishes, the presence of a larger family with more resources comes into play.

We also examined the persistence of performance separately for the individual years occurring two and three years after the forecast. Persistence is still strong two years after the ranking year. The coefficient on past return is statistically and economically significant, although its size and significance is lower than that in the first year. Persistence has disappeared by the third year, with some reversal in performance. This is consistent with the **two** and three-year holding results. This reversal in the third year is not of sufficient magnitude to undo the ability of rank alpha to have predictive power for three-year holding periods.[19]

5. Conclusion

Berk and Green (2004) have made a strong theoretical argument for why past performance should not predict future performance. There are two possible economic explanations that are consistent with their

[19] We also examined this separately for each type of fund. There was no consistent pattern across type of fund that was related to what would be considered differential trading costs.

model: increasing expenses or increase in size following good performance along with diseconomies of scale. We use weekly data for the period 1998-2009 to examine these explanations.

We have shown that expense ratios and management fees decline with size and decline with success, with the top-performing funds decreasing fees and the poor-performing funds increasing fees. This makes sense, since management fee schedules normally decline with size and administrative costs have a large fixed component.

The other possible way that predictability might disappear is for funds to grow with good performance and for diseconomies of scale to erode performance. If this is true, then we should see no predictability when funds get larger.

We examined this in a number of ways. First, we divided funds in each objective in half by size and combined them into the largest and smallest funds. Both the largest and the smallest groups showed significant predictability. Next we sequentially eliminated funds by size, examining funds over $500 million, $1 billion, $3 billion and $8 billion sequentially. We still found predictability even when we examined only very large funds. Finally we regress future alpha on past alpha and a number of other variables that have been hypothesized in the literature as affecting the predictability of performance. Future alpha was related to past alpha at values that were both economically and statistically significant. Size was not significantly related to future alpha. The results held up when we repeated the analysis forecasting for two- and three-year holding periods. When we examined the forecast for years two and three separately, the results for year three showed some reversal of performance.

Why doesn't alpha persistence disappear for larger funds? We can only speculate. First, expense ratios decrease with size. Thus, for the Berk and Green results to hold, diseconomies of scale have to be large enough to offset the decrease in expense ratio as funds increase in size. In addition, large funds might offset any increase in transactions costs and the need to take a larger number of investments by commanding a larger share of the resources of the fund's family. Large funds may have greater access to the best traders or command more time of the best analysts. Since fund family flows depend on the performance of the best performing funds (see Nanda, Wang and Zheng (2004)), they may get the pick of or early access to the best investment opportunities that the fund family discovers. Gaspar Massa and Matos (2006) provide evidence that would support fund families favoring good-performing funds.

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Table 1

Distribution by Fund Size

Panel A

Sample Year	Number of Funds	Average TNA (Millions)
1999	1,377	$1,798.2
2000	1,539	$1,565.4
2001	1,680	$1,302.7
2002	1,711	$1,021.4
2003	1,843	$1,302.7
2004	1,890	$1,485.8
2005	1,894	$1,600.5
2006	1,919	$1,795.3
2007	1,940	$1,901.2
2008	1,950	$1,135.9
All Years	17,743	$1,488.5

Panel B

	Percentage of Funds in Range										
TNA Range (Millions)	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	All Years
$15 - $50	12.9%	14.2%	15.0%	18.0%	15.6%	14.1%	14.1%	13.1%	12.3%	18.2%	14.8%
$50 - $100	11.8%	12.5%	13.8%	14.8%	13.6%	13.2%	12.6%	12.9%	12.4%	15.9%	13.4%
$100 - $250	19.2%	19.4%	20.5%	22.9%	21.3%	21.1%	20.8%	19.7%	19.5%	19.9%	20.5%
$250 - $500	14.7%	16.0%	16.3%	14.6%	15.0%	15.6%	14.0%	13.5%	13.7%	14.7%	14.8%
$500 -$1,000	14.3%	13.5%	13.4%	11.9%	13.2%	13.4%	14.6%	14.2%	15.3%	12.9%	13.7%
$1,000 - $2,000	10.7%	9.4%	8.3%	7.7%	9.4%	9.4%	10.2%	11.0%	11.1%	8.2%	9.6%
$2,000 -$4,000	7.3%	7.0%	5.8%	4.6%	5.0%	5.7%	5.9%	6.9%	6.6%	5.1%	6.0%
$4,000 - $10,000	5.2%	4.6%	4.5%	3.7%	4.5%	4.9%	5.0%	5.5%	5.9%	3.4%	4.7%
$10,000 -$20,000	2.1%	1.8%	1.3%	1.2%	1.1%	1.4%	1.4%	1.5%	1.8%	1.0%	1.4%
> $20,000	1.6%	1.5%	1.2%	0.5%	1.1%	1.3%	1.4%	1.5%	1.4%	0.8%	1.2%

This table presents descriptive data for our sample.
Panel A reports the number of funds and the average size of the funds for each year in our sample period.
Panel B shows the percentage of funds of various sizes, both in each sample year and on average.

