On the Performance of Mutual Fund Managers

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Abstract

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This study examines the performance of mutual fund managers using a newly constructed database that tracks 2,086 managers of domestic diversified equity mutual funds during their careers from 1992 to 1999. This paper recognizes that one never observes performance outcomes of managers and funds independently but only in conjunction with each other. First, I find some evidence for performance persistence among managers. Second, to study the attribution of performance outcomes between managers and funds, I model abnormal performance as a Cobb-Douglas production function with manager and fund inputs and find that the manager’s contribution ranges from approximately 10 to 50 percent. This study concludes that the fund is more important than the manager for performance.
1 Introduction

The popular press pays much attention to mutual fund managers, reporting at length about their performance record, investment philosophy, and job changes. There is even the notion of “star managers” with reputations for their stock-picking skills. Perhaps, one of the most striking examples in the mutual fund industry is Peter Lynch who ran the Fidelity Magellan Fund from 1977 to 1990, earning his investors 2,700 percent over thirteen years. Is all of this attention justified? To what extent do managers determine fund performance?

It seems reasonable to entertain the notion that part of the performance of a mutual fund resides in the manager, who is responsible for the investment decisions, and part resides in the fund organization, which can influence performance through administrative procedures, execution efficiency, corporate governance, quality of the analysts, relationships with companies, etc. Although a few academic papers explicitly recognize that both the manager and the fund organization are relevant for performance outcomes, they treat these two entities individually and as if their attributes are observable. In reality, however, one never observes performance outcomes of managers and funds separately, but only in conjunction with each other. This environment is analogous to a production process, where two unobservable inputs, managers and funds, jointly “produce” manager-fund combination attributes such as returns and assets under management. Thus I explicitly identify three entities: managers, funds, and manager-fund combinations, with only the latter corresponding to observable returns and assets under management.

In order to distinguish between funds, managers, and manager-fund combinations, this paper uses a newly constructed dataset that tracks 2,086 managers of domestic diversified equity funds during their careers from January 1992 to December 1999. I create career profiles for each of these managers and document their fund changes during these eight years. Only when managers change funds or manage multiple funds simultaneously does one learn about the differences between funds, managers, and manager-fund combinations.

To study the performance of mutual funds, all previous papers essentially combine the attributes of a number of manager-fund combinations, and treat these attributes as if they belong to the “fund.” The evidence among these papers regarding the existence of abnormal performance for mutual funds has been controversial, and as a consequence the question of whether actively managed mutual funds are worth their expenses has occupied the finance profession for decades. Starting with Jensen (1968), most studies find that the universe of
mutual funds does not outperform its benchmarks after expenses.\(^1\) However, recent studies that focus on managers suggest a strong relation between managers’ characteristics and their performance. For example, Golec (1996) and Chevalier and Ellison (1999a) find that future abnormal returns ("alphas") can be forecast using manager age, education and SAT scores. Khorana (1996) finds an inverse relation between fund performance and the probability of the manager being replaced, suggesting that managers play an important role in determining the performance of a manager-fund combination. Moreover, Hu, Hall, and Harvey (2000) distinguish between promotions and demotions and find that promotions are positively related to the fund’s past performance and demotions are negatively related to the fund’s past performance. This paper attempts to relate the performance literature at the fund and manager levels.

Accounting for manager changes might also shed a different light on the fund performance persistence literature. Several studies have documented persistence in mutual fund performance over short horizons of one to three years.\(^2\) This research has shown that alphas can be forecast using past returns or past alphas. Carhart (1997) attributes this short term persistence to momentum in stock returns and expenses. Moreover, he shows that the highest performing funds do not consistently implement a momentum strategy, but just happen by chance to hold relatively larger positions in last year’s winning stocks, suggesting that skilled or informed mutual fund managers do not exist. However, if fund performance is to a large extent determined by the manager, and managers change funds frequently, then Carhart’s (1997) findings are not surprising, since fund returns would not necessarily exhibit performance persistence. In fact, the arrival of a new manager usually means that a large portion of the existing portfolio is turned over, thereby possibly distorting a fund momentum strategy that was in place. Thus, by taking manager changes into account, one may be able to determine better whether performance persistence exists, and if it can be attributed to informed managers.

In the first part of this paper I construct manager attributes by combining the information in different manager-fund combinations and assess if, and to what extent, managers exhibit performance persistence. Using a frequentist framework I find some evidence that manager performance is persistent. I then ask in the second part of the paper what the manager contributes to fund performance. I model abnormal return or "alpha," as a linear combination of two terms, one associated with the manager’s performance and the other

\(^1\)Recently, Malkiel (1995), Gruber (1996), Carhart (1995) and Daniel, Grinblatt, Titman, and Wermers (1997) all find small or zero average abnormal returns by using modern performance-evaluation methods on samples that are relatively free of survivor bias.

associated with the fund’s performance. The division of alpha into two parts is interpreted as a log-linearized approximation of a Cobb-Douglas production function, where alpha, the output by a manager-fund combination, is a function of two unobserved inputs, one associated with the manager and one associated with the fund. In this setting the weight on the term associated with the manager is interpreted as the manager’s contribution to output. Because all terms in the production function are unobserved, identifying the manager’s and fund’s contribution to output is problematic. This paper employs a Bayesian framework with economically motivated prior beliefs to identify the model. Using the Gibbs sampler in combination with data augmentation and economically informative prior beliefs, I obtain the posterior beliefs for the weight on the term associated with the manager. In addition to identifying the model, the Bayesian approach avoids a number of computational difficulties that would confront a frequentist approach, such as maximum likelihood. For investors who believe that about 15% of managers, funds, and manager-fund combinations have the ability to generate abnormal returns of at least 2 percent per year, I find that on average approximately 50 percent of performance is attributed to the manager and 50 percent to the fund. That is, if a new manager who is only half as productive as the previous manager commences at a fund, then that fund needs to be 50 percent more productive in order to maintain the same alpha. For investors more skeptical about the potential abilities of managers, funds and manager-fund combinations, the importance of the manager rapidly declines and that of the fund organization rapidly increases. Summarizing, the fund contributes at least as much to the abnormal performance of a manager-fund combination as the manager.

