# Brain Drain: Are Mutual Funds Losing Their Best Minds?

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Abstract

I investigate how increased competition from hedge funds has affected the mutual fund industry. I use the lead manager's age along with the region of the US in which the mutual fund is based to identify the effect of hedge funds. I find evidence of increased turnover among best-performing young managers, a drop in mutual fund returns, and deterioration in recruiting standards. These findings are not explained by differences in fund characteristics, risk loadings, fund styles, or the intervening dot-com bubble. My results provide original evidence for the importance of managerial ability in generating performance.

JEL: G10, G11

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Over the last decade, the hedge fund industry has become a major player in financial markets and in the labor market for money managers. The first hint of this trend came in May 1996 when Jeffrey Vinik, the 37-year-old manager of the largest mutual fund in the United States (Fidelity Magellan) announced that he was leaving to start up his own hedge fund (Vinik Partners). By 2006, nearly a quarter of Harvard Business School graduates found jobs in the alternative investments industry. In addition, the financial press has continued to document an ever-growing number of high-profile star managers who followed Vinik into hedge funds, citing better compensation and greater flexibility as the main reasons for their moves. In response to these trends, top mutual fund executives like Mario Gabelli have admitted that the "brain drain to hedge funds from the traditional money management industry is for real." However, they argue that the quality of management, and more importantly, fund performance, has not been affected[1].

The purpose of this paper is to go beyond the anecdotal evidence pervading the financial press to investigate and measure the effect of the brain drain of managerial talent to hedge funds on the mutual fund industry. The ability of the mutual fund industry to retain its best employees is critical for both the survival of the industry and for the welfare of its investors. Khorana (2001) finds that turnover of outperforming managers results in deteriorating performance going forward. Furthermore, manager changes are often followed by a spike in the turnover of holdings incurring additional transactions costs and tax liabilities for fund investors (Bergstresser, Poterba, and Zarutskie (2002)). On the other hand, the possibility of promotion to hedge funds can work to mitigate agency problems, by creating additional incentives for managerial effort

[1] "Brain Drain to Hedge Funds for Real – Gabelli", Herbert Lash (Reuters), September 7, 2005. http://www.reuters.com/article/Funds05/idUSHAR76019620050907

and also by counteracting risk avoidance from "career concerns" (Chevalier and Ellison (1999), Khorana (1996)).

I also investigate the role of managerial talent in generating returns. The question of whether mutual fund managers can persistently outperform the market has been debated extensively in the mutual fund literature (Malkiel (1995), Daniel et al. (1997), Wermers (2000)), so it's possible that even a massive exit of managerial talent had little or no effect on returns since so few managers could outperform the market in the first place. Put simply: *A brain drain won't affect returns if brains don't affect returns*. I contribute to this debate by showing that the brain drain had a negative effect on mutual fund returns and then using the contrapositive: *If a brain drain affects returns then brains must affect returns.*

I construct a dataset of mutual fund managers from 1993 to 2005 that links managerial names, tenures, and characteristics (such as age and education), to fund characteristics and performance measures. My first hypothesis is that successful mutual fund managers left the industry for better opportunities at an increasing rate. I focus on *managerial exit*s which occur when a manager's tenure at a mutual fund ends and the manager is not managing a different mutual fund over the next twelve months. This definition is different from the traditional idea of *manager turnover* which does not require that the manager leave the industry entirely, allowing me to focus on departures to other industries rather than promotions or demotions within the mutual fund universe. I then separate the sample period into two six-year sub-periods, from 1993 to 1998, and from 1999 to 2004[2], and compare the managerial exit rate between periods.

[2] In order to construct the *managerial exit* variable, we need data for the next twelve months to ensure that the manager is not managing another mutual fund, so 2005 is not used in these tests.

I find an overall increase in the annual managerial exit rate (the number of managerial exits divided by the total number of managers) of 1.7 percentage points (or 18%) from 9.2% to 10.9% between sub-periods (statistically significant at the 5% level). In order to distinguish voluntary managerial exits from retirements or involuntary terminations, I divide managers into five quintiles based on manager age and five quintiles based on their fund's relative performance over the previous twelve months. Comparing the managerial exit rates within each of the twenty-five age-performance subgroups, I find that the overall increase in exits was driven by young successful managers. Among managers in the highest quintile of performers and in the two lowest age quintiles (younger than 44), the annual managerial exit rate went up by 7 percentage points or 200% from 3.5% to 10.5% (statistically significant at the 1% level). While the managers in these two (of twenty-five) sub-groups made up only 8% of the manager population, the increase in their exit rate drove almost half of the overall increase in the managerial exit rate.

I next examine the factors that determine a manager's decision to leave the mutual fund industry for outside opportunities using a multivariate regression. Not surprisingly, the managerial departure decision is explained by the opportunity cost of departure, i.e. the compensation that the manager could receive by staying. Managers with a larger "pie" (assets under management) are less likely to leave the mutual fund industry, while managers who have to share their pie with others, i.e. bigger fund families or more co-managers, are more likely to exit the industry. More interestingly, the effects of fund size, family size, and number of managers are about three times as strong during the second sub-period compared to the first period. This is consistent with the increased role of incentives as outside opportunities for managers have become more viable. I also find a negative effect of manager age on the decision to leave mutual fund management, a result driven entirely by the second sub-period. Again, this is consistent with younger managers moving to better opportunities after gaining experience in the mutual fund industry. It also makes sense in light of legendary hedge fund manager Julian Robertson's reference to hedge funds as "a young man's game."[3]

My second hypothesis is that increasing labor market competition from hedge funds had a negative impact on mutual fund performance and recruitment. For identification, I use a "difference-in-differences" approach to disentangle the hedge fund effect from other time-series variation. I focus on two cross-sectional characteristics to identify the effect of the "brain drain": manager age and geographic region. Gallaway (1969) points out that "increasing age acts to discourage workers from changing jobs," so labor market frictions should allow mutual funds to retain older talented managers while they lose their best young managers to hedge funds. Massa, Reuter, and Zitzewitz (2007) provide evidence that hedge fund employment is heavily concentrated in the Northeast. I use their argument that since a disproportionate percentage[4] of hedge fund assets are managed from the Northeast, mutual funds headquartered in this region of the country should be more affected by competition from hedge funds than those based in other areas.

I find that younger managers underperformed older managers in the post-hedge-fund sub-period relative to the pre-hedge-fund sub-period[5], and that this effect is concentrated in the Northeast where hedge funds are concentrated and conduct most of their recruiting. For each

[3] "A Glimpse Behind the Hedge Fund Curtain", Riva D. Atlas (International Herald Tribune), December 22, 2005.
[4] More than 80% of U.S. hedge funds with at least $1 billion in assets are managed from the Northeast according to HedgeFund Intelligence Magazine. The same is true for only about 50% of mutual fund assets.
[5] 1993-1998 is the pre-hedge fund period when hedge funds were in their infancy and 1999-2005 is the post-hedge-fund period when the hedge fund industry became massive enough to compete with mutual funds. I also check to ensure that my results are robust to choice of boundary date.

year of age, a typical young manager's net returns dropped by approximately 15 basis points annually (statistically significant at the 1% level), for funds based in the Northeast relative to those outside the Northeast. Even after controlling for other cross-sectional characteristics that may affect mutual fund performance and adjusting returns for risk using the Carhart (1997) four-factor model, younger managers from the Northeast still underperform by 8.6 basis points annually for each year of age (statistically significant at the 5% level). A two standard deviation negative shock in age (twenty years) yields approximately a 1.7% decrease in annual risk-adjusted returns, an economically significant effect for an industry in which a typical fund generates zero or slightly negative risk-adjusted returns.

I also perform a series of robustness checks. I drop the "dot-com" bubble years from the sample, look at the returns of mutual fund holdings rather than the reported fund returns, add style dummy variables, and drop newly opened funds from the sample. I use a randomized inference method to verify that standard errors are correctly estimated. I find that my results are robust to these additional tests.

Finally, I explore whether the effect on mutual fund performance is linked to changes in the skills of the mutual fund managerial talent pool. Hedge funds, unlike most mutual funds, use a variety of arbitrage strategies to make profits that are uncorrelated with returns from market or risk factors. Since finding these arbitrage opportunities is likely to be a more skill-intensive process than the buy-and-hold strategies employed by mutual funds, I expect that hedge funds have attracted a significant number of graduates from the best educational institutions in the country who might have otherwise become mutual fund managers.

I find that the overall proportion of mutual fund managers with degrees from top business schools declined by 1.5 percentage points for the entire mutual fund industry from 37.2% to 35.7% between sub-periods. Consistent with cross-sectional differences in the effect of hedge funds, most of this effect is due to a decrease of 17.1 percentage points (statistically significant at the 1% level) or 31% among young managers from the Northeast. This result supports the hypothesis that the growth of hedge funds had a significant effect on the recruiting of top talent by mutual funds.

In addition to quantifying a phenomenon with significant implications for the multi-trillion dollar US mutual fund industry, this paper makes a number of other contributions. First, I connect the decreasing preference for employment in mutual funds to a decline in mutual fund performance, thus providing new evidence of heterogeneous ability among managers. Second, my results highlight the importance of labor market frictions in the efficient allocation of talent in the financial management industry. Third, I collect a unique dataset which matches over 90% of mutual funds with mutual fund manager characteristics such as age and educational institution. As a result, this paper avoids selectivity bias problems that affected earlier studies that used managerial characteristics. Finally, my research has important implications for the debate over the superiority of active or passive mutual fund management. If the best-skilled mutual fund managers left for hedge funds, and small investors are institutionally barred from following them[6], there is even more reason to opt for the lower fees of index funds.

The paper is organized in the following manner. Section I explains the data sets used for this study and discusses several issues of methodology. Section II presents results on managerial

[6] SEC regulations restrict hedge fund access to investment capital from small retail investors.

exits from the mutual fund industry, and examines what factors affect the managerial exit decision. Section III looks at the effect of the brain drain on mutual fund performance. Section IV focuses on the recruitment of talent. Section V concludes. A supplementary appendix includes the results of an in-depth study of a subset of managers who left the mutual industry since 1993.

## I. Data and Methodology

### *A. Data*

The data for this study comes from three main sources: the Center for Research in Security Prices (CRSP) Survivorship-Bias-Free US Mutual Fund Database which I use to obtain fund returns and other fund characteristics, a set of Morningstar Principia CD-ROMs which I use for managerial names and characteristics, and Thomson Financial which I use for mutual fund holdings data. Although CRSP has data from as early as 1961, the available Morningstar data begins in 1993, so I restrict my sample to the 1993 to 2005 time period. Following much of the prior literature on mutual funds, I first focus my analysis on domestic diversified equity mutual funds.[7] Because managers of index funds have little or no influence on their returns, I eliminate index funds from my sample by dropping any funds that have the words “index”, “S&P”, or common abbreviations like “Indx” or “Idx” in their names.

Fund-of-funds and life-cycle funds are two additional types of mutual funds whose stock exposure is not controlled by their managers. I eliminate these types from my sample by

[7] I look at the S&P Objective Code variable which is available throughout the 1993 to 2005 period, and only include funds with codes AGG (Aggressive Growth), GRI (Growth & Income), GMC (Midcaps), GRO (Growth), ING (Income & Growth), and SCG (Small Companies).

dropping any mutual funds that have more than 90% of their holdings in the “other” class of securities, since holdings of other mutual funds are typically classified as “other” securities. Since derivatives are also classified as “other” securities, this cleaning further eliminates many funds that trade primarily in derivatives, and that are actually pseudo-hedge funds marketed to retail investors as mutual funds[8]. To limit any problems from database backfilling, I drop all observations with missing fund names.