Table 2
Evaluation Alphas when Funds Are Ranked by Size or Alpha

	Panel A: Ranked within Objective Category by Relative Size, Carhart Plus Bond Model (17,743 Fund Years)				Panel B: Ranked by Alpha, Carhart Model (17,705 Fund Years)				Panel C: Ranked by Alpha, Carhart Plus Bond Model (17,743 Fund Years)			
Rank	Evaluation Alpha	Average Rel. TNA	Exp. Ratio	Turn-over	Evaluation Alpha	TNA	Exp. Ratio	Turn-over	Evaluation Alpha	TNA	Exp. Ratio	Turn-over
Decile 1	-0.018	0.016	1.37	1.032	-0.052	$739	1.38	1.24	-0.048	$831	1.37	1.23
Decile 2	-0.015	0.035	1.29	0.957	-0.030	$1,440	1.23	0.94	-0.027	$1,329	1.22	0.95
Decile 3	-0.013	0.061	1.24	0.934	-0.020	$1,244	1.19	0.88	-0.020	$1,339	1.20	0.85
Decile 4	-0.019	0.102	1.25	0.989	-0.021	$1,684	1.14	0.80	-0.021	$1,621	1.14	0.84
Decile 5	-0.011	0.161	1.25	0.954	-0.017	$1,952	1.10	0.80	-0.016	$1,913	1.11	0.80
Decile 6	-0.019	0.256	1.19	0.901	-0.011	$1,490	1.09	0.76	-0.015	$1,546	1.08	0.74
Decile 7	-0.008	0.417	1.14	0.858	-0.007	$1,659	1.10	0.77	-0.011	$1,543	1.09	0.79
Decile 8	-0.013	0.701	1.10	0.795	-0.003	$1,544	1.14	0.81	-0.003	$1,668	1.13	0.81
Decile 9	-0.005	1.352	1.04	0.755	0.004	$1,761	1.16	0.88	0.004	$1,749	1.18	0.86
Decile 10	-0.007	6.900	0.93	0.590	0.019	$1,402	1.27	0.94	0.030	$1,369	1.27	0.95
Overall Avg.	-0.013	1.000			-0.014	$1,491	1.18	0.88	-0.013	$1,491	1.18	0.88
Rank Corr.	0.624				0.988				0.988			
p-Value	0.054				<.0001				<.0001			

Panel A of this table is based on ranking funds by size (total net asset value) within each objective category, dividing into deciles and then combining across objectives within each decile in a given sample year. The yearly decile averages of the evaluation alpha, relative TNA, expense ratio and turnover ratio are then averaged across all sample years for each decile.
Panels B and C are based on dividing funds into deciles by alpha using the model indicated in the panel.
All evaluation alphas are computed over the year following the ranking year.
All alphas are reported in weekly percent form. Deciles are numbered from lowest to highest. TNA is reported in millions of dollars.
Ranking years are 1999 through 2008.

Table 3
Average Evaluation Alphas from Different Factor Models
when Funds Are Ranked by the Five-Factor (Carhart Plus Bond) Model

Decile	Ranking Alpha	Fama-French 1-factor*	Fama-French 3-factor	Carhart 4-factor model	Fama-French 3-Factor Plus Bond Factor (4-factor)	Carhart 4-Factor Plus Bond Factor (5-factor)	Carhart 4-Factor Plus Bond Factor (conditional 5-factor)**	Carhart 4-Factor Plus Bond Factor (adj. betas 5-factor)***
Decile 1 (lowest)	-0.245	-0.043	-0.064	-0.049	-0.061	-0.048	-0.056	-0.051
Decile 2	-0.126	-0.023	-0.032	-0.026	-0.032	-0.027	-0.027	-0.025
Decile 3	-0.084	-0.020	-0.022	-0.019	-0.024	-0.020	-0.022	-0.017
Decile 4	-0.054	-0.017	-0.023	-0.018	-0.026	-0.021	-0.021	-0.017
Decile 5	-0.028	-0.012	-0.019	-0.014	-0.021	-0.016	-0.017	-0.015
Decile 6	-0.003	-0.010	-0.022	-0.014	-0.022	-0.015	-0.016	-0.014
Decile 7	0.026	-0.007	-0.013	-0.010	-0.014	-0.011	-0.012	-0.013
Decile 8	0.062	0.005	-0.007	-0.005	-0.005	-0.003	-0.005	-0.004
Decile 9	0.114	0.020	-0.001	0.000	0.004	0.004	0.000	0.002
Decile 10 (highest)	0.249	0.028	0.026	0.019	0.037	0.030	0.017	0.032
Spearman Corr.	1.000	1.000	0.976	0.988	0.976	0.988	1.000	0.988
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001

This table reports the evaluation alphas obtained by using the models indicated in the columns when funds are divided into deciles by alpha in the ranking period using the 5-factor (Carhart plus bond) model.