This paper starts from the premise that managers of actively managed mutual funds might add value. A natural question to ask is how reasonable is this premise. As indicated before, the academic literature has been inconclusive about the possibility of positive expected alphas (“skill”). Perhaps 0.1 percent of managers have skill. Perhaps none do. However, given current data and methods it is impossible to distinguish between those two possibilities. Nevertheless, as pointed out by Baks, Metrick, and Wachter (2001), such small differences have large consequences for investors. They find that extremely skeptical prior beliefs about the possibility of skill among manager-fund combinations lead to economically significant allocations to active managers. Moreover, Pástor and Stambaugh (2002b) show that even a dogmatic belief that manager-fund combinations do not have skill combined with an ex ante belief that the factor model used to define this measure of skill misprices assets to a certain degree, leads to allocations in actively managed mutual funds and their managers. Thus, even if one entertains only a small probability that a manager-fund combination may have skill, or that the factor model used to define this measure of skill has some degree of mispricing, the issues addressed in this paper are relevant.
Even with dogmatic beliefs that managers and funds do not add value, and that the factor model is correctly specified, this paper can still yield some insights. In the absence of skill and mispricing, the manager or fund is expected to have a negative abnormal return, consisting of two components: total fees and transactions costs. Instead of interpreting abnormal returns as skill (associated either with the manager, the fund, or a combination of the two), one can re-interpret them as a measure of cost efficiency, and view the results in this paper from an organizational perspective.

The remainder of this paper is organized in five sections. Section 2 discusses the construction of the data and gives summary statistics. Section 3 studies whether manager returns exhibit performance persistence. Section 4 develops the Bayesian model to explore the attribution of performance outcomes between managers and funds and discusses the results of this model. Section 5 concludes with an interpretation of the results.

2 Data

A Construction

The monthly data used in this study are drawn from the Center for Research in Security Prices (CRSP) mutual-fund database (CRSP (2000)). This database includes information collected from several sources and is designed to be a comprehensive sample, free of survivor bias of all mutual funds from January 1962 to December 1999. The CRSP mutual-fund data is organized by fund. To construct the manager database used in this paper, I reorient the data by manager and create a career profile of each manager consisting of all the funds he has managed during his career. To ensure that manager entities stay the same over time, I only consider manager or manager teams who are identified by a specific person(s), For example, I omit names such as “Fidelity Investment Advisors.” In addition, manager teams are treated as a single manager. The responsibilities of each member in a management team may not be equal, and there may be positive, or negative synergies among the members of a management team. Thus to treat each member of a management team as a separate manager may bias the analysis.

To match manager names across different funds, I only use the name as a criterion. Because names are often abbreviated differently and have spelling errors in them I manually check the output generated by the computer-program that matches manager names. If there is uncertainty about the equality of two manager names, I create two separate managers. Starting in 1992, the CRSP database contains annual information on the year and month in
which a manager commenced at a fund. This starting date is an error-prone field, frequently containing different starting dates for the same manager in consecutive years of reporting. If this information is incomplete or inconsistent I remove that fund from the career profile of the manager.

Because the CRSP mutual fund database contains all funds, the manager database comprises all managers by construction and is consequently without survivor bias. However, since a date at which a manager starts at a fund is necessary to build a career profile of a manager and this information is only available in or after 1992, any sample that includes managers before 1992 exhibits a selection bias. To avoid this bias in the analysis I only use data in or after 1992.

Many funds, and especially equity funds, have multiple share-classes representing a different fee and load structure for the same underlying pool of assets. Different share classes appeal to different investors and widen the investment opportunity set available to them. For example, a share-class with a high load fee and a low expense ratio suits long-term investors, whereas a share-class with a low load fee and high expense ratio better suits short-term investors. Although these share classes represent a claim on the same underlying pool of assets, they are recorded as different entities in the CRSP mutual fund database. To prevent the over-counting of funds, and consequently of the number of funds a manager manages, I combine different share classes of a fund into one new fund, by aggregating the assets under management, and value weighting returns, turnover, and expense ratios by the assets under management of each of the share classes. Thus I treat a fund as a unit of observation as opposed to a share-class. Approximately twenty percent of funds have on average 2.9 share-classes, and thus in the order of 35 percent of the entries in the CRSP database are eliminated when I adjust for share-classes.

The resulting sample consists of 8,017 managers managing 10,552 of the total sample of 12,683 mutual funds. The remaining 2,131 funds have either no manager data or are not identified by a specific manager name. I limit the analysis in this study to managers who only manage funds that hold diversified portfolios of US equities during their entire career. Generally, I include managers who manage funds that have self-declared investment objective “small company growth,” “aggressive growth,” “growth,” “growth and income” and “maximum capital gains.” Excluded are managers who manage any balanced, income, international or sector funds during their career, since they hold a minimal amount of domestic diversified equities. For a small number of funds the style information is inconsistent across years, and in those instances I manually check the style objectives, and the types of securities mainly held by the fund to determine if they should be included in the sample of managers of domestic diversified equity funds. The resulting sample consists of 2,086 man-
agers of domestic diversified equity funds. Going forward this study only considers these 2,086 managers which I refer to as “domestic diversified equity managers.” This is the first comprehensive dataset that tracks managers during their careers.

B Manager database summary

As indicated in the introduction, one never observes fund or manager characteristics; instead they are only observed in conjunction with each other. It is important to realize that inferred fund and manager attributes are derived ultimately from the same information. However, managers and funds differ in two aspects. First, managers leave and enter funds, and second, managers could manage multiple funds simultaneously. Tables I to IV summarize these differences along with other manager characteristics.

Table I provides an overview of the career characteristics of domestic diversified equity managers. The 2,086 managers in the sample manage a total of 1,602 funds with a total of 6,287 fund years during the period from January 1992 to December 1999. The number of managers of domestic diversified equity funds has grown rapidly in the last decade, with an average annual net growth rate of approximately nine percent per year. Although the number of managers has grown rapidly, funds have done so at an even faster rate of twelve percent per year, indicating that the number of funds under management per manager has gone up over time. This is also indicated by the growing difference between the number of manager-fund combinations and the number of managers.