CRSP devotes one observation per period for each class of each mutual fund. Using a unique portfolio code from Morningstar and the unique WFICN code which links CRSP data to Thomson Financial Stock Holdings data, I aggregate data across share classes into one observation per mutual fund. For characteristics that vary across share classes such as returns and expense ratios, I take a weighted average using the total net assets of each class as the weights. For the total net assets of a fund, I use the sum of total net assets of all the classes of that fund.

In total, I collect six variables directly from CRSP for each fund-month observation: total net assets, expense ratio, total load, fund turnover, fund age, and fund return. In addition, I use the CRSP data to calculate four other variables: family name, family total net assets, prior 12 month flows, and prior 12 month returns. Since nearly all mutual fund names start with the name of the family, I obtain the fund family for each observation by hand from the fund name. Table I reports summary statistics along with detailed definitions for all fund characteristic variables. Table II shows time-series averages of cross-sectional correlations between these variables. Statistics and correlations are similar to those found in other mutual fund studies. The number of

[8] See Agarwal, Boyson, Naik (2006) for a discussion of mutual funds that use hedge-fund instruments and trading strategies.

funds and the size of funds and families have increased over time, inflows and returns have decreased, while other characteristics have been stable between sub-periods.

**<< Insert Table I here >>**

**<<Insert Table II here>>**

I gather managerial data from a quarterly set of Morningstar Principia CD-ROMs from March 1993 to December 2006. The Principia disks provide the past management history of each mutual fund. This includes names of all current and past managers, the dates when their tenures began and ended, and sometimes biographical data such as educational institutions attended and dates of graduation. Because there is often a time lag between a managerial change and the time when it enters the Principia disk, I use the last available disk that contains a particular fund. For example, I would use the December 2006 disk for each fund that survived to that time, and the September 2002 disk for a fund that was liquidated in November of 2002. However, I make use of prior disks to check for time consistency, and to fill in periods where Morningstar doesn't report any managers at all. I also hand check all manager names to make sure duplicates such as "Bill Miller", "William Miller", and "William H. Miller III" all have the same name in my database. In addition to managerial data, I also obtain each fund's size-value style from Morningstar.

While Morningstar has full data on managers' names and their tenures, it has biographical information on less than half of those managers. This can lead to serious selectivity bias because mutual funds are more likely to omit biographical information on managers with less than impressive credentials or those whom investors may deem too young and inexperienced to control a large pool of assets. Therefore, I use another source to get the age and education data on the remaining managers: the Internet. By looking through online SEC filings, mutual fund family websites, and several other useful sites[9], I am able to collect biographical data on more than 90% of all managers. Thus, for most fund-month observations, I obtain a list of managers, dates of tenure for each manager, estimated year of birth of each manager, undergraduate and graduate institutions attended by each manager, and degree obtained at each of these institutions. I merge this managerial data to the CRSP database using ticker symbol when available, and match by hand using fund names otherwise.

I gather mutual fund holdings data from the Thomson Financial database. At the end of each quarter, I take the last reported holdings from the previous six months and use those holdings to generate holdings' returns for the next quarter. Thus, I am making the assumption that holdings stay fairly constant over short horizons. I am able to match almost 90% of observations with their holdings using the MFLINKS database.

The last variable that I gather for this study is the region of the country in which a mutual fund's manager(s) operate. Using the dataset developed by Chen, Hong, and Kubik (2006), supplemented with data from the Principia disks, I determine the main advisor firm for each mutual fund family's stock funds, and use online SEC filings to find the principal address for this advisor. Some mutual fund families such as TA IDEX and American Skandia are pure marketing vehicles for other advisors, while others like Vanguard outsource their active equity management to sub-advisors such as Wellington Capital. Mutual funds of these families often have multiple advisors that change over time which makes it difficult to establish the exact location of its

[9] The two most important sources are www.zoominfo.com in which you can enter a person's name and get a large number of links to websites (including cached sites that are otherwise unavailable) that have information on this person, and www.zabasearch.com which has dates of birth on a huge set of American residents.

managers. Thus, to ensure that such "outsourced funds" don't add random error to my results, I drop them from all analyses that include fund region.

*B. Methodology*

Although all mutual funds are managed by a group of investment professionals, there is an important distinction between funds that have a lead manager who makes the final decisions for the entire portfolio, and funds where final decisions are made by committee or where each member of a team is responsible for a portion of the portfolio. However, most mutual funds just report one or more manager names without explaining how fund management decisions are made, making it difficult for fund shareholders to assign responsibility for a fund's performance. Papers that use managerial characteristics to predict fund outcomes have come up with different solutions to this problem[10]. In this paper, I assign funds with four or more named managers to the "team-managed" category along with anonymous teams, and drop them from my sample in any tests that use managerial characteristics. For funds with two or three managers, I define the longest-tenured manager as the "lead manager".

In order to estimate the effect of hedge funds, I separate the sample period into two sub-periods and use a dummy variable, which equals one for observations in the later sub-period and zero otherwise, to estimate the change between sub-periods. This approach makes the coefficients in my tests easy to interpret as the change between sub-periods. I use 1999 as the first year of my "post-hedge-fund" sub-period because anecdotal evidence suggests that it was

[10] See Golec (1996), Chevalier and Ellison (1999), and Ding and Wermers (2004) for different methodologies.

the first big year of mutual fund managers going over to hedge funds[11], and because it is the median year in my sample period which gives me two nearly equal sub-periods. However, I also check my results for robustness by removing the years from 1998 to 2000 from my sample altogether.

Since the U.S. hedge fund industry is heavily concentrated in the Northeast region of the country, the location of a mutual fund's headquarters is a useful variable for identifying the brain drain effect. Massa, Reuter, and Zitzewitz (2007) create dummy variables for New York City and Boston to test whether the advent of hedge funds caused a larger shift from individual to team management for mutual funds headquartered in those cities. For this study, I modify their approach by assigning a dummy variable, NORTHEAST, which equals one for mutual funds from Washington DC and the eleven states to its north, and zero otherwise. My rationale is that the Northeast region is geographically compact; nearly all mutual funds in the Northeast are located within 200 miles of New York or Boston while nearly twice that distance separates San Francisco and Los Angeles, which are in the same state. Therefore, I assume that the costs of job mobility within the Northeast are sufficiently low that mutual fund managerial recruiting in one area of the Northeast is affected by hedge funds operating in different parts of the region.

### II. Measuring the "Brain Drain"

The investigation of how the labor market for money managers has changed over the last decade starts with a simple "head count". Table III shows the number of lead managers at the end of each calendar year, as well as how many new managers entered the sample over the

[11] Barron's Magazine called it the "Class of '99" in an April 8, 2002 article.

previous calendar year (*IN*) and how many left the sample over the previous calendar year (*OUT*). The annual rate of new managers over the first sub-period (23.0%) is about 50% greater than over the second period (15.4%) reflecting the growth in the number of funds over the first sub-period. On the other hand, the rate of departures increased slightly from 13.3% to 15.8%. However, from this simple analysis, it's impossible to determine what is causing these increases, or whether they have any economic significance. Are more managers leaving due to fund closures after the burst of the dot-com bubble? Or perhaps managers are leaving one fund and then taking positions in a different fund in the next calendar year.

**<< Insert Table III here >>**

I focus on the effect of outside opportunities on mutual fund turnover by studying *managerial exits*. I define managerial exits using the dummy variable $\text{MGR\_EXIT}_{i,t}$ for mutual fund *i* in month *t*, which is set to one if the lead manager of fund *i* changes from month *t* to month *t+1* AND if the departing manager is not in my database from months *t+1* to *t+12*, and which equals zero otherwise. In order to distinguish promotions from terminations for bad performance or end-of-career retirements, I also sort managers each month into quintiles based on manager age and quintiles based on returns (net of expenses) over the last twelve months[12].

**<< Insert Table IV here >>**

Table IV reports the annualized rates of managerial exit from the mutual fund industry for managers from different age-performance subgroups and compares how the exit rates changed between sub-periods. In the overall sample, there is an increase of 1.7 percentage points in the managerial exit rate between sub-periods from 9.2% to 10.9% (t-statistic of 2.11). The last

[12] As a robustness check, I replace raw returns with risk-adjusted returns and obtain similar results.

row reports results sorted by performance quintile and shows that while managerial exits increased by 1.2, 0.6, 2.0, and 1.1 percentage points per year for the first four quintiles (containing the 80% of managers with the worst performance in the trailing 12 months), there was a much larger 3.5 percentage point increase between sub-periods for the top quintile of best performing managers. The top quintile of past performers was the only quintile whose increase was statistically significant at the 10, 5, or 1 percent level (t-statistic of 3.32). These results demonstrate that while there was some overall positive drift in managerial separations due to other factors, most of the aggregate increase was a result of more successful mutual fund managers voluntarily leaving for better opportunities rather than involuntary terminations due to bad performance.

Retirement or death are two other potential reasons for a manager's exit from the mutual fund database. I use the age of the manager to test these explanations since departures of older managers are more likely to be driven by these factors. The last column of Table IV reports results for subgroups sorted by age of the manager. The smallest increases between sub-periods are in the two oldest quintiles (managers older than 50), suggesting that career-ending factors are not driving the overall increase.

Finally, I examine each of the twenty-five age-performance sub-groups. The only two sub-groups which show a statistically significant increase in the exit rate are the first two age quintiles (managers younger than 44) in the top (best 20%) performance quintile. Among managers in the highest quintile of performers and in the two lowest age quintiles, the annual managerial exit rate went up by 7.9 (t-statistic of 3.08) and 6.4 (t-statistic of 3.30) percentage points, respectively. While the managers in these two (of twenty-five) sub-groups make up only

8% of all managers each month, the increase in their exit rate is driving almost half of the overall increase in the managerial exit rate between sub-periods.

Table IV contributes several stylized facts about the mutual fund managerial labor market and its transformation during the period from 1993 to 2004. First, it shows that there was a secular increase of about 1 percentage point in the annualized rate of managerial exit that was prevalent across all age-performance sub-groups. Second, it shows that younger managers in the top quintile of prior performers were less likely to leave the mutual fund industry in the first sub-period than any other age-performance sub-group. This is consistent with anecdotal evidence that prior to the advent of hedge funds, such managers were at the height of prestige, with little reason or opportunity to leave the mutual fund industry. Hedge funds gave these money managers the option to utilize their record of superior performance as a marketing tool for raising capital, and thus to take advantage of the superior compensation and flexibility of having their own hedge funds. Third, it shows that the yearly rate at which successful young managers left the mutual fund industry increased by about 6 percentage points between sub-periods, even after controlling for the overall drift of one percentage point in other sub-groups. Overall, these results suggest that more young successful managers used the mutual fund industry as a stepping stone to the better opportunities that arose in the second sub-period.

I next investigate the role of incentives in the managerial exit decision. If the increase in managerial exits is due to the rise of new opportunities in the second sub-period (voluntary exits), then we should expect more turnover in that sub-period among managers who receive less compensation (ceteris paribus) as mutual fund managers. On the other hand, if the increase is driven by other factors, the null hypothesis is that there is no change in the effect of incentives. I run a pooled OLS regression[13] of managerial exits on fund and managerial characteristics using the following specification:

$$(1)\quad MGR\_EXIT_{i,t} = \mu + \varphi_1 * LogFundSize_{i,t} + \varphi_2 * LogFamilySize_{i,t} + \varphi_3 * FundAge_{i,t} + \varphi_4 * Prior1\text{-}yearPercentile_{i,t} + \varphi_5 * ManagerAge_{i,t} + \varphi_6 * MedianUndergradSAT_{i,t} + \varphi_7 * GraduateDegree_{i,t} + \varphi_8 * No.ofManagers_{i,t} + TIME\ DUMMIES + \varepsilon_{i,t},\ \mathrm{i} = 1, \ldots , \mathrm{N}$$

Table V presents the estimated coefficients from this regression. Column 1 shows the estimates for the entire sample period. Columns 2 and 3 show estimates over the first and second sub-period, respectively. For Column 4, I interact all variables with a dummy variable $\mathrm{AFTER1999}_t$ (which equals one in the 1999-2004 sub-period and zero otherwise), run the regression over the entire sample period, and report the results of interaction terms in order to obtain statistical estimates of the change in coefficients between sub-periods. In all regressions, I omit funds from the highest age quintile and the lowest performance quintile to eliminate managers who likely left for retirement reasons or were fired for bad performance.