*Market factor in excess-return form.

**Betas and alphas are conditional on dividend-price ratio and T-bill rate, following Christopherson, Ferson and Turner (1999).

***Betas adjusted using Dimson-Marsh (1979) procedure.

TABLE 4
(ranking years 1999 - 2008)
Evaluation Alphas when Funds Are Ranked and Evaluated by 5-Factor (Carhart Plus Bond) Model

	Bottom Half of TNA		Top Half of TNA		TNA >= $500 million		TNA >= $1 billion		TNA >= $3 billion		TNA >= $8 billion	
Rank	Alpha	TNA	Alpha	TNA	Alpha	TNA	Alpha	TNA	Alpha	TNA	Alpha	TNA
Decile 1	-0.054	$103	-0.043	$1,904	-0.034	$2,599	-0.029	$4,225	-0.033	$7,820	-0.032	$16,284
Decile 2	-0.024	$108	-0.026	$2,881	-0.022	$3,747	-0.020	$5,285	-0.012	$10,323	-0.022	$20,729
Decile 3	-0.030	$110	-0.010	$2,464	-0.012	$3,536	-0.016	$5,663	-0.018	$9,922	-0.017	$19,497
Decile 4	-0.024	$106	-0.016	$3,522	-0.014	$4,577	-0.013	$7,170	-0.014	$15,613	-0.012	$29,401
Decile 5	-0.021	$105	-0.019	$3,274	-0.018	$4,066	-0.018	$5,992	-0.011	$12,462	0.009	$27,126
Decile 6	-0.013	$110	-0.016	$2,788	-0.010	$3,602	-0.014	$5,081	-0.006	$9,812	-0.002	$24,010
Decile 7	-0.011	$110	-0.006	$2,942	-0.008	$3,919	-0.006	$5,794	0.011	$11,617	-0.005	$19,487
Decile 8	-0.010	$108	-0.002	$3,097	0.003	$3,811	0.007	$5,643	-0.015	$10,460	-0.008	$20,767
Decile 9	0.009	$112	0.003	$3,184	0.001	$4,312	-0.004	$5,656	0.006	$12,571	0.009	$22,771
Decile 10	0.026	$109	0.034	$2,608	0.030	$3,333	0.027	$5,122	0.015	$8,748	0.028	$17,726
Overall Avg.	-0.015	$108	-0.010	$2,867	-0.008	$3,750	-0.009	$5,563	-0.008	$10,935	-0.005	$21,780
Fund Years	8,872		8,872		6,492		4,063		1,700		615	
Rank Corr.	0.9636		0.9152		0.9394		0.9273		0.7455		0.8303	
p-Value	<.0001		0.0002		<.0001		0.0001		0.0133		0.0029	

This table shows persistence in alpha for mutual funds of different sizes. Alphas are reported in percent per week.
TNA is at end of ranking period and is in $ millions.
Decile 1 is lowest ranking alpha decile; decile 10 is highest.

Table 5
Average Expense Ratios and Management Fees

Fund Group	Expense Ratio	Management Fee	Differential
Overall	1.18	0.71	0.47
Bottom Half of TNA	1.28	0.73	0.55
Top Half of TNA	1.09	0.70	0.39
TNA >= $500 million	1.04	0.67	0.37
TNA >= $1 billion	0.99	0.64	0.35
TNA >= $3 billion	0.90	0.57	0.33
TNA >= $8 billion	0.79	0.49	0.30

This table shows the average expense ratios, management fees and that part of expense ratios not due to managent fees for funds of different sizes.
Expense ratios and fees are shown as annual fees and in percent form.

Table 6

Change in Expense Ratios and Change in Management Fees Regressed on Change in Size

Variable	Total Funds	No. Sig. Positive	No. Sig. Negative	No. Positive	No. Negative
Change in Expense Ratio	953	15	78	259	666
Change in Management Fee	953	28	32	410	495
Change in Differential	953	8	86	263	690

This table shows the number of coefficients that are positive and the number that are negative, along with the number that are statistically significant at the 5% level when the yearly changes in expense ratios, management fees, and expense ratios net of management fees are regressed on the yearly change in fund size (TNA).