The middle part of Table I reports statistics about manager career changes. Since most managers do not have well defined career events where they for example leave a fund and immediately start managing a new fund, the notions of promotion and demotion cannot be defined in those terms. Instead I introduce the concept of a manager change, defined as a manager either leaving or starting at a fund. This definition “double counts” career events in the sense that, for example, the traditional concept of a promotion, i.e. leaving a fund and starting at a “better” fund, amounts to two manager changes. As indicated in Table I, on average approximately 45 percent of managers leave or start at a fund in any given year from 1992 to 1999.

Following Chevalier and Ellison (1999b) and Hu, Hall, and Harvey (2000), I define a promotion as a manager change where the average monthly total assets under management by that manager in the year after the change is greater than the average total net assets under management in the year prior to the change, multiplied by the average growth rate of total net assets under management by managers of domestic diversified equity funds over
that same period. Similarly, I define a demotion as a manager change after which the manager has fewer total net assets under management, adjusted for the average growth rate of assets under management by managers of domestic diversified equity funds over that same period. Since assets under management are not recorded for all funds in the CRSP database, promotions and demotions can only be determined for a limited number of manager changes.

Table II examines managers changes more closely, and documents style transitions of managers when they start managing a new or additional fund. If a manager has multiple funds under management when he starts managing a new fund, all entries in the table that represent a transition from a style associated with one of the funds already under management to the style of the new fund are increased by one. As indicated before, funds self-report their fund style in the CRSP database, with the exception of the fund style “other,” which represents funds which had no, or conflicting, style information, and could not be classified. The large diagonal elements in Table II show that most manager changes are within one fund style. With the exception of the fund style categories maximum capital gains, aggressive growth, and income, which have a relative small number of manager changes, all style categories have at least 60 percent of their changes within the same fund style category. This suggests that most managers specialize in a particular investment style during their career. As far as changes to other fund styles is concerned, manager style transitions appear to be approximately reciprocal. For example the number of managers who manage a growth and income fund and start managing a growth fund is approximately equal to the number of managers who manage a growth fund and start managing a growth and income fund. If Table II is interpreted as a transition probability matrix then this reciprocity indicates a fund style “steady state” in which there is no gravitation over time to a limited set of fund styles.

Tables III and IV document cross-sectional and time-series moments of manager attributes. In an average year between 1992 and 1999 there are 708 managers of domestic diversified equity funds with average total net assets of $659 million under management. Table III indicates that, in the eight years from 1992 to 1999, a manager of a domestic diversified equity fund works on average for 3.6 years, manages on average 1.7 funds, stays at one fund on average 3.1 years, and works for 1.16 management companies. The fact that most managers have more funds under management than the number of management companies they work for, implies that if managers change funds, then they do so mostly within their fund family. Finally, note that the cross-sectional distribution of the aforementioned statistics tends to be quite variable and right skewed. For example a large number of managers have just one fund under management during their career, however, a few managers change jobs frequently and increase the average funds under management to 1.7.
Table IV shows that there have been large changes in the mutual fund industry over the last ten years. Not only has the number of managers increased greatly, the number of funds under simultaneous management, turnover, expense ratio, and the assets under management, both in terms of total assets and assets per fund, have increased substantially as well. In addition, although the average load fees have gone down over the last decade, more funds have started to charge them.

To gain a better understanding of the data I split the sample in Tables III and IV along two dimensions: manager style and whether or not the manager is still active. A manager is defined to belong to a certain style category when all the funds he manages during his career belong to that same category. The “other” style category contains managers who could either not be classified, or have multiple funds under management with different styles.

Tables III and IV indicate that the characteristics of the different style categories vary considerably. As expected, managers with “aggressive” management styles such as small company growth and aggressive growth have fewer assets under management and have higher expense ratios than managers with less aggressive management styles such as growth and income. Moreover, the “other” style category is markedly different from all other styles. For example, managers in this category have more funds under management during their career, manage more funds simultaneously, and have worked at more management companies than managers of any other style category. In fact, the characteristics of the average manager of a domestic diversified equity fund are driven to a large extent by managers in the “other” style category.

The bottom parts of Tables III and IV show the differences between active and retired managers. Active managers are those who are managing a fund at the end of the sample in December 1999. Retired managers are those who appear in the sample, but are not active at this date. Active managers manage on average more funds during the eight years from 1992 to 1999, manage more funds simultaneously, spend a longer period of time at each fund, and work at more management companies. In addition, active managers have higher expense ratios and manage larger funds, both in terms of total net assets under management and assets per fund under management. These differences can, at least to some degree, be attributed to survivor bias. Relatively good managers tend to work longer and manage more assets.
C Endogeneity of career events of managers

This section presents the final summary statistics and compares the characteristics of managers who change funds with those of the general population of domestic diversified equity managers. Tables V and VI examine the average return, performance, residual risk, and turnover of managers of domestic diversified equity mutual funds who leave and enter funds, respectively. Before examining the results in these tables, I define how to measure performance for managers, funds, and manager-fund combinations.

The standard method of performance evaluation is to compare the returns earned by a fund manager to relevant benchmarks. In academic practice, this usually involves regression of manager returns on a set of benchmark returns. The intercept ("alpha") in this regression is commonly interpreted as a measure of performance, and is what I will use in this paper. Carhart’s (1997) four factor model will serve as a benchmark for performance evaluation:

\[ r_{it} = \alpha_i + \beta_{1i}RMRF_t + \beta_{2i}SMB_t + \beta_{3i}HML_t + \beta_{4i}UMD_t + \epsilon_{it}, \]  

where \( r_{it} \) is the time \( t \) return on asset \( i \) in excess of the one month T-bill return, \( \alpha_i \) is the performance measure, and \( RMRF_t, SMB_t, HML_t, \) and \( UMD_t \) are the time \( t \) returns on value-weighted, zero-investment, factor-mimicking portfolios for market, size, book-to-market equity, and one-year momentum in stock returns. I interpret this model as a performance evaluation model, and do not attach any risk-interpretation. All returns used in this study are net of all operating expenses (expense ratios) and security-level transaction costs, but do not include sales charges.