**<< Insert Table V here >>**

Column 1 shows that the variables that explain managerial exits in the entire sample are *Log Fund Size*, *Log Family Size*, *No. of Managers*, *Fund Age*, *Prior 1-year Percentile*, and *Manager Age*. The first three variables are excellent proxies for a manager's compensation. Having more assets under management increases a mutual fund manager's salary and thus the opportunity cost of leaving the industry. Not surprisingly then, the coefficient on *Log Fund Size* is negative, -1.467% (t-statistic of 6.07). One standard deviation shock in this variable (of 2.15)

[13] I also run a probit specification with nearly identical results. I show the results of OLS regression to simplify the interpretation of coefficients.

decreases the rate of annual managerial exits by about 3.1%. This is a large effect considering that the average managerial exit rate is about 10%. Columns 2 through 4 show that the second sub-period is driving the overall coefficient on *Log Fund Size*. In the first sub-period, fund size makes little difference in the decision to leave (coefficient of -0.479%) while in the second sub-period, the effect more than quadruples (to a coefficient of -2.065%). This result makes sense if more exits in the second period came from voluntary decisions to leave which should be contingent on the opportunity cost of exit.

The explanatory effects of family size and number of managers also make sense when we recall that they are inversely related to compensation. Taking fund size fixed, bigger family size and more managers imply that the "pie" of managerial fees has to be shared by more people. Not surprisingly, there are positive coefficients on *Log Family Size* (0.490%) and *No. of Managers* (2.192%) since higher values for these variables lower incentives and reduce the opportunity cost of exit. And just as with *Log Fund Size*, the second sub-period is driving the increase in both coefficients. The effects of family size and number of managers are about three times as strong in the second sub-period as in the first sub-period, and the difference in the coefficients between sub-periods are statistically significant.

There are three other variables of interest that explain the exit decision. One variable is *Fund Age* which comes in a with a positive coefficient of 0.105%, so each extra decade that a fund is operating increases the annual manager exit rate by about 1%. One possible explanation for this result is that managers of new funds recently started at their position so they are unlikely to change their minds quickly and decide to leave the industry. In other words, *Fund Age* is a proxy for the length of time since the manager last considered leaving the industry.

*Prior 1-year Percentile* is the most recent performance of the fund (relative to its peers) and it comes in with a negative coefficient. While it obviously picks up the increased chance of termination following bad performance, it is interesting that the effect of performance significantly weakened between sub-periods. This makes sense in the context of promotions since better prior performance gives departing managers a track record useful for raising capital for their own firms. Finally, *Manager Age* comes in with a negative coefficient of -0.108%, a result driven entirely by the second sub-period. This is consistent with the labor literature finding that younger managers are more likely to (voluntarily) change jobs or careers. Overall, the results in Table V support the thesis that increased opportunities in the second sub-period increased the role of incentives (and opportunity costs) in affecting exit rates of mutual fund managers.

To conclude this section, I should point out that the main result, i.e. that young mutual fund managers with good performance records have left in growing numbers, is not necessarily ominous for the mutual fund industry. First of all, it does not automatically imply that the industry is losing a group of managers with special abilities to outperform their peers. It is easy enough to imagine a world where all mutual fund managers shoot darts at the stock pages to pick which stocks to buy, and those that get lucky and have the best performance, cash in on that luck by starting their own hedge fund.

A counter-argument is that since managers often put up a large sum of their own money when they start a hedge fund, only mutual fund managers with a high degree of confidence in their superior skills would risk their money and career on such a venture. But anecdotal evidence about mutual fund stars who fail at hedge fund management along with a growing behavioral literature on overconfidence of decision makers tells us that in many cases, managers don't know whether their performance was due to luck or skill. Another important reason why mutual fund managers might not suffer from the growing rates of departures is that these managers may be easily replaced by new recruits with comparable abilities. In the next section, I explore the effect of the brain drain on mutual fund performance and hiring.

## III. Effect of the Brain Drain on Mutual Fund Returns

*A. Main Result*

This section explores the effect of hedge funds on mutual fund returns. Throughout this section, I run all regressions separately for the 1993-1998 sub-period and the 1999-2005 sub-period and then add interactions of all independent variables with the dummy variable $AFTER1999_t$ (which equals one in the 1999-2005 sub-period and zero otherwise) to measure how coefficients changed between sub-periods. I start by running a pooled OLS regression using the following specification with standard errors clustered at the fund level:

(2) $$NET\_RETURNS_{i,t} = \mu + \varphi * ManagerAge_{i,t-1} + \gamma * Controls_{i,t-1} + TIME\ DUMMIES + \varepsilon_{i,t}\ ,\ \mathrm{i} = 1, \ldots, \mathrm{N}$$

where $NET\_RETURNS_{i,t}$ is the annualized monthly return on fund *i* in month *t*, net of expenses, $Manager\ Age_{i,t-1}$ is the age in years of the manager of fund *i* in month *t-1*, and $Controls_{i,t-1}$ is a set of eight lagged control variables described in Table I including *Log Fund Size*, *Log Family Size*, *Expense Ratio*, *Total Load*, *Turnover*, *Fund Age*, *Prior 1-year flows*, and *Prior 1-year Return*. I anticipate an increase in the coefficient φ on *Manager Age,* since successful younger managers are more likely to move to hedge funds so those remaining in the mutual fund industry should be generating lower average returns as hedge funds became more prevalent.

**<< Insert Table VI here >>**

Table VI shows the estimation results for coefficient φ in Equation (2) with and without control variables. Column 1 shows that the differential yearly return for one year of age rose from -6.06 basis points to 0.54 basis points between sub-periods, a statistically significant increase of 6.60 basis points (t-statistic of 2.42). In other words, during the first sub-period, older managers underperformed younger managers, while during the second sub-period, they slightly outperformed. This result is consistent with the hypothesis that funds with younger managers outperformed those with older managers before the rise of hedge funds, but this superior performance disappeared in the second sub-period as young top talent turned to hedge fund management.

Still, there is an alternative explanation for these results: the "new economy hypothesis." Greenwood and Nagel (2006) find that younger mutual fund managers held more of their portfolios in technology stocks during the dot-com bubble of the late 1990s. As a result, it is possible that differences in holdings, and not the emergence of hedge funds, could be driving the difference in returns. In order to disentangle the "new economy hypothesis" from my original "brain drain hypothesis", I add an additional variable to my analysis: region. I expect that the brain drain to hedge funds should have a predominant effect on mutual fund managers working in the Northeast. On the other hand, the "new economy hypothesis" would suggest the opposite result based on the findings of Coval and Moskowitz (1999) of a local bias to portfolio holdings, and the fact that technology companies are mostly headquartered outside the Northeast.

I re-estimate Equation (2) separately for funds in the Northeast and for funds outside the Northeast. Columns 2 and 3 of Table VI show the estimates of coefficient φ for the two regions without control variables. In the Northeast, younger managers outperformed by 9.67 basis points annually for each age year, during the first sub-period, while they underperformed by 3.98 basis points annually for each age year, during the second period, for a strongly statistically significant increase of 13.66 basis points (t-statistic of 3.43) between sub-periods. In contrast, there was an insignificant 1.36 basis point *decrease* in the age effect between sub-periods for mutual funds outside the Northeast. Adding control variables explains some of the variation in returns, but does not overturn the main result. With controls, Column 5 shows a 7.64 basis point increase in the differential return to age for funds in the Northeast, a result that is statistically significant at the 5% level (t-statistic of 2.39), while Column 6 shows an insignificant *decrease* of 2.06 basis points in φ for funds outside the Northeast. These results are consistent with the predictions of the brain drain hypothesis and are contradictory to the predictions of the new economy hypothesis.

I make my framework more robust by adding region directly to my regression, allowing me to use mutual funds outside the Northeast as a control group. It is simple to come up with alternative stories why the return to age should have increased over time, as I have suggested with my new economy hypothesis. It's also possible to explain why returns should be different across regions by alluding to regional differences in the managerial job market. However, it is more difficult to plausibly explain why the return to age should increase over time but only for Northeast funds, without alluding to the rise of hedge funds. I run a pooled OLS regression using the following specification with standard errors clustered at the fund level:

(3) $NET\_RETURNS_{i,t} = \mu + \varphi_1 * ManagerAge_{i,t-1} + \varphi_2 * Northeast_{i,t-1} + \varphi_3 * ManagerAge_{i,t-1} * Northeast_{,t-1} + \gamma * Controls_{i,t-1} + TIME\ DUMMIES + \varepsilon_{i,t}$ , i = 1, … , N

where $Northeast_{i,t-1}$ is a dummy variable which equals one for mutual funds managed from the Northeast and zero otherwise, and all other variables are defined as in Equation (2). My coefficient of interest is $\varphi_3$ which measures the difference in the age effect between Northeast and non-Northeast mutual funds.

**<< Insert Table VII here >>**

Table VII shows the estimation results for coefficient $\varphi_3$ in Equation (3) with and without control variables and with different performance measures as dependent variables. In Column 1 of Panel A, we see an increase of 15.01 basis points between sub-periods in the annual return to age for funds in the Northeast relative to those outside the Northeast, a result significant at the 1% level (t-statistic of 2.85). Column 1 of Panel B shows that, even after controlling for other characteristics that affect mutual fund returns, there was an increase in $\varphi_3$ of 9.71 basis points between sub-periods, significant at the 5% level (t-statistic of 2.30).

I also check that these results are truly due to a difference in performance rather than differences in managerial expenses or risk loadings. I replace the dependent variable $NET\_RETURNS_{i,t}$ in Equation (2) with three other measures of returns: $GROSS\_RETURNS_{i,t}$ which is the return of the fund portfolio before deducting managerial expenses, $CAPM\_RETURNS_{i,t}$ which is the net return of the fund after adjusting for the market return using the Capital Asset Pricing Model (CAPM) of Sharpe (1964), and

$CARHART4F\_RETURNS_{i,t}$ which is the net return of the fund after adjusting for the three risk factors of Fama and French (1993) and a fourth momentum factor as in Carhart (1997).

The results are similar for all four types of performance measures. Without controls, Panel A shows that the coefficient $\varphi_3$ on the interaction term increased by somewhere between 13.82 and 15.01 basis points between sub-periods. With controls, Panel B shows smaller increases in the interaction term, ranging from 8.59 to 9.71 basis points. Differences in expenses and risk-taking clearly do not explain the relative underperformance of young managers from the Northeast providing additional evidence for the brain drain hypothesis.

### *B. Robustness Checks*

In this subsection, I perform a number of tests to verify the robustness of my results. Panel A of Table VIII repeats the analysis from Tables VI and VII, but drops 36 months from January 1998 to December 2000 from the sample, allowing us to compare the five years from 1993 to 1997 to the five years in 2001 to 2005.

This check is critical for two reasons. First, 1998 to 2000 saw the rise and fall of the dot-com bubble which caused extreme volatility in stock prices and gave rise to many temporary phenomena which are not present in normal conditions. By dropping those years from the sample, I can check whether events surrounding the dot-com bubble are driving my results. Second, the 1998 to 2000 are the three middle years of my sample period during which hedge funds were just starting to make an impact. Although I choose December 1998 as the last month of my “pre-hedge-fund” sub-period, dropping the three intermediate years altogether ensures that my results are not driven by that somewhat arbitrary choice of boundary.