Table 7
Average Change in Expense Ratio by Ranking Decile in Years Following Ranking Year

Decile	1 Year	2 Year	3 Year
1	0.0144	0.0155	0.0066
2	0.0070	0.0043	-0.0005
3	0.0054	0.0031	-0.0001
4	0.0018	0.0011	0.0004
5	-0.0004	0.0027	0.0029
6	0.0021	-0.0046	0.0007
7	0.0017	-0.0024	0.0040
8	-0.0043	0.0036	-0.0035
9	-0.0052	-0.0012	-0.0049
10	-0.0217	-0.0059	-0.0057

This table shows, for each ranking decile, the average change in expense ratio from the end of the ranking year to the end of the year following the ranking year (labeled "1 Year"), the average change in expense ratio from the end of the first year following the ranking year to the end of the second year following the ranking year (labeled "2 Year"), and the average change in expense ratio from the end of the second year following the ranking year to the end of the third year following the ranking year (labeled "3 Year").

Ranking deciles are based on 5-factor (Carhart plus bond) model alphas calculated using weekly data over ranking year.

Decile 1 is lowest ranking decile; decile 10 is highest.

Expense ratio changes are changes in the annual percentages.

The average annual expense ratio was 1.18%.

Averages are calculated across all available sample years.

Table 8
Regression Output from Regressing Evaluation Alphas on Listed Variables
(objective and sample year dummy variables included in regressions)

			Regression Independent Variables					
Regression	Adj. R-Square	Intercept	Ranking Alpha	Cash Flow %	Log TNA	Expense Ratio	Turnover Ratio	Family Size Differential
1	0.168	0.04475	0.11920	-0.00008	-0.00029	-1.56556	-0.01033	0.00068
		(6.32)	(16.47)	(-3.06)	(-0.44)	(-6.36)	(-8.82)	(1.28)
2	0.168	0.04908	0.11910	-0.00008	-0.00044	-1.61420	-0.01017	
		(7.88)	(16.44)	(-3.11)	(-0.68)	(-6.64)	(-8.73)	
Effects of a 1-Standard-Deviation Change for Regression 2			0.01874	-0.00348	-0.00058	-0.00809	-0.00896	

t-Values are in parentheses.

This table shows regression results from regressing the evaluation alpha on the listed independent variables.

All alphas are calculated using 5-factor (Carhart plus bond) model.

The evaluation alpha is the alpha obtained from weekly data over the year following the end of ranking year;

Family size differential is log of fund family size minus log of fund size.

All alphas are calculated using 5-factor (Carhart plus bond) model.

Table 9
Regression Output from Regressing Evaluation Alphas on Listed Variables
(objective and sample year dummy variables included in regressions)

Dependent Variable Is First Year Evaluation Alpha

Adj. R-Square	Intercept	Ranking Alpha	Cash Flow %	Log TNA	Expense Ratio	Turnover Ratio	Family Size Differential
0.2145	0.02257	0.1802	-0.00011	-0.00081	-1.5654	-0.0092	0.00039
	(3.00)	(23.53)	(-3.95)	-1.15	(-6.18)	-7.58	(0.67)

Dependent Variable Is Average of First and Second Year Evaluation Alphas

Adj. R-Square	Intercept	Ranking Alpha	Cash Flow %	Log TNA	Expense Ratio	Turnover Ratio	Family Size Differential
0.14566	0.00183	0.0753	-0.00009	-0.00092	-1.8159	-0.0113	0.00085
	(0.34)	(13.67)	(-4.46)	(-1.82)	(-9.96)	-12.96	(2.05)

Dependent Variable Is Average of First, Second and Third Year Evaluation Alphas

Adj. R-Square	Intercept	Ranking Alpha	Cash Flow %	Log TNA	Expense Ratio	Turnover Ratio	Family Size Differential
0.12108	0.01228	0.0279	-0.00008	-0.0003	-1.7974	-0.0099	0.00125
	(2.83)	(6.32)	(-4.82)	(-0.75)	(-12.31)	(-14.19)	(3.76)

This table shows regression results from regressing the given dependent variables on the listed independent variables.

All alphas are calculated using 5-factor (Carhart plus bond) model.

First year evaluation alpha is alpha obtained from weekly data over year following end of ranking year;
second year evaluation alpha is alpha obtained from weekly data over year starting one year after end of ranking year;
third year evaluation alpha is alpha obtained from weekly data over year starting two years after end of ranking year.

t-Values are in parentheses.

Family size differential is log of fund family size minus log of fund size.

Results for first year evaluation alpha differ from those shown in Table 8 (regression 1) because two years of data had to be dropped due to lack of data for evaluation years 2 and 3 in the sample's last ranking year, and all three regressions were run over same number of fund years.