Since one does not observe manager or fund returns separately and consequently cannot calculate their performance, one needs to make assumptions to create a “surrogate” returns series associated with the fund and the manager. For the fund, I use the same approximation that is used in other papers, and consider the sequence of manager-fund combination returns for one fund the return series for that fund. For a manager there are multiple alternatives to create a return series, since a manager may manage multiple funds simultaneously at any time during his career. In this study I use equal and value-weighted portfolios of manager-fund combinations’ returns that one manager manages as the return series for that manager and use the \( \alpha \) of these portfolios as a measure of performance. Depending on the number of funds under simultaneous management, the return series for a manager and fund may be

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3 There are several other studies that specifically examine the characteristics of managers, including for example Khorana (1996) and Hu, Hall, and Harvey (2000). They find an inverse relation between the probability of managerial replacement and fund performance.
highly correlated, or in case the manager has only one fund under management in his entire career, coincide. In the latter case one cannot separate manager and fund performance.

Panels A and B of Table V separate the managers who leave a fund into those who leave the sample and those who return in the sample at a different fund, respectively. Panels C and D of that same table then separate the managers who return in the sample at a different fund, into those who are promoted and those who are demoted, where promotion and demotion are defined according to the change in assets under management relative to the growth in total net assets for all domestic diversified equity managers before and after leaving a fund (see Section 2.B for more details). For each of these groups of managers I investigate the average return, \( \alpha \), residual risk and turnover characteristics in the year before the manager leaves the fund. To do so I rank all domestic diversified equity managers into ten decile portfolios according to the four aforementioned characteristics, and determine which percentage of managers who leaves a fund falls in each of these decile portfolios. For example, the top left entry in Panel A of Table V indicates that 5.8 percent of all managers who leave the sample fell in the decile portfolio that had the highest average returns in the year prior to leaving the sample. A clear ascending or descending pattern in one of the columns of a panel indicates that there is interaction between a manager characteristic and a group of managers leaving a fund. Moreover, by construction, the percentages in each column add up to one hundred percent and no interaction is represented by each cell of a column containing ten percent of the managers who leave. The nonparametric statistic “interaction” reported at the bottom of each column in Table V formalizes this intuition.\(^4\) This statistic tests for independence in a two-way contingency table and is asymptotically chi-square distributed with nine degrees of freedom.

Ex ante, one would expect that the event of a manager leaving a fund is preceded by relatively good or bad performance, and Table V confirms this. The average return and \( \alpha \) of managers who leave the sample is significantly worse than that of the overall sample of domestic diversified equity managers. For managers who leave a fund but remain active in the sample (Panel B), there is no significant evidence of relative different average returns or \( \alpha \), but when the managers in Panel B are divided into two groups according to whether they are demoted (Panel C) or promoted (Panel D), it appears that the results in Panel B are composed of two opposing forces. Managers that are demoted perform significantly worse before their demotion than the average domestic diversified equity manager measured in terms of average return and \( \alpha \), whereas managers who are promoted exhibit precisely the opposite performance behavior. Finally, observe that the \( \alpha \) characteristics of managers who

\(^4\)By construction, 10% of all managers fall into one decile portfolio, and thus the sample sizes along one dimension of the contingency table are known. Conditioning on either the row or column sums in a two-way contingency table does not alter the test statistic, as shown by e.g. Lehmann (1986).
leave a fund and subsequently manage more assets, are not significantly different from the α characteristics of the overall sample of domestic diversified equity managers.

The last two columns of Panels A through D in Table V study the residual risk and turnover characteristics in the year before a manager leaves a fund. Managers exhibiting relatively poor returns may anticipate that they will be fired, and in an effort to prevent this, they may gamble and change their portfolio composition to increase the riskiness of the stocks held in it. In doing so they increase their chances of getting an extremely good or bad return realization. In case of a bad return realization, the manager is not any worse off since he already anticipates to be fired. However, in case of a good return realization the management company may not fire him. This option-like behavior of the manager in anticipation of being replaced manifests itself in increased residual risk and increased turnover before he leaves a fund. Ex ante, one would expect to see these effects most clearly for managers who are demoted, and indeed, Table V confirms that only for this group both effects are significant at the five percent level.\(^5\) Note that the results in Table V do not necessarily imply a change in the manager’s behavior in the year prior to a promotion or demotion. Instead, they may have these turnover and residual risk characteristics during their entire tenure at the fund. Another explanation for high turnover is large in- and/or outflows of the fund, perhaps generated by good or bad performance.

Table VI examines the characteristics of domestic diversified equity managers in the year prior to entering a fund, and can be considered the counterpart of Table V, which studies fund exit characteristics. The structure of Table VI is similar to Table V and Panels A through C in Table VI correspond to Panels B through D in Table V. I study the behavior of managers who start at a fund and split them into two groups; those who are demoted (Panel C) and those who are promoted (Panel D), where demotion and promotion are defined as before. Similar to Table V, I examine how the characteristics of managers who start at a fund differ from those of the general population of domestic diversified equity managers, and the entries in the table represent the fraction of all managers who leave a fund (Panels A, B, and C) and fall in particular characteristic decile portfolio.

Table VI suggests that managers who start at a new fund and are promoted (Panel C) have significantly higher average returns, and significantly higher α’s compared to the population of all domestic diversified equity managers. Also, the group of managers that starts at a new fund and are demoted, have a relatively low average return in the year before

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\(^5\) An empirical investigation by Brown, Harlow, and Starks (1996) of the performance of 334 growth-oriented mutual funds during 1976 to 1991 demonstrates that “losers” tend to increase fund volatility to a greater extent than “winners.” This is attributed to the fact that managers’ compensation is linked to relative performance.
the change and up to quarter of this group of managers falls within the decile portfolio with the lowest returns. Finally, Table VI suggests that managers who start at a new fund do not have significantly different risk or turnover characteristics in the year preceding their start at a new fund.

Overall Tables V and VI suggest that managers who either leave or start a fund have significantly different characteristics than the population of all domestic diversified equity managers. As indicated before, Tables V and VI use a value weighted method to construct manager returns and manager attributes are measured over the year before a change. The results, not reported here, when one uses equal weighted returns, or different time periods before a change ranging from nine months to three years, are qualitatively similar.