**<< Insert Table VIII here >>**

In Panel A of Table VIII, Columns 1 through 3 show the estimation results for coefficient $\varphi$ on MGR_AGE in Equation (2) with control variables, for 1993 to 1997, for 2001 to 2005, and the change between sub-periods. The increase in the differential return to age between sub-periods is actually slightly stronger here than in the corresponding columns (columns 4 to 6) of Table VI. Columns 4 through 5 present the estimation results for coefficient $\varphi_3$ in Equation (3) with control variables, for 1993 to 1997, for 2001 to 2005, and the change between sub-periods. We can see that dropping the bubble years leads to slightly smaller increases in $\varphi_3$ for net returns and slightly larger increases in $\varphi_3$ for risk-adjusted returns. Overall, it appears that my main results are not driven by the dot-com bubble or by the choice of December 1998 as a boundary between sub-periods.

Another way of checking robustness is by focusing on $\text{HOLDINGS\_RETURNS}_{i,t}$, the returns of a mutual fund's previously reported holdings rather than its actual reported returns. By removing differential performance arising from differences in fund expenses, transactions costs, IPO allocations, non-stock holdings, or short-term trading[14], holdings' returns are more attributable to managerial skill in selecting stocks that outperform their peers. In Panel B of Table VIII, Columns 1 through 3 show the estimation results for coefficient $\varphi$ on MGR_AGE in Equation (2) for 1993 to 1998, for 1999 to 2005, and the change between sub-periods with holdings' returns as the dependent variable. I do not add fund characteristics as controls since holdings' returns are determined by the portfolio choice of the fund manager rather than any characteristics such as size, expenses, or turnover of the fund itself.

[14] See Kacperczyk, Sialm, and Zheng (2006) for explanations of the "return gap" between reported fund returns and holdings returns.

The results are similar to those using fund returns as the dependent variable: there is an increase in φ over time that is caused by a large increase in φ for funds based in the Northeast. Column 4 shows the estimation results for the coefficient on the interaction variable $\varphi_3$. Again, there is an increase between sub-periods and it is statistically significant. Column 5 shows the estimation results for $\varphi_3$ but with holdings' returns adjusted for risk factors using the Daniel, Grinblatt, Titman, and Wermers (1997) method (DGTW). The DGTW-adjusted return for a mutual fund is obtained by placing each stock holding in one of 125 portfolios based on size, book-to-market, and prior 12 month returns[15] and subtracting the return of the entire portfolio of which the stock is a member from the return of the stock. Then, the excess returns of the stock holdings are aggregated to get the excess return of the entire fund portfolio. The coefficient increased by more than 5 basis points between sub-periods suggesting that my results are mostly due to differences in stock-picking ability rather than holding stocks with different risk characteristics.

Another possibility is that the effect on returns is driven by changes in the performance of different investment styles, and that manager age or the interaction between age and region is correlated with one of these style variables. In order to ensure that this is not the case, I add style dummy variables to my specifications based on each fund's style characteristics from Morningstar. Morningstar assigns fund styles by putting a fund into one of three size categories based on the size of its stock holdings (small-cap, mid-cap, and large-cap), one of three valuation categories based on the growth characteristics of its stock holdings (growth, blend, or value), and taking the intersection to put a fund in one of nine style boxes.

[15] The DGTW benchmarks are available via http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm

Panel C of Table VIII shows that adding style dummies largely does not affect the results. Column 1 shows that the change in coefficient φ on MGR_AGE for the entire mutual fund industry is positive but of borderline statistical significance. In columns 2 and 3, we see that this increase comes entirely from funds based in the Northeast where the increase in the coefficient on MGR_AGE is statistically significant (t-statistic of 2.44). Columns 4 and 5 which show the change in coefficient $\varphi_3$ between sub-periods are again very similar to those in Table VII. Overall, controlling for style does not seem to explain the increase in the age effect.

I next test whether dropping new funds, those in existence less than two years, has an impact on my results. Previous research has found that newly opened funds face significant startup costs which cause them to under-perform in the first couple of years after they begin operation. New funds are often run by younger managers, and it's possible that the fund age control variable is not picking up this nonlinear effect. However, Panel D suggests that this is not the case. The coefficient changes in columns 1 through 5 are similar to the corresponding changes in the full sample.

Bertrand, Duflo, and Mullainathan (2004) explain that difference-in-differences estimators such as the ones used in this section can have downward biased standard errors because of serial correlations in both the outcomes and the treatment variables. While mutual fund returns don't suffer from significant serial correlation, I use a randomized inference method suggested in their paper to check whether my standard errors suffer from this problem. This technique works by randomly resorting the treatment variables while keeping the time-series structure fixed, and then estimating coefficients after each new random sort. The standard deviations of the coefficients should reflect the downward bias imposed by the time structure and thus provide us with a robust standard error.

**<< Insert Table IX here >>**

I apply this procedure to my study by randomly assigning years of birth to each manager from the actual distribution of years of birth and randomly assigning fund families to be outside the Northeast or in the Northeast, again from the actual distribution of regions. I then generate a pseudo-interaction variable from the random manager ages and family regions and run pooled OLS regression on Equation (3) with net returns and Carhart four-factor returns as the dependent variables and save the coefficient on the change in the interaction variable. I repeat this process 500 times and use the standard deviation across runs of the coefficients as my robust estimate of the standard error on the real interaction variable. Table IX shows that the standard errors estimated from randomized inference are about 5% *lower* than those from pooled OLS making the t-statistics slightly higher than in pooled OLS. This confirms that serial correlation is not causing our t-statistics to be too high.

### *C. Analysis*

The results presented in this section have a number of broader implications for mutual fund performance. They show that the rise of hedge funds had the largest impact on the returns of a fraction of the mutual fund industry, funds managed in the Northeast by younger managers. However, if the cross-sectional differences in performance are due to labor market frictions, it necessarily implies that the effect of hedge funds on performance will spread over time throughout the mutual fund industry. As older managers retire and are replaced by the current crop of young managers, and as more hedge funds are opened outside the Northeast, the decrease in returns that is now concentrated among mutual funds managed by younger managers in the Northeast will increasingly affect all funds.

Another important point is that the estimate of the change between sub-periods in coefficient $\varphi_3$ is really a lower bound for the overall effect of hedge funds. Because the hedge fund industry existed before 1999 (although smaller in size) and because there are some hedge funds outside the Northeast, my difference-in-differences test only picks up the effect on returns from the *relative* growth of the hedge fund industry (between sub-periods) and from its *relative* regional importance, and not from its overall effect on mutual fund performance.

Furthermore, a mutual fund can always apply an indexing strategy as a lower bound on its returns, and it’s probably true that a significant proportion of actively-managed mutual funds are effectively closet index funds. Since a brain drain would only affect the right tail of the return distribution, i.e. those mutual funds whose managers actually have the ability to outperform the market, it’s unlikely to have a huge effect on the entire distribution of returns. Of course, it’s exactly those skilled managers that provide a rationale for having an actively-managed mutual fund industry in the first place. The growing trend toward investing in index funds and ETFs is consistent with the notion that actively-managed mutual funds are increasingly becoming anachronisms.

### IV. Effect of the Brain Drain on Mutual Fund Recruitment

When hiring someone without a prior performance record, money management firms can use education as an informative signal of the intelligence, skills, and network assets that a future manager will use to generate superior performance. I examine whether hedge funds have successfully competed away managers from top educational institutions forcing mutual funds to lower their hiring standards. I define a dummy variable $TOP\_SCHOOLS_{i,t}$ for mutual fund *i* in month *t*, which is set to one if the lead manager of fund *i* has a degree from one of the top fifteen business schools in the United States, ranked by average GMAT of its entering class, and which equals zero otherwise[16].

I analyze the level of graduate rather than undergraduate education because hedge funds are more skills-intensive so they are more likely to compete for managers with graduate degrees. Mutual funds can offset their losses of recruits from top business schools by hiring graduates of top undergraduate institutions without graduate degrees, so I would not necessarily expect to find a similar effect in undergraduate education levels. I use a dummy variable approach rather than using GMAT scores because I am specifically interested in the effect on recruiting from the *best* business schools, and not the entire distribution.

**<< Insert Table X here >>**

Table X shows how the fraction of mutual funds with managers having advanced degrees from top schools evolved over time for different age-region subgroups. The top row shows that when breaking down the results by region, the proportion of Northeast funds with managers from top schools went down by a statistically significant 3.9 percentage points (t-statistic of 2.03) while it actually *increased* slightly for funds outside the Northeast. Nevertheless, even in the second sub-period, Northeast funds have a much higher proportion of managers from top business schools, 44.0%, than non-Northeast funds, 26.6%. The larger number of top business

[16] I run robustness checks using TOP 10 or TOP 5 business schools and the results are not significantly different.

school graduates in the Northeast job market helps explain why most hedge funds are based in the region, while mutual funds, which often cater to regional clienteles and are not as skills-intensive, are spread out around the country.

Table X also breaks down the analysis into four age sub-groups of (approximately) equal size. In Column 1, we can see that the overall decrease in the proportion of lead managers from top schools can be attributed to an 11 percentage point decrease (t-statistic of 4.20) between sub-periods among managers who are 40 or younger. Columns 2 and 3 break down the results by region. Although only 8 of the top 15 business schools are located in the Northeast, there is a 17.1 percentage point drop (t-statistic of 4.66) in the fraction of youngest Northeast managers from top business schools, and only a 1 percentage point drop in the fraction of youngest non-Northeast managers from top business schools. This is in line with my prediction that hedge funds have attracted a lion's share of young talent from top business schools that would have gone to mutual funds in earlier years, and that this effect is predominant in the Northeast labor markets where hedge funds do most of their hiring. In fact, the absolute value of the change in the under 41-Northeast sub-group is more than three times that of any of the other seven age-region sub-groups. The results of Table X support the "brain drain hypothesis" by showing that mutual funds based in the Northeast had difficulty attracting graduates from top business schools as hedge funds became a more lucrative career choice for those graduates.

## V. Conclusion

Should we care whether more graduates of top business schools are becoming hedge fund managers rather than mutual fund managers or that more successful mutual fund managers are leaving the industry to start their own hedge funds? One affirmative answer to this question is that the advent of hedge funds has given us a natural experiment with which to investigate the role of managerial ability in generating returns. Because of their flexibility, hedge funds provide higher marginal return to ability than mutual funds so they would be expected to attract managers with the best skills. If mutual fund returns fell because hedge funds became more prevalent, that *would* necessarily imply that the identity of a manager matters for performance and that an average replacement can't be expected to generate the same performance.

However, many different factors can cause returns to change over time, and we need to convincingly connect the change to hedge funds. Fortunately, because of labor market frictions, hedge funds are more likely to attract young managers from the Northeast than other mutual fund managers. We know this from both anecdotal evidence (hedge funds are a "young man's game", more than 80% of the largest hedge funds are in the Northeast), and we can see it in the results of this paper on managerial separations and the proportion of managers with degrees from top business schools. Thus, we can use age and regional control groups to control for any time-series variation in returns not pertaining to hedge funds.

Following this procedure, I find a connection between the advent of hedge funds and lower mutual fund returns. I estimate that the relative return for younger Northeast managers (for each year of age) fell by at least 8 annual basis points and by as much as 15 annual basis points between sub-periods. In spite of the fact that only a fraction of mutual fund managers are likely to be effective at generating excess returns (and thus would be affected by hedge funds), these results are statistically and economically significant. And of course, these top-notch managers provide the rationale for the very existence of the active mutual fund industry. If they no longer contribute to the mutual fund distribution, the actively managed mutual fund industry will increasingly resemble indexes, except with higher fees, a combination unlikely to survive long in the money management market.

## Appendix

While I have found a significant increase in the rate of managerial exits, especially among young successful managers, it would be instructive to know the destination of these departing managers. To this end, I focus on the two sub-groups showing sharp increases in departure rates, and perform an exhaustive investigation (using the Internet) to determine the destinations of these managers. Table A1 decomposes the average managerial exit rate for each sub-period into five possible destinations: departures for hedge funds, non-hedge fund startups, promotions within the mutual fund family, departures for other financial firms, and retirements or unknown destinations.

**<< Insert Table A1 here >>**

Panel A of Table A1 shows results for departing managers from the two lowest age quintiles (managers younger than 44) and the fifth (best 20%) performance quintile. There is an overall increase in the exit rates for these two groups of 7 percentage points from 3.5% to 10.5%. More than half of the overall increase is driven by the 3.6 percentage point increase in departures to hedge funds, from 0.6% in the first sub-period to 4.2% in the second sub-period. About a quarter of the overall increase (1.9 percentage points) is driven by managers who leave for other (non-mutual fund) financial firms. Some of these managers take executive positions while others obtain money management positions that include managing assets of institutions or high networth individuals. Departures to non-hedge fund startups, promotions within the mutual fund firm, and retirements are not significant drivers of the overall increase.

For comparison, I also look at departing managers from the same age quintiles but from the second-best performance quintile. The results are reported in Panel B of Table A1. Here, the overall increase of 0.8 percentage points is much smaller and statistically insignificant. I again decompose the exits by destination as in Panel A. The big differences between Panel A and Panel B are the much smaller increases in departures to hedge funds and to other financial firms. Clearly, a truly outstanding track record is a critical ingredient for a manager to leave the firm for outside opportunities which is why the increase in the exit rate is concentrated in the 20% of best-performing managers.

**<< Insert Table A2 here >>**

Since hedge funds seem to be driving much of the results, I focus in on managers who leave for hedge funds[17] (from all subgroups). Table A2 reports a list of these managers with additional information on the mutual fund they left, the hedge fund that was their destination, the date of exit, the age at exit, and whether they founded a new hedge fund or joined an existing one. It is important to emphasize that this is just a sample of the population of mutual fund managers who left for hedge funds. However, it provides some interesting information on the brain drain phenomenon. More than three-quarters left during the second sub-period. Their mean age (about 40) is lower than the average exiting manager. Most of them depart from large mutual fund families where their salary is probably much smaller than the managerial fees collected by the firm. Over two-thirds start their own firms rather than join an existing hedge fund. Overall,

[17] Again, I looked for manager bios or online references to departures to hedge funds.

we can see a portrait of a young manager who gets a job at a large mutual fund family, performs well, and then leaves to start her own hedge fund where she can keep more of the surplus from her own talents.

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**Table I**

**Mutual Fund Characteristics – Summary Statistics**

Table I reports summary statistics for mutual fund characteristics obtained from the CRSP database. The first column reports summary statistics on the entire period from 1993 to 2005 while the second and third columns report statistics for two sub-periods. Number of funds is the total number of mutual funds in the sample. *Fund Size* is the total net assets under management of all fund classes in millions of dollars. *Log Fund Size* is the natural logarithm of *Fund Size*. *Log Family Size* is the natural logarithm of one plus the total net assets managed by the fund's family excluding the *Fund Size* of the fund itself. *Expense Ratio* is the total fees paid for a fund's operating expenses as a ratio of total net assets. *Total Load* is the maximum front-end, deferred, and rear-end loads as a percentage of new investments. *Turnover* is the fund turnover, defined as the minimum of aggregated sales or aggregated purchases of securities, divided by the average 12 month *Fund Size* of the fund. *Fund Age* is the number of years since the fund was first offered. *Prior 1-year Flows* is the net inflows into the fund over the past twelve months as a ratio of the *Fund Size* one year earlier. *Prior 1-year Returns* is the cumulative net returns of the fund over the last twelve months. Because it often takes extreme values, *Prior 1-year Flows* is winsorized within each month at the 5% and 95% level. *Prior 1-year Returns* is winsorized within each month at the 1% and 99% level. All other variables are winsorized within each month only above the 99% level. For each variable, the table reports time series averages of monthly cross-sectional means and also reports time series averages of monthly cross-sectional standard deviations in brackets.

| **Variable** | **Entire Sample 1993-2005** | **Subperiod1 (1993-1998)** | **Subperiod2 (1999-2005)** |
|---|---|---|---|
| *Number of Funds* | 1813.5 | 1388.4 | 2177.9 |
| *Fund Size* | 855.3 | 671.2 | 1013.1 |
| ($ million) | [3221.6] | [2352.5] | [3966.6] |
| *Log Fund Size* | 4.71 | 4.57 | 4.83 |
| ($ million) | [2.14] | [2.10] | [2.17] |
| *Log Family Size* | 6.31 | 5.63 | 6.90 |
| ($ million) | [3.37] | [3.41] | [3.33] |
| *Expense Ratio* | 1.32 | 1.27 | 1.36 |
| (% per year) | [0.53] | [0.56] | [0.50] |
| *Total Load* | 1.93 | 1.95 | 1.99 |
| (%) | [2.30] | [2.38] | [2.24] |
| *Turnover* | 91.55 | 80.44 | 101.09 |
| (% per year) | [89.08] | [70.40] | [105.09] |
| *Fund Age* | 11.62 | 11.74 | 11.52 |
| (years) | [13.35] | [14.09] | [12.71] |
| *Prior 1-year Flows* | 31.89 | 41.89 | 23.32 |
| (% per year) | [75.81] | [86.45] | [66.70] |
| *Prior 1-year Ret.* | 11.68 | 16.60 | 7.46 |
| (% per year) | [11.96] | [8.59] | [14.85] |

**Table II**

**Mutual Fund Characteristics – Cross-Sectional Correlations**

Table II reports time-series averages of monthly cross-sectional correlations between the mutual fund variables obtained from the CRSP database. *Log Fund Size* is the natural logarithm of the fund's assets under management. *Log Family Size* is the natural logarithm of one plus the total net assets managed by the fund's family excluding the total net assets of the fund itself. *Expense Ratio* is the total fees paid for a fund's operating expenses as a ratio of total net assets. *Total Load* is the maximum front-end, deferred, and rear-end loads as a percentage of new investments. *Turnover* is the fund turnover, defined as the minimum of aggregated sales or aggregated purchases of securities, divided by the average 12 month total net assets of the fund. *Fund Age* is the number of years since the fund was first offered. *Prior 1-year Flows* is the net inflows into the fund over the past twelve months as a ratio of the *Fund Size* one year earlier. *Prior 1-year Returns* is the cumulative net returns of the fund over the last twelve months. Because it often takes extreme values, *Prior 1-year Flows* is winsorized within each month at the 5% and 95% level. *Prior 1-year Returns* is winsorized within each month at the 1% and 99% level. All other variables are winsorized within each month only above the 99% level.

| **Correlation Table** | Log Fund Size | Log Family Size | Expense Ratio | Total Load | Turnover | Fund Age | Prior 1-year Flows | Prior 1-year Returns |
|---|---|---|---|---|---|---|---|---|
| *Log Fund Size* | 1.00 | 0.52 | -0.35 | 0.10 | -0.10 | 0.39 | -0.09 | 0.10 |
| *Log Family Size* | | 1.00 | -0.21 | 0.13 | 0.04 | 0.11 | 0.01 | 0.05 |
| *Expense Ratio* | | | 1.00 | 0.20 | 0.21 | -0.15 | 0.07 | -0.08 |
| *Total Load* | | | | 1.00 | -0.01 | 0.09 | -0.02 | -0.02 |
| *Turnover* | | | | | 1.00 | -0.07 | 0.04 | 0.01 |
| *Fund Age* | | | | | | 1.00 | -0.24 | -0.04 |
| *Prior 1-year Flows* | | | | | | | 1.00 | 0.27 |
| *Prior 1-year Returns* | | | | | | | | 1.00 |

**Table III**
**Mutual Fund Management – Time Series Trends**

Table III reports the total number of lead managers in December of each year from 1993 to 2004. Columns (2) – (3) show the (gross) number of incoming managers and the rate of incoming managers (as a fraction of total managers in the previous year) in each year. Columns (4) – (5) show the (gross) number of outgoing managers and the rate of outgoing managers (as a fraction of total managers in the previous year) in each year. It also reports time-series means for each statistic, time-series means for the first sub-period from 1993 to 1998, time-series means for the second sub-period from 1999 to 2004, and the difference between sub-periods. A manager is counted under "IN" for a certain year if that manager was the lead manager of a mutual fund in December of that year, and was not the lead manager of a mutual fund in December of the previous year. A manager is counted under "OUT" for a certain year if that manager was the lead manager of a mutual fund in December of the previous year and was not the lead manager of a mutual fund in December of the current year.

| Year | No. of Lead Managers (1) | IN (2) | %IN (3) | OUT (4) | %OUT (5) |
|---|---|---|---|---|---|
| 1993 | 700 | 141 | 22.3% | 72 | 11.4% |
| 1994 | 800 | 179 | 25.6% | 79 | 11.3% |
| 1995 | 863 | 172 | 21.5% | 109 | 13.6% |
| 1996 | 932 | 184 | 21.3% | 115 | 13.3% |
| 1997 | 1021 | 221 | 23.7% | 132 | 14.2% |
| 1998 | 1098 | 239 | 23.4% | 162 | 15.9% |
| 1999 | 1149 | 208 | 18.9% | 157 | 14.3% |
| 2000 | 1182 | 218 | 19.0% | 185 | 16.1% |
| 2001 | 1174 | 175 | 14.8% | 183 | 15.5% |
| 2002 | 1153 | 166 | 14.1% | 187 | 15.9% |
| 2003 | 1130 | 162 | 14.1% | 185 | 16.0% |
| 2004 | 1070 | 129 | 11.4% | 189 | 16.7% |
| Overall Mean | 1023 | 183 | 19.2% | 146 | 14.5% |
| 1993-1998 | 902 | 189 | 23.0% | 112 | 13.3% |
| 1999-2004 | 1143 | 176 | 15.4% | 181 | 15.8% |
| Change | 241 | -13 | -7.6% | 70 | 2.5% |

**Table IV**

**Managerial Exits Sorted by Manager Age and Prior 1-Year Performance**

Table IV reports annualized managerial exit rates for various subgroups, sorted by the lead manager's age and prior performance. For each sub-group, time-series means for the first and second sub-periods, and the change between sub-periods are displayed. A *Managerial Exit* occurs when a manager-fund pairing differs in a month from that of the previous month and when the departing manager is not managing any mutual funds in the next twelve months. Columns 1 through 5 decompose funds into five quintiles by net returns over the last twelve months. Rows 1 through 5 decompose funds into five quintiles based on the lead manager's age. Managerial exit rates are calculated for each month as the proportion of exits over the total number of managers and then annualized by multiplying the monthly rate by twelve. Heteroskedasticity-robust t-statistics, allowing for clustering by family, are reported in brackets.