3 Performance persistence of managers

Previous papers have employed a variety of methodologies to measure the performance of funds. In this section I will apply a simple regression framework that relates past and current manager performance to investigate persistence. At the beginning of each year from 1993 to 1999 I perform a cross-sectional linear regression of the current manager $\alpha$ ($\alpha_{mgr, current}$) on the past manager $\alpha$ ($\alpha_{mgr, past}$)

$$\alpha_{mgr, current} = \rho_0 + \rho_1 \alpha_{mgr, past} + \xi_{mgr}.$$  

(2)

The independent variable in each regression, $\alpha_{mgr, current}$, is estimated using the factor model in equation (1), and is calculated using an equal or value weighted portfolio of returns of manager-fund combinations that the manager is in charge of over the coming year. The dependent variable $\alpha_{mgr, past}$ is similarly defined, except for the fact that last year’s manager returns are used to calculate $\alpha$’s. Finally, I assume that the error term $\epsilon$ of the factor model in equation (1), used to estimate the various $\alpha$’s in equation (2), is independent of $\xi_{mgr}$, the error term of the regression in equation (2).

To estimate this model one approach is to pool all the data in the seven years. Under the assumption that $\xi_{mgr}$, the disturbance term in equation (2), are independent within each year, this model produces consistent estimates. If this assumption is incorrect the $t$-statistics in this regression may be inflated, since one does not correct for appropriate variance-covariance structure of $\xi$. To accommodate this concern I also use a more robust approach and report the time-series averages of the coefficients of the seven annual performance regressions, a

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procedure first outlined by Fama and MacBeth (1973). The $t$-statistics are then calculated using the time-series variance among the estimated regression coefficients. In the remainder of this paper I use this latter approach frequently. The one year intervals to perform the cross-sectional regressions are motivated by the trade-off to estimate $\alpha$’s accurately and to have as many cross-sectional regressions as possible. Using other time periods to estimate the dependent variable, ranging from nine months to three years, yield qualitatively similar results.

Table VII shows the results of the regression in equation (2), and uses the two methods indicated above to estimate the regression parameters. Panel A reports the time-series average of each of the annual regression coefficients, as outlined in Fama and MacBeth (1973), and Panel B pools all the observations used for the annual regressions. The coefficient on past manager performance is significantly positive only in Panel B. Approximately 15 percent of a manager’s performance in the last year is relevant for this year’s performance. The fact that this relation does not show up significantly when one applies the Fama and MacBeth (1973) methodology indicates that ignoring the cross-correlation among managers in Panel B may induce spurious effects. In columns two and four of Table VII, I control for past manager promotions and demotions, by including two dummy variables which are one when the manager gets promoted or demoted in the past year, respectively, and zero otherwise. In this case, the coefficient on past manager performance is significant in both the Fama and MacBeth (1973) and pooled regression. Thus despite the fact that the measurement error biases the coefficients in this regression towards zero, and only seven cross-sectional regressions are used, there is some evidence for performance persistence among managers.

Surprisingly, past promotions tend to negatively impact current performance, whereas past demotions tend to positively impact current performance; both effects, however, are not significant. This is in contrast to the intuition that promoted managers have “skill” and demoted managers lack “skill.” A possible explanation is that these two variables pick up a mean-reverting effect in the dependent variable, and decrease the variance of the coefficient on past manager performance ($\alpha_{\text{mgr,past}}$), allowing the persistence coefficient to become significant.

Although the regression in equation (2) is perhaps a natural way to examine the importance of managers for fund performance, it suffers from a potential source of bias. All the variables in the regression in equation (2) are measured with error. Ideally one would like to use “true” $\alpha$’s instead of estimated $\alpha$’s; however, $\alpha$’s are unobserved, and one has to use estimates in its place. Standard econometric theory on measurement error indicates that in the special case of only one badly measured independent variable, the coefficients in such a regression are biased towards zero (attenuation bias). As a consequence it is harder to detect
If the persistence coefficient $\rho_1$ is unequal to zero. Moreover, an estimate of this parameter not significantly different from zero does not necessarily imply that past performance of managers is irrelevant for current manager performance; instead, the measurement errors may be so large that they overwhelm any evidence in favor of manager persistence. Thus one needs to interpret an estimated $\rho_1$ not significantly different from zero with caution.

4 Performance attribution

As indicated in the introduction, it is not unreasonable to assume that part of the performance of a mutual fund resides in the manager who is responsible for the investment decisions, and part in the fund organization, which may influence performance through administrative procedures, execution efficiency, corporate governance, quality of the analysts, relationships with companies, etc. Given the results in the previous section that suggest that manager performance is persistent to a certain degree, one may ask how important the manager is for a manager-fund combination’s performance. In this section I will attempt to answer this question.

Section 4.A discusses a regression framework to disentangle manager and fund performance. Although this framework is perhaps an intuitive way to approach this problem, I show that such a methodology lacks statistical power and is fraught with econometric problems. This motivates the use of a more structural environment to examine this question, and in Section 4.B I develop a Bayesian model to determine to what extent the manager versus the fund is responsible for performance.

A Regression framework

If managers have skill and contribute to a fund’s performance one would expect that a manager’s experience at previous funds is relevant when he commences at a new fund. This section asks the question if performance at the current fund can be forecasted by performance of the current manager at all funds he has managed before commencing at the current fund, while controlling for past fund characteristics. One way to address this question is by regressing the fund’s $\alpha$ onto the fund’s past $\alpha$ and the manager’s past $\alpha$, or

$$\alpha_{\text{fund, current}} = \kappa_0 + \kappa_1 \alpha_{\text{fund, past}} + \kappa_2 \alpha_{\text{mgr, past}} + \eta_{\text{mgr, fund}}. \quad (3)$$
where $\alpha_{\text{fund, current}}$ is a fund’s performance measured over the year after a new manager arrived, $\alpha_{\text{fund, past}}$ is a fund’s performance measured over the year prior to the arrival of the new manager, and $\alpha_{\text{mgr, past}}$ is a manager’s performance measured over the year prior to starting at the current fund. The time subscripts “past” and “current” are defined relative to the event of a manager change and refer to the year before and the year after such an event, respectively. Thus funds included in the regression have at least one manager change. As before, both the independent and dependent variables in equation (3) are defined as the ordinary least squares estimates of the intercept in the factor model in equation (1), using the appropriate excess return data. Finally, I assume that the error term $\epsilon$ of the factor model in equation (1), used to estimate the various $\alpha$’s in equation (3), is independent of $\eta$, the error term of the regression in equation (3). Since by construction the returns used to calculate $\alpha_{\text{mgr, past}}$ are unrelated to the returns used to calculate $\alpha_{\text{fund, past}}$, the coefficient on past manager performance $\kappa_2$ is interpreted as an effect purely associated with the manager. If past manager- and fund performance do not systematically contribute to the current performance of a fund, one would expect the regression coefficients in equation (3) to be zero. Similarly, if past manager or fund performance contributes to the current fund’s performance, one would expect $\kappa_1$ or $\kappa_2$ to be positive, respectively.