| | | **Prior 1-Year Performance Quintiles** | | | | | |
|---|---|---|---|---|---|---|---|
| **Age Quintiles** | | **1** | **2** | **3** | **4** | **5** | **All** |
| 1993-1998 | **1** | 16.0% | 10.3% | 11.6% | 8.0% | 4.2% | 9.9% |
| 1999-2004 | | 14.7% | 13.6% | 10.1% | 7.9% | 12.1% | 12.1% |
| Change | | -1.3% | 3.3% | -1.5% | -0.1% | 7.9% | 2.2% |
| t-stat | | [0.30] | [1.05] | [0.49] | [0.06] | [3.08] | [1.33] |
| 1993-1998 | **2** | 15.5% | 11.3% | 8.9% | 8.1% | 2.2% | 8.6% |
| 1999-2004 | | 17.2% | 12.3% | 11.2% | 8.9% | 8.6% | 11.4% |
| Change | | 1.7% | 1.0% | 2.2% | 0.9% | 6.4% | 2.8% |
| t-stat | | [0.40] | [0.28] | [0.68] | [0.27] | [3.30] | [1.81] |
| 1993-1998 | **3** | 19.8% | 7.8% | 8.0% | 10.3% | 4.0% | 9.6% |
| 1999-2004 | | 19.3% | 11.8% | 10.9% | 9.7% | 5.4% | 11.3% |
| Change | | -0.5% | 4.0% | 2.9% | -0.7% | 1.5% | 1.7% |
| t-stat | | [0.11] | [1.57] | [1.12] | [0.22] | [0.73] | [1.10] |
| 1993-1998 | **4** | 12.5% | 11.5% | 10.2% | 8.1% | 4.1% | 8.6% |
| 1999-2004 | | 17.7% | 7.5% | 13.8% | 5.4% | 4.6% | 9.6% |
| Change | | 5.2% | -4.0% | 3.6% | -2.7% | 0.5% | 1.0% |
| t-stat | | [1.31] | [1.44] | [1.36] | [1.17] | [0.26] | [0.72] |
| 1993-1998 | **5** | 15.7% | 13.6% | 11.0% | 6.3% | 9.0% | 10.7% |
| 1999-2004 | | 13.7% | 10.5% | 8.5% | 11.4% | 8.3% | 10.2% |
| Change | | -2.0% | -3.1% | -2.5% | 5.1% | -0.7% | -0.5% |
| t-stat | | [0.48] | [0.84] | [0.70] | [1.74] | [0.20] | [0.29] |
| 1993-1998 | **All** | 15.2% | 10.7% | 8.5% | 7.9% | 4.4% | 9.2% |
| 1999-2004 | | 16.5% | 11.3% | 10.6% | 9.0% | 7.9% | 10.9% |
| Change | | 1.2% | 0.6% | 2.0% | 1.1% | 3.5% | 1.7% |
| t-stat | | [0.58] | [0.45] | [1.60] | [0.84] | [3.32] | [2.11] |

**Table V**

**Regression of Managerial Exits on Manager Characteristics**

Table V reports estimated coefficients from pooled OLS regressions of *Managerial Exits* on fund and lead manager characteristics. Regressions are conducted for the entire sample period and then over the first and second sub-periods. To calculate the difference, a regression is run over the entire sample period with independent variables interacted with a dummy variable *AFTER1999* which equals one in the second sub-period zero otherwise. The dependent variable is *Managerial Exit* which occurs when a manager-fund pairing differs in a month from that of the previous month and when the departing manager is not managing any mutual funds in the next twelve months. *Prior 1-year Return %ile* is a continuous variable from 0 to 1 which is the fund's performance in the previous 12 months relative to its peers. Other predictor variables are defined in Table I. All specifications include monthly fixed effects. Coefficients are annualized by multiplying them by 12. Heteroskedasticity-robust t-statistics, allowing for clustering by family, are reported in brackets. Managers from the highest age and lowest performance quintiles are dropped.

| **Predictor Variables** | **Entire Sample (1)** | **Subperiod 1 (1993-1998) (2)** | **Subperiod 2 (1999-2004) (3)** | **Difference (4)** |
|---|---|---|---|---|
| *Log Fund Size* ($MIL) | -1.467% | -0.479% | -2.065% | -1.586% |
| | [6.07] | [1.38] | [6.32] | [3.32] |
| *Log Family Size* ($MIL) | 0.490% | 0.212% | 0.688% | 0.476% |
| | [4.01] | [1.34] | [3.75] | [1.97] |
| *Fund Age* | 0.105% | 0.075% | 0.131% | 0.056% |
| | [3.32] | [1.95] | [3.00] | [1.04] |
| *Prior 1-year Return %ile* | -6.603% | -8.898% | -4.883% | 4.015% |
| | [4.17] | [4.99] | [2.07] | [1.38] |
| *Manager Age* | -0.108% | 0.014% | -0.215% | -0.229% |
| | [1.84] | [0.21] | [2.52] | [2.33] |
| *Median Undergrad SAT* | 0.000% | 0.001% | 0.000% | -0.000% |
| | [0.16] | [0.22] | [0.14] | [0.06] |
| *Graduate Degree* | -0.658% | -1.369% | 0.036% | 1.405% |
| | [0.75] | [1.12] | [0.03] | [0.93] |
| *No. of Managers* | 2.192% | 1.012% | 2.933% | 1.921% |
| | [3.25] | [1.30] | [3.40] | [1.91] |
| *Constant* | 17.421% | 11.024% | 21.601% | 10.578% |
| | [4.09] | [1.96] | [3.64] | [1.03] |
| Time Dummies | YES | YES | YES | YES |
| Clustering | Family | Family | Family | Family |
| Observations | 96454 | 40563 | 55891 | 96454 |
| Clusters | 716 | 526 | 509 | 716 |

**Table VI**
**Regressions of Fund Returns on Manager Age**

Table VI reports estimated coefficients on *Manager Age* from pooled OLS regressions of annualized net returns on fund and managerial characteristics. For each specification, regressions are run over the first sub-period, over the second sub-period, and then over the entire sample period with independent variables interacted with a dummy variable $AFTER1999_t$ which equals zero in the first sub-period and one in the second sub-period. The first row shows the estimated coefficient on *Manager Age* over the first sub-period from 1993 to 1998. The second row shows the estimated coefficient on *Manager Age* over the second sub-period from 1999 to 2005. The third row shows the estimated coefficient on *Manager Age*×AFTER1999, in other words, the estimated change in *Manager Age* between sub-periods. Columns 1 and 4 include regressions over the entire sample. Columns 2 and 5 restrict the sample to funds managed from the Northeast while columns 3 and 6 restrict the sample to funds managed from outside the Northeast. Specifications 1 through 3 are univariate regressions while specifications 4 through 6 add eight control variables to the regression: *Log Fund Size*, *Log Family Size*, *Expense Ratio*, *Total Load*, *Turnover*, *Fund Age*, *Prior 1-year Flows*, and *Prior 1-year Returns*. These variables have the same definition as in Table I. All specifications include monthly fixed effects. Standard errors are clustered at the fund level. T-statistics are shown below each coefficient in brackets.

| Dependent Variable: | Annualized Net Returns | | |
|---|---|---|---|
| Sample Period: | January 1993 - December 2005 | | |
| | **Without Controls** | | |
| **Coefficients** | **Entire Country (1)** | **Northeast (2)** | **Outside NE (3)** |
| *Manager Age* 93-98 | -0.0606% | -0.0967% | -0.0160% |
| [t-statistic] | [3.35] | [3.53] | [0.77] |
| *Manager Age* 99-05 | 0.0054% | 0.0398% | -0.0295% |
| [t-statistic] | [0.26] | [1.35] | [1.06] |
| *Manager Age* CHANGE | 0.0660% | 0.1366% | -0.0136% |
| [t-statistic] | [2.42] | [3.43] | [0.39] |
| No. of Observations | 141118 | 74220 | 66898 |
| Controls? | NO | NO | NO |
| Fixed Effects | Monthly | Monthly | Monthly |

**Table VI (continued)**

| | With Controls | | |
|---|---|---|---|
| **Coefficients** | **Entire Country (4)** | **Northeast (5)** | **Outside NE (6)** |
| *Manager Age* 93-98 | -0.0265% | -0.0474% | -0.0035% |
| [t-statistic] | [1.90] | [2.50] | [0.19] |
| *Manager Age* 99-05 | 0.0036% | 0.0290% | -0.0242% |
| [t-statistic] | [0.19] | [1.07] | [1.00] |
| *Manager Age* CHANGE | 0.0301% | 0.0764% | -0.0206% |
| [t-statistic] | [1.33] | [2.39] | [0.69] |
| No. of Observations | 141118 | 74220 | 66898 |
| Controls? | YES | YES | YES |
| Fixed Effects | Monthly | Monthly | Monthly |

**Table VII**

**Regressions of Fund Returns on Age-Region Interaction**

Table VII presents estimated coefficients on the interaction term, *Manager Age*×*Northeast*, from pooled OLS regressions of various performance metrics on fund and managerial characteristics. For each specification, regressions are run over the first sub-period, over the second sub-period, and then over the entire sample period with independent variables interacted with a dummy variable $\text{AFTER1999}_t$ which equals zero in the first sub-period and one in the second sub-period. The first row shows the estimated coefficient on *Manager Age*×*Northeast* over the first sub-period from 1993 to 1998. The second row shows the estimated coefficient on *Manager Age*×*Northeast* over the second sub-period from 1999 to 2005. The third row shows the estimated coefficient on *Manager Age*×*Northeast*×AFTER1999, in other words, the estimated change in *Manager Age*×*Northeast* between sub-periods. Panel A shows the estimates of simple regressions while Panel B adds eight control variables: *Log Fund Size*, *Log Family Size*, *Expense Ratio*, *Total Load*, *Turnover*, *Fund Age*, *Prior 1-year Flows*, and *Prior 1-year Returns*. These variables have the same definition as in Table I. The columns show the results of regressions with four different performance metrics as the dependent variables. Column 1 of each Panel uses net returns, column 2 uses returns before expenses, column 3 uses net returns adjusted for risk using the CAPM-model, and column 4 uses returns adjusted for risk using the four-factor Carhart (1997) model. All dependent variables are monthly annualized fund returns. All specifications include monthly fixed effects. Standard errors are clustered at the fund level. T-statistics are shown below each coefficient in brackets.

Panel A: Regression of Fund Returns on Interaction Term Without Controls
Sample Period: January 1993 - December 2005

| | Dependent Variables | | | |
|---|---|---|---|---|
| **Coefficients** | **Net Returns (1)** | **Gross Returns (2)** | **CAPM Adjusted (3)** | **Carhart4F Adjusted (4)** |
| *Manager Age*×*Northeast* 93-98 | -0.0808% | -0.0622% | -0.0802% | -0.1000% |
| [t-statistic] | [2.35] | [2.12] | [2.29] | [2.91] |
| *Manager Age*×*Northeast* 99-05 | 0.0694% | 0.0796% | 0.0623% | 0.0384% |
| [t-statistic] | [1.72] | [1.98] | [1.54] | [0.96] |
| *Manager Age*×*Northeast* CHANGE | 0.1501% | 0.1418% | 0.1424% | 0.1382% |
| [t-statistic] | [2.85] | [2.80] | [2.68] | [2.67] |
| No. of Observations | 141118 | 141118 | 141118 | 141118 |
| Controls? | NO | NO | NO | NO |
| Fixed Effects | Monthly | Monthly | Monthly | Monthly |

**Table VII (continued)**

Panel B: Regression of Fund Returns on Interaction Term With Controls
Sample Period: January 1993 - December 2005

| | Dependent Variables | | | |
|---|---|---|---|---|
| **Coefficients** | **Net Returns (1)** | **Gross Returns (2)** | **CAPM Adjusted (3)** | **Carhart4F Adjusted (4)** |
| *Manager Age×Northeast* 93-98 | -0.0438% | -0.0368% | -0.0421% | -0.0648% |
| [t-statistic] | [1.76] | [1.57] | [1.68] | [2.55] |
| *Manager Age×Northeast* 99-05 | 0.0533% | 0.0596% | 0.0461% | 0.0212% |
| [t-statistic] | [1.53] | [1.72] | [1.33] | [0.62] |
| *Manager Age×Northeast* CHANGE | 0.0971% | 0.0965% | 0.0882% | 0.0859% |
| [t-statistic] | [2.30] | [2.30] | [2.08] | [2.05] |
| No. of Observations | 141118 | 141118 | 141118 | 141118 |
| Controls? | YES | YES | YES | YES |
| Fixed Effects | Monthly | Monthly | Monthly | Monthly |

**Table VIII**
**Regressions of Fund Returns – Robustness Checks**

Table VIII presents the results of several checks of the robustness of the results in tables VI and VII. In Panel A, the "dot-com bubble" years of 1998, 1999, and 2000 are dropped from the sample. Columns 1 through 3 show the estimated coefficient on *Manager Age* after regressing annualized net returns on that variable along with controls as in columns 4 through 6 of table VI. Columns 4 and 5 show the estimated coefficient on the interaction term, *Manager Age×Northeast*, with net returns and Carhart 4-factor risk-adjusted returns as in columns 1 and 4 of table VII, panel B. In Panel B, the dependent variables are based on the return of the portfolio holdings of the mutual fund instead of its reported returns. Columns 1 through 3 show the estimated coefficient on *Manager Age* after regressing annualized net holdings' returns on that variable along with controls as in columns 4 through 6 of table VI. Columns 4 and 5 show the estimated coefficient on the interaction term, *Manager Age×Northeast*, with annualized net holdings' returns and DGTW risk-adjusted holdings' returns as the dependent variables, and with controls. Panel C adds style dummies based on the three-by-three size-value boxes of Morningstar to each regression, along with interaction of style dummies with the dummy variable AFTER1999 to ensure that the variables of interest are not simply picking up changes in performance of different styles. Panel D removes new funds, in operation less than two years, from the sample. T-statistics are shown below each coefficient in brackets.