Although the regression in equation (3) is perhaps a natural way to examine the importance of managers for fund performance, it suffers from two potential sources of bias. First, like the regression in Section 3, all the variables in equation (3) are measured with error. In a univariate framework this causes an attenuation bias. However, in the multivariate case with measurement error on more than one of the independent variables, one badly measured variable will bias all of the least squares estimates in unknown directions, and thus one needs to interpret the results with caution.

More importantly perhaps, a second bias arises from the limited inclusion of managers in this regression. Only those managers who start at a new or existing fund are included in the sample, and they may not be representative of the population of all managers. The evidence in Section 2.C indicates that the subset of managers who change funds has significantly different performance characteristics compared to the sample of all domestic diversified equity managers. Having established that the managers included in this regression are not representative of all managers, the question becomes if, and in which direction the coefficients in the regression in equation (3) are biased.

The impact and direction of these two types of bias depends on the parameters in the model. As indicated in Tables V and VI, managers who do relatively well, or relatively

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7This finding is also reported by a number of other studies. For example, Khorana (1996) and Hu, Hall, and Harvey (2000) find that the probability of managerial turnover is inversely related to fund performance.
poorly compared to the sample of all managers of domestic diversified equity funds, tend to subsequently be promoted or demoted. Therefore I work from the assumption that the regression in equation (3) only includes funds that have managers with relatively extreme performance. There are two reasons for extreme performance to arise. The first and perhaps most obvious reason is managers who have relatively high or low \( \alpha \)'s due to “skill,” or lack thereof. This is an effect that the regression in equation (3) intends to capture.

Second, one or more extreme realizations of the disturbance term in the factor model in equation (1) may generate extraordinary returns. These extreme realizations may be due to managers who assume a large amount of idiosyncratic risk, a misspecified factor model, or a random event. The dependent variable in the regression in equation (3) exhibits reversal to mean in the latter case only. Moreover, the coefficients \( \kappa_1 \) and \( \kappa_2 \) are unbiased in that case. For managers who take on a large amount of idiosyncratic risk, the coefficients in the regression in equation (3) are unbiased, but tend to increase the variance of the estimates of \( \kappa_1 \) and \( \kappa_2 \), making it harder to detect departures from zero. In case the factor model in equation (1) is misspecified in the sense that one or more factors are missing, |\( \alpha \)| is proportional to the residual risk in the factor model, and the mispricing biases the coefficients on the right hand side of equation (3) in an unknown direction. In addition, in all three cases extreme realizations of the disturbance term in the regression in equation (1) tend to exacerbate the measurement error of the dependent variable, and bias the coefficients on the right hand side of equation (3) in an unknown direction.

To overcome the selection bias described in the preceding paragraphs one may redefine the “current” and “past” time periods used in the regression in equation (3). For example, similar to the methodology in Section 3, one may run a cross-sectional regression at the beginning of each of the seven years in the sample and take the time-series average of the annual regression coefficients as in Fama and MacBeth (1973), where the dependent variable is measured over the coming year, and the independent variables are measured over the past year. This involves a series of predetermined dates, regardless of a manager change, and includes all managers in the sample. A benefit of such a method is that one learns about the differences between managers and funds not only from those managers who change funds, but also from those who manage multiple funds simultaneously. A drawback of this methodology is that the definition of the return series for the fund and the manager may induce an undesired correlation between the past manager \( \alpha \) and past fund \( \alpha \). If the number of managers in charge of solely one fund during their career is relatively large, this correlation is potentially high, and consequently this approach will lack statistical power.

Table VIII shows the results of the regression in equation (3), and uses the two methods indicated above to estimate the regression parameters. Thus, Panel A reports the regressions
in which the variables are defined with respect to the event of a manager change, whereas and Panel B reports the regressions in which the variables are defined with respect to a calendar date. The numbers in Panel B represent time-series average of annual regression coefficients as outlined in Fama and MacBeth (1973). Table VIII suggests that the coefficient on the manager’s past performance is positive and equal to approximately 0.15. Past performance of the fund seems to be less relevant. It is noteworthy that the coefficients in the individual annual regressions used to construct panel B are varying widely. Moreover, the significance of the regressions in panel B is driven primarily by the 1994 data. Given all the caveats with equation (3) indicated in the previous paragraphs, one has to be careful to draw too strong a conclusion from this table.

B Structural framework

The problems with the regression methodology outlined in Section 4.A, motivate the use of a more structural environment, where the relation between the performance of funds and managers is defined in a precise manner. In the next few sections I develop a Bayesian model to provide such an environment. As opposed to the performance regression framework with its associated measurement problems and “surrogate” return series of the managers or funds, the structural approach introduces latent fund and manager performance variables. Although this approach is intuitively appealing, the latency of these variables introduces identification problems. In contrast to for example a maximum likelihood estimation procedure, the use of a Bayesian estimation technique in conjunction with economically motivated prior beliefs is uniquely equipped to deal with these identification problems.

Section 4.B.1 gives an overview of the model, Section 4.B.2 interprets the model and Section 4.B.3 examines the identification of the model. Most of the intuition of the model is contained in these three sections, and starting with Section 4.B.4 I will discuss a formal stochastic set up of the model and the likelihood. Sections 4.B.5 through 4.B.7 study the prior beliefs, posterior beliefs, and missing data issues in the model, respectively. Part of the details of the prior and posterior beliefs are discussed in appendices A and B, respectively. Finally, Section 4.B.8 applies the model developed in sections 4.B.1 through 4.B.7 to the data.