Panel A: Excluding the 1998 to 2000 "bubble" period

Dependent Variables: Annualized Net Returns (1)-(4), Annualized Carhart Returns (5)

Sample Period: January 1993 - December 2005, excluding 1998 to 2000

| | Sample Groups | | | | Dependent Variables | |
|---|---|---|---|---|---|---|
| | **Entire Country** | **Northeast** | **Outside NE** | | **Net Returns** | **Carhart4F Adjusted** |
| ***Manager Age*** | **(1)** | **(2)** | **(3)** | ***Manager Age* × *Northeast*** | **(4)** | **(5)** |
| 93-97 COEF. | -0.0373% | -0.0637% | -0.0071% | 93-97 COEF. | -0.0565% | -0.0892% |
| [t-statistic] | [2.42] | [2.86] | [0.40] | [t-statistic] | [2.10] | [3.24] |
| 01-05 COEF. | 0.0042% | 0.0154% | -0.0076% | 01-05 COEF. | 0.0229% | 0.0017% |
| [t-statistic] | [0.25] | [0.54] | [0.45] | [t-statistic] | [0.70] | [0.05] |
| CHANGE | 0.0415% | 0.0791% | -0.0004% | CHANGE | 0.0796% | 0.0908% |
| [t-statistic] | [1.90] | [2.22] | [0.02] | [t-statistic] | [1.93] | [2.20] |
| No. of Obs. | 107290 | 56748 | 50542 | No. of Obs. | 107290 | 107290 |
| Controls? | YES | YES | YES | Controls? | YES | YES |
| Fixed Effects | Monthly | Monthly | Monthly | Fixed Effects | Monthly | Monthly |

**Table VIII (continued)**

| Panel B: Holdings' Returns | | | | | | |
|---|---|---|---|---|---|---|
| Dependent Vars: | Annualized Holdings' Net Returns (1)-(4), DGTW-Adjusted Holdings' Returns (5) | | | | | |
| Sample Period: | January 1993 - December 2005 | | | | | |
| | | **Sample Groups** | | | **Dependent Variables** | |
| | **Entire Country** | **Northeast** | **Outside NE** | | **Net Returns** | **DGTW Adjusted** |
| ***Manager Age*** | **(1)** | **(2)** | **(3)** | ***Manager Age* × *Northeast*** | **(4)** | **(5)** |
| 93-98 COEF. | 0.0035% | -0.0167% | 0.0272% | 93-98 COEF. | -0.0440% | -0.0355% |
| [t-statistic] | [0.23] | [0.81] | [1.16] | [t-statistic] | [1.40] | [1.49] |
| 99-05 COEF. | 0.0559% | 0.0913% | 0.0205% | 99-05 COEF. | 0.0708% | 0.0182% |
| [t-statistic] | [2.78] | [3.56] | [0.67] | [t-statistic] | [1.78] | [0.77] |
| CHANGE | 0.0523% | 0.1080% | -0.0067% | CHANGE | 0.1147% | 0.0538% |
| [t-statistic] | [1.99] | [3.13] | [0.17] | [t-statistic] | [2.19] | [1.63] |
| No. of Obs. | 125267 | 65788 | 59479 | No. of Obs. | 125267 | 125075 |
| Fixed Effects | Monthly | Monthly | Monthly | Fixed Effects | Monthly | Monthly |

**Table VIII (continued)**

Panel C: Regression with Style Dummy Variables

Dependent Variables: Annualized Net Returns (1)-(4), Annualized Carhart 4F Returns (5)
Sample Period: January 1993 - December 2005

| | Sample Groups | | | | Dependent Variables | |
|---|---|---|---|---|---|---|
| | **Entire Country** | **Northeast** | **Outside NE** | | **Net Returns** | **Carhart4F Adjusted** |
| ***Manager Age*** | **(1)** | **(2)** | **(3)** | ***Manager Age × Northeast*** | **(4)** | **(5)** |
| 93-98 COEF. | -0.0305% | -0.0508% | -0.0094% | 93-98 COEF. | -0.0413% | -0.0593% |
| [t-statistic] | [2.24] | [2.67] | [0.53] | [t-statistic] | [1.67] | [2.35] |
| 99-05 COEF. | 0.0036% | 0.0200% | -0.0143% | 99-05 COEF. | 0.0343% | 0.0028% |
| [t-statistic] | [0.23] | [0.81] | [0.73] | [t-statistic] | [1.10] | [0.09] |
| CHANGE | 0.0341% | 0.0707% | -0.0049% | CHANGE | 0.0756% | 0.0622% |
| [t-statistic] | [1.80] | [2.44] | [0.21] | [t-statistic] | [2.04] | [1.66] |
| No. of Obs. | 139428 | 73227 | 66201 | No. of Obs. | 139428 | 139428 |
| Controls? | YES | YES | YES | Controls? | YES | YES |
| Style Dum? | YES | YES | YES | Style Dum? | YES | YES |
| Fixed Effects | Monthly | Monthly | Monthly | Fixed Effects | Monthly | Monthly |

**Table VIII (continued)**

Panel D: Excluding New Funds (less than two years in operation)

Dependent Variables: Annualized Net Returns (1)-(4), Annualized Carhart 4F Returns (5)
Sample Period: January 1993 - December 2005

| *Manager Age* | **Entire Country (1)** | **Sample Groups** Northeast (2) | **Outside NE (3)** | *Manager Age × Northeast* | **Dependent Variables** Net Returns (4) | **Carhart4F Adjusted (5)** |
|---|---|---|---|---|---|---|
| 93-98 COEF. | -0.0276% | -0.0466% | -0.0064% | 93-98 COEF. | -0.0402% | -0.0612% |
| [t-statistic] | [1.99] | [2.45] | [0.35] | [t-statistic] | [1.59] | [2.37] |
| 99-05 COEF. | 0.0058% | 0.0318% | -0.0226% | 99-05 COEF. | 0.0544% | 0.0224% |
| [t-statistic] | [0.31] | [1.18] | [0.93] | [t-statistic] | [1.57] | [0.66] |
| CHANGE | 0.0334% | 0.0784% | -0.0161% | CHANGE | 0.0946% | 0.0836% |
| [t-statistic] | [1.48] | [2.45] | [0.54] | [t-statistic] | [2.22] | [1.98] |
| No. of Obs. | 140275 | 73956 | 66319 | No. of Obs. | 140275 | 140275 |
| Controls? | YES | YES | YES | Controls? | YES | YES |
| Fixed Effects | Monthly | Monthly | Monthly | Fixed Effects | Monthly | Monthly |

**Table IX**

**Regressions of Fund Returns –Standard Errors with Randomized Inference**

Table IX reports t-statistics using standard errors obtained from the randomized inference method described in Bertrand, Duflo, and Mullainathan (2004). Each lead manager is randomly assigned a year of birth from the existing distribution of years of birth, and each fund family is randomly assigned *Northeast* equal to one or zero from the existing distribution of regions. With these randomly-assigned control variables, the regressions from specifications (1) and (4) in Table VII, Panel B are run and the coefficient of interest, *Manager Age*×*Northeast*×AFTER1999, is saved. This process is repeated 500 times and the standard deviation of the coefficients across runs is used as a standard error to generate robust t-statistics.

Randomized Inference with Age and Region Reshuffling

| | Dependent Variables | |
|---|---|---|
| ***Manager Age×Northeast Change*** | **Net Returns (1)** | **Carhart4F Adjusted (2)** |
| Coefficient | 0.0971% | 0.0859% |
| Pooled OLS SEs | 0.0422% | 0.0419% |
| Pooled OLS t-statistics | [2.30] | [2.05] |
| Randomized Inference SEs | 0.0395% | 0.0401% |
| Randomized Inference t-statistics | [2.46] | [2.14] |

**Table X**
**Managers from Top Schools by Subgroups**

Table X reports the proportion of mutual funds with managers that have advanced degrees from one of the top fifteen business schools in the United States. Row 1 shows results for all funds while rows 2 through 5 decompose funds into four approximately equal-sized sub-groups by the age of their lead manager. Column 1 shows results for all funds. Columns 2 and 3 show results for funds based in the Northeast and outside the Northeast, respectively. Column 4 shows the difference between funds in the Northeast and outside the Northeast. For each sub-group, the table reports the mean proportion of funds led by managers with advanced degrees, from 1993 to 1998, from 1999 to 2004, and the change between sub-periods. It also shows the t-statistic on the change between sub-periods. For calculation of t-statistics, standard errors are clustered at the fund level.

| | | Region of the Country | | |
|---|---|---|---|---|
| | **Entire Country** | **Northeast** | **Outside NE** | **Difference** |
| ***Manager Age*** | **(1)** | **(2)** | **(3)** | **(4)** |
| All Ages (1) | | | | |
| 1993-1998 | 37.2% | 47.9% | 25.5% | 22.5% |
| 1999-2005 | 35.7% | 44.0% | 26.6% | 17.5% |
| Change | -1.5% | -3.9% | 1.1% | -5.0% |
| t-stat | [1.16] | [2.03] | [0.62] | [1.92] |
| Ages under 41 (2) | | | | |
| 1993-1998 | 40.8% | 55.5% | 21.1% | 34.4% |
| 1999-2005 | 29.7% | 38.5% | 20.1% | 18.4% |
| Change | -11.0% | -17.1% | -1.0% | -16.1% |
| t-stat | [4.20] | [4.66] | [0.30] | [3.30] |
| Ages 41 to 46 (3) | | | | |
| 1993-1998 | 33.3% | 48.3% | 21.1% | 27.3% |
| 1999-2005 | 39.7% | 50.8% | 26.3% | 24.5% |
| Change | 6.5% | 2.5% | 5.2% | -2.8% |
| t-stat | [2.08] | [0.53] | [1.37] | [0.46] |
| Ages 47 to 55 (4) | | | | |
| 1993-1998 | 36.1% | 42.3% | 29.6% | 12.6% |
| 1999-2005 | 34.5% | 42.5% | 26.6% | 16.0% |
| Change | -1.6% | 0.3% | -3.1% | 3.3% |
| t-stat | [0.56] | [0.06] | [0.84] | [0.61] |
| Ages over 55 (5) | | | | |
| 1993-1998 | 36.2% | 42.1% | 29.7% | 12.4% |
| 1999-2005 | 37.4% | 42.5% | 32.2% | 10.4% |
| Change | 1.3% | 0.4% | 2.4% | -2.0% |
| t-stat | [0.38] | [0.09] | [0.52] | [0.30] |