B.1 Overview of the framework

Traditionally, to conduct inference about, say, a fund’s performance in an asset pricing model, the unit of observation is at the fund level. That is, the model parameters are fund specific.
In this section I want to assess the performance of funds and managers simultaneously, and thus constructing a model at the fund- or manager level is inadequate. Instead, I use a factor model that uses combinations of funds and managers as units. The parameters in this model are specific to each manager-fund combination, and thus each manager-fund combination has its own skill level, factor loadings and residual risk. This is a natural and flexible way to set up the model since upon the arrival of a new manager at a fund, the aforementioned model parameters are likely to change.

If \( r_{t,p} \) denotes the excess return of manager-fund combination \( p \), and \( F_t \) denotes a \( S \times 1 \) vector of factors, all realized in period \( t \), then the factor model can be written as

\[
 r_{t,p} = \alpha_p + F_t \beta_p + \epsilon_{t,p},
\]

(4)

where \( \alpha_p \) is an indicator of skill associated with manager-fund combination \( p \), and \( \epsilon_{t,p} \) is a normally distributed disturbance term at time \( t \), with mean zero and variance \( \sigma^2_p \). I assume that disturbance term is independent over time, and dependent across different manager-fund combinations.

I interpret \( \alpha_p \) as the performance measure associated with manager-fund combination \( p \). However, as pointed out by Pástor and Stambaugh (2002a) and Pástor and Stambaugh (2002b) a non-zero intercept in this model may not only represent skill (or lack thereof) but also be due to a misspecified model. For example if the model in equation (4) erroneously omits a factor, then part of the expected \( \alpha_p \) reflects this missing factor. In this section I abstract from model mispricing and assume that the factors \( F_t \) span all systematic risk in the economy, and thus that there is no model misspecification.

In addition to the factor model in equation (4) the cost structure of each manager-fund combination also provides information about the relative importance of managers and funds. Similar to Baks, Metrick, and Wachter (2001), I assume that \( \alpha_p \) has a normal distribution

\[
\alpha_p \mid \sigma_p, \delta_p \sim N \left( \delta_p, \sigma^2_p \sigma^2_{\alpha} / s^2 \right),
\]

(5)

where \( \sigma_\alpha \) represents the belief in the possibility of skill of a manager-fund combination, and \( s^2 \) is the average level of residual risk among all manager-fund combinations. \( \delta_p \equiv (-fee_p - cost_p) < 0 \), which implies that ex ante one expects the performance of manager-fund combination \( p \), \( \alpha_p \), before transactions costs \( (cost_p) \) and total fees \( (fee_p) \) to be zero. The normal distribution in equation (5) is chosen for analytic tractability. To understand why the conditional variance of \( \alpha_p \) is proportional to \( \sigma^2_p \) consider a fully invested manager-fund combination which has a skill level \( \alpha_p \) and is taking on \( s \) units of residual risk. Then,
if this manager-fund combination were to take on a 50 percent cash position, the residual risk would decrease to $s/2$ and $\alpha_p$ would fall to $\alpha_p/2$. Equation (5) recognizes this relation, and incorporates the fact that a skilled manager-fund combination can control the expected $\alpha_p$ through the strategic use of leverage. The ratio $\sigma_p^2/s^2$ effectively links the posterior distributions of $\sigma_p^2$ and $\alpha_p$.

The prior link between $\alpha_p$ and $\sigma_p^2$ is first suggested by MacKinlay (1995) and is implemented in a univariate version by Pástor and Stambaugh (1999), and subsequently in a multivariate version by Pástor and Stambaugh (2000), Pástor (2000), Pástor and Stambaugh (2002a), and Pástor and Stambaugh (2002b). Mathematically, the link in equation (5) is identical to theirs, although their motivation is somewhat different. In these papers $\sigma_a$ is an index of potential “mispricing,” and the motivation for the link is to reduce the ex ante probability of very high Sharpe ratios among portfolios that combine benchmark and non-benchmark assets.

Thus there are two observable quantities to conduct inference in the model: the returns in the factor model in equation (4) and the costs of a manager-fund combination in equation (5). For the remainder of the study these two quantities will also be known as the return likelihood and the cost structure likelihood, respectively.

The last building block of the model specifies how the performance measure associated with manager-fund combination $p$, $\alpha_p$, relates to manager and fund “skill.” As pointed out in the previous sections, both manager and fund are likely to play a role in determining the abnormal returns and cost structure of a manager-fund combination. I model this feature by dividing $\alpha_p$, which is interpreted as the “skill” associated with manager-fund combination $p$, into two parts. One part associated with the manager and the other part associated with the fund, where the weight on the manager’s part is $\lambda$ and the weight on the fund’s part is $1 - \lambda$. In addition, I assume that the manager has the same “skill” parameter throughout his career, no matter which manager-fund combination he works for. I make a similar assumption for the fund, and let the fund “skill” parameter be constant across different managers. Finally, although the two parts of alpha associated with the fund and manager may vary with the manager-fund combination, lambda remains constant across different manager-fund combinations. And thus, besides the correlation between different disturbance terms in equation (4), the cross-section of returns is related through the non-zero covariance structure of the $\alpha_p$’s. If $i$ and $j$ denote the index of the manager and fund, respectively, that comprise manager-fund combination $p$, then the previous assumptions allows one to write $\alpha_p$ as

$$\alpha_p = \lambda \gamma_i^m + (1 - \lambda) \gamma_j^f,$$

(6)
where $\gamma^m_i$ is a parameter associated with the “skill” of the manager and $\gamma^f_j$ is a parameter associated with the “skill” of the fund.

$\alpha_p$ in equation (6) is modelled as the sum of two unknown parts. One learns about managers and funds through the cross-sectional variation in $\alpha_p$. Intuitively, if one observes a high $\alpha_p$ every time manager $i$ is active, then one would conclude that that manager is an important determinant for the performance of the manager-fund combinations in which manager $i$ is active.