**Table A1**
**Destinations of Departing Managers**
Table A1 reports the destination of departing managers. Panel A decomposes destinations of young managers in the top quintile of performers into hedge funds, non-hedge fund startups, promotions within, other financial firms, and unknown/retired. Panel B does the same for young managers in the fourth quintile. For each category, Table A1 reports means for the first sub-period from 1993 to 1998, the second sub-period from 1999-2004, the change between sub-periods. T-statistics are reported in brackets.

| Panel A:<br>Performance Quintile 5<br>Age Q 1 & 2 (Age < 44) | **Total Exits (1)** | **Hedge Fund (2)** | **Non-HF Startup (3)** | **Promo Within (4)** | **Other Finance (5)** | **Unknown or Retired (6)** |
|---|---|---|---|---|---|---|
| 1993-1998 | 3.5% | 0.6% | 0.3% | 0.9% | 1.5% | 0.3% |
| 1999-2004 | 10.5% | 4.2% | 1.1% | 0.6% | 3.4% | 1.3% |
| Change | 7.0% | 3.6% | 0.8% | -0.2% | 1.9% | 1.0% |
| t-stat | [4.03] | [2.31] | [0.41] | [0.12] | [1.03] | [0.39] |
| Panel B:<br>Performance Quintile 4<br>Age Q 1 & 2 (Age < 44) | | | | | | |
| 1993-1998 | 7.7% | 1.3% | 0.3% | 1.3% | 2.3% | 2.3% |
| 1999-2004 | 8.5% | 1.9% | 0.8% | 1.4% | 2.2% | 2.2% |
| Change | 0.8% | 0.6% | 0.5% | 0.0% | -0.1% | -0.1% |
| t-stat | [0.25] | [0.23] | [0.10] | [0.02] | [0.04] | [0.03] |

**Table A2**
**Managers Departing to Hedge Funds**
Table A2 presents a sample of mutual fund managers that left for the hedge fund industry, and summary statistics on those managers. For each manager, it shows manager names, names of the mutual fund company that the manager exited, the name of the hedge fund that the manager entered, date of exit, age at exit, and whether the manager founded a new hedge fund or joined an existing hedge fund.

| | | | |
|---|---|---|---|
| Mean Age | 40.6 | | |
| % Founded | 67.1% | 1993-1998 | 23.8% |
| % Joined | 32.9% | 1999-2004 | 76.2% |

| **Name** | **MF Company** | **Hedge Fund** | **DOE** | **Age** | **Status** |
|---|---|---|---|---|---|
| Adams Jr., Clarke | Friess Assoc. | Petros Capital | 03/1998 | 53 | Founder |
| Albert, Gavin | Oppenheimer | Ulysses Capital | 01/1999 | 31 | Joined |
| Altschul, Christopher | Mitchell Hutchins | Citadel Inv. | 10/2000 | 36 | Joined |
| Ammann, Robert T. | Dreyfus Founders | RK Capital | 05/2004 | 34 | Founder |
| Angrist, Jonathan | Kornitzer Capital | Helzberg Angrist | 07/2005 | 35 | Founder |
| Armstrong, Arden C. | Morgan Stanley | Redstone Inv. | 05/2002 | 42 | Founder |
| Auslander, William | Morgan Stanley | Sandell Asset | 07/2004 | 43 | Joined |
| Azari, Nicholas G. | Meridian | Aperta Asset | 09/2003 | 43 | Joined |
| Bagby, David R. | UMB Inv. | Trinity Capital | 10/2006 | 56 | Joined |
| Balkin, Michael P. | William Blair | Magnetar Inv. | 03/2005 | 47 | Founder |
| Barish, Michael S. | Cambiar | Lazarus Inv. | 12/2001 | 62 | Founder |
| Barneby, T. Kirkham | UBS Global | Old Iron Hill Cap. | 04/2005 | 59 | Founder |
| Barr, Dean S. | Deutsche Asset | Thunder Bay Cap. | 05/2003 | 42 | Founder |
| Barrett, Thomas D. | MFS | Sirios Capital | 05/2001 | 38 | Joined |
| Barry, Richard | RS Investment | Eastbourne Cap. | 05/2002 | *n/a* | Founder |
| Beckham, Daniel | Essex Inv. | Criterion Capital | 07/2003 | *n/a* | Founder |
| Bernstein, Jeffrey M. | BT of New York | Manhasset Cap. | 04/2003 | 37 | Joined |
| Betterton, Soraya | GT Capital | Green Street Inv. | 05/1997 | 35 | Founder |
| Bowman, Lawrence | Fidelity | Bowman Capital | 09/1993 | 35 | Founder |
| Brennan Jr., John F. | MFS | Sirios Cap. | 02/1999 | 40 | Founder |
| Callaghan, John P. | Weiss, Peck. | Odyssey Partners | 03/1996 | 38 | Joined |
| Carmen, Michael T. | State Street | Kobrick Capital | 10/1997 | 35 | Joined |
| Cheung, Alexander | Monument Cap. | Long Bow Capital | 03/2000 | 45 | Joined |
| Chulik, Steve | Morgan Stanley | Redstone Inv. | 01/2002 | 35 | Founder |
| Coons, Richard S. | Wall Street Assoc. | Viewpoint Inv. | 04/1999 | 46 | Founder |
| Corman, Robert | Jennison Assoc. | RiverRock Capital | 04/1999 | 46 | Founder |
| Crawford, Leigh R. | TCW | Anacapa Asset | 03/2004 | 32 | Founder |
| Cunneen, Mark | J&W Seligman | Churchfield Capital | 03/2002 | 42 | Founder |
| DiCarlo, Michael P. | John Hancock | DFS Advisors | 03/1996 | 40 | Founder |
| Donahue Jr., Robert | Salomon Bros. | Harpoon Equity | 04/2003 | 36 | Founder |
| Felipe, Christian A. | MFS | Sirios Capital | 02/1999 | 41 | Founder |
| Felman, David | Fidelity | Andor Capital | 06/2001 | 35 | Joined |
| Feuerman, Kurt A. | Morgan Stanley | Caxton Assoc. | 09/1998 | 43 | Joined |
| Gendelman, Robert I. | Neuberger Ber. | Cobble Creek | 05/2003 | 45 | Founder |

| | | | | | |
|---|---|---|---|---|---|
| Glancy, David | Fidelity | *Unknown* | 07/2003 | 42 | Founder |
| Gordon, Michael S. | Fidelity | Vinik Asset | 03/1996 | *n/a* | Founder |
| Greenberg, Lawrence | Fidelity | Greenberg Summit | 12/1996 | 33 | Founder |
| Gutfleish, Ronald | Goldman Sachs | HPB Associates | 09/1998 | 39 | Joined |
| Harvey, Robert E. | Barrett Funds | The Ashforth Co. | 01/2004 | 51 | Joined |
| Haubold, Gary D. | Pilgrim Baxter | Edge Capital | 06/1999 | 41 | Founder |
| Hillary, James A. | Marsico Capital | Independence Cap. | 11/2004 | 41 | Founder |
| Jermain, Robert K. | Dreyfus | Soros Capital | 06/1994 | 35 | Joined |
| Karns, John K. | Denver Inv. | Agger Capital | 06/2003 | 40 | Joined |
| Keefe, Timothy | John Hancock | Thomas Weisel | 04/2000 | 38 | Joined |
| Kerrigan, Jeff | Fidelity | Gartmore Quant | 02/2004 | 33 | Joined |
| Kluiber, Rudolph | State Street | GRT Capital | 05/2001 | 42 | Founder |
| Kobrick, Fred | State Street | Kobrick Capital | 08/1997 | 50 | Founder |
| Krochuk, Timothy | Fidelity | GRT Capital | 05/2001 | 31 | Founder |
| Lammert, Warren | Janus | Granite Point Cap. | 04/2003 | 41 | Founder |
| Marcin, Robert J. | MAS | Defiance Asset | 11/2001 | 41 | Founder |
| Marcus, David E. | Franklin Mutual | Marcstone Cap. | 02/2000 | 35 | Founder |
| Margolies, Ross | Salomon Bros. | Saranac Capital | 05/2004 | 46 | Founder |
| Mayo, R. Scott | GMO | Mayo Capital | 03/2002 | 30 | Founder |
| Mayo, Richard A. | GMO | Mayo Capital | 12/2001 | 59 | Founder |
| Midler, Andrew R. | Fidelity | Odyssey Partners | 01/1993 | 32 | Joined |
| Muresianu, John | Fidelity | Lyceum Capital | 06/2002 | 49 | Founder |
| Newman, William J. | Phoenix Inv. | *Unknown* | 11/1998 | 59 | Founder |
| Otness, Chip | JP Morgan Chase | Dolphin Asset | 03/1998 | 51 | Founder |
| Pearce, Elizabeth | HighMark | EGM Capital | 07/2001 | 40 | Joined |
| Petner, Edward | Lynch & Mayer | Petner Asset | 02/2000 | 41 | Founder |
| Posner, Brian S. | Credit Suisse | Hygrove Partners | 12/1999 | 38 | Founder |
| Putnam, William H. | Van Wagoner | Lehman Bros. | 09/2003 | 36 | Joined |
| Quinlisk, Timothy E. | John Hancock | Mayo Capital | 12/2001 | 38 | Joined |
| Rapuano, Lisa | Legg Mason | Lane Five Cap | 12/2003 | 37 | Founder |
| Rubin, Mitchell | Baron Asset | RiverPark Cap | 03/2006 | 40 | Founder |
| Schachter, Howard | Needham Inv. | Schachter Cap. | 12/1997 | *n/a* | Founder |
| Schlarbaum, Gary | Morgan Stanley | Schlarbaum Cap. | 04/2002 | 59 | Founder |
| Schroer, John | INVESCO | Itros Capital | 01/2001 | 36 | Founder |
| Segalas, Anthony A. | Lynch & Mayer | Segalas Group | 10/1997 | 39 | Founder |
| Shiel, J. Fergus | Fidelity | *Unknown* | 04/2003 | 45 | Founder |
| Slattery, Frank P. | Pilgrim Baxter | Azure Capital | 04/2000 | 27 | Joined |
| Sobieski, Emmy | Nicholas Applegate | Palantir Capital | 07/2000 | 34 | Joined |
| Sonnett, Kevin | Dreyfus Founders | RK Capital | 03/2003 | 34 | Founder |
| Stack, Brian E. | MFS | Cyllenius Capital | 06/2001 | 45 | Founder |
| Sullivan, Erin | Fidelity | Spheric Capital | 02/2000 | 31 | Founder |
| Szemis, Daniel | Merrill Lynch | Chilton Investment | 02/2002 | 43 | Joined |
| Tesseo, Jon K. | Harris Insight | The Oak Group | 04/2004 | 39 | Joined |
| Trapp, Peter J.R. | Needham Inv. | *Unknown* | 04/2003 | *n/a* | Founder |
| Treick, Philip | Transamerica | Aesop Cap | 08/1999 | 34 | Founder |
| Tymoczko, Robert | Zurich Scudder | AlphaStream Cap | 05/2002 | 32 | Founder |
| Unschuld, Ira L. | Schroder | Brant Point Cap. | 05/2003 | 38 | Founder |

| | | | | | |
|---|---|---|---|---|---|
| Vinik, Jeffrey N. | Fidelity | Vinik Asset | 06/1996 | 37 | Founder |
| Waterhouse, Mark E. | Wellington | Thomas Weisel | 05/2000 | 38 | Joined |
| Wyper, George U. | Warburg Pincus | Wyper Cap. | 03/1998 | 43 | Founder |
| Yeager, Tara | Alliance Cap. | Petner Asset | 08/2001 | *n/a* | Joined |