B.2 Interpretation of the model

All parameters on the right hand side of equation (6) are unknown, and as result understanding their economic meaning is difficult. This subsection illustrates these interpretation problems, and shows that equation (6) can be interpreted as a production function, with “manager skill” and “fund skill” as the factors of production.

The goal of this subsection is to economically characterize the quantities $\gamma^m_i$, $\gamma^f_j$, and $\lambda$. What economic meaning can one attach to these quantities? To answer this question I interpret equation (6) as a log-linearized Cobb-Douglas production function, where “manager skill” and “fund skill” are the factors of production. First recognize that the following equation,

$$1 + \alpha_p = (1 + \gamma^m_i \lambda) \left(1 + \gamma^f_j \right)^{1-\lambda}$$

approximately equals equation (6) – that is, applying the “log” operator to both sides of equation (7) and using the approximation that $\log (1 + x) \approx x$ for small $x$ gives equation (6). The approximation is necessary because the factor model in equation (4) describes expected returns, not continuously compounded returns. That is, the expected next period value of a one dollar investment in manager-fund combination $p$ is $1 + \alpha_p$ dollars, not $\exp (\alpha_p)$ dollars. The error of this approximation roughly equals one half of the variance of $\alpha_p$. Thus, the left hand side of equation (7) can be interpreted as the return on manager-fund combination $p$, or the “output” that this manager-fund combination generates. If $Y_p \equiv 1 + \alpha_p$ denotes output, $L_i \equiv 1 + \gamma^m_i$ denotes the production factor associated with manager, and $K_j \equiv 1 + \gamma^f_j$ denotes the production factor associated with the fund, then equation (7) can be written as

$$Y_p = L_i^\lambda K_j^{1-\lambda},$$

which is the familiar Cobb-Douglas production function encountered in the theory of the firm.
In this setting $\lambda$ is interpreted as the elasticity of “output” with respect to the manager input. Alternatively $\lambda$ is the fraction of output contributed by the manager, or

$$
\lambda = \frac{MPL_i \times L_i}{Y_p} = \frac{MPL_i \times L_i}{MPL_i \times L_i + MPK_j \times K_j},
$$

where $MPL_i$ and $MPK_j$ are defined as the marginal productivity of the production factors associated with manager $i$ and fund $j$, respectively. Alternatively, the ratio $\lambda/(1-\lambda)$ is interpreted as the percentage decrease in the “fund” input needed to offset an one percent increase in the “manager” input so that “output” remains constant. This quantity is also known as the marginal rate of technical substitution between the factor associated with the manager and the factor associated with the fund expressed in percentages, or

$$
\lambda/(1-\lambda) = \frac{\partial Y_p}{\partial L_i} = -\frac{d \log K_i}{d \log L_j} \bigg|_{Y_p}.
$$

Continuing the analogy with the theory of the firm, equation (10) says that the slope, expressed in percentages, along a set of inputs generating the same level of output (also known as an isoquant), is constant and equals $\lambda/(1-\lambda)$.

### B.3 Identification

Although the model presented in the previous two sections is intuitively appealing, identifying the parameter of interest $\lambda$ is problematic. There are four sources of non-identification. The first two sources of non-identification are intrinsic to the model, whereas the latter two depend on the dimensions of the data.

The first source of non-identification arises from the fact that $\gamma_i^m$ and $\gamma_j^f$ are known up to a constant. This can easily be seen by rewriting the intercept of the factor model defined in equation (6) as

$$
\lambda\gamma_i^m + (1-\lambda)\gamma_j^f = \lambda(\gamma_i^m + (1-\lambda)c) + (1-\lambda)(\gamma_j^f - \lambda c),
$$

which holds for any constant $c$. Equation (11) indicates that for a given $\lambda$ there are multiple values of $\gamma_i^m$ and $\gamma_j^f$ that result in the same value of $\alpha_p$, and thus the intercept of the model is not identified. Put another way, $c$ changes the fund’s and manager’s contributions ($\gamma_i^m$ and $\gamma_i^m$), but does not impact $\lambda$ or $\alpha_p$. Expressing equation (11) in terms of the production function given in equation (7), indicates that the inputs in the production function are unobservable, and unidentified up to a constant.
This source of non-identification may arise more than once in a setting with multiple funds and managers. To illustrate this, suppose all manager-fund combinations can be split into two clusters such that the managers and funds active in one cluster are not active in the other cluster. For each cluster all manager and fund γ’s are known up to a constant and thus there is one degree of freedom per cluster, similar to equation (11).

Another way of interpreting equation (11), is to observe that the first moments of \( \gamma_i^m \) and \( \gamma_j^f \) are unidentified. Intuitively, since one only observes returns and \( \alpha \)'s on manager-fund combinations, it is impossible to distinguish between the situation where a manager and fund would both add no value and the situation where that same manager would “add” one hundred basispoints value and that same fund would “destroy” one hundred basispoints value. Thus the model cannot make any statements about the level of \( \gamma_i^m \) and \( \gamma_j^f \).

The statistical power to conduct inference on \( \lambda \) depends on the cross-sectional variation in \( \alpha_p \). Section 4.B.6 studies the cross-sectional variance decomposition of \( \alpha_p \) more closely.

The second source of non-identification arises from the fact that the units in which one measures deviations from the mean of \( \gamma_i^m \) and \( \gamma_j^f \) is only known up to a constant. More precisely, for a given set of \( \alpha_p \)'s, there exists multiple combinations of \( \lambda, \gamma_i^m \) and \( \gamma_j^f \) that will satisfy equation (6). That is, for any \( \pi \neq \{0,1\} \) there holds

\[
\lambda \gamma_i^m + (1 - \lambda) \gamma_j^f = \pi \left( \frac{\lambda \gamma_i^m}{\pi} \right) + (1 - \pi) \left( \frac{(1 - \lambda) \gamma_j^f}{1 - \pi} \right). \tag{12}
\]

Closely related to the non-identification illustrated in equation (12) and the interpretation given in Section 4.B.2, is the fact that the model cannot identify whether the production function has decreasing, constant, or increasing returns to scale. In other words, the assumption that the coefficients on \( \gamma_i^m \) and \( \gamma_j^f \) in equation (6) sum to one is not restrictive or informative for the parameter of interest \( \lambda \). The reason for this is that \( \gamma_i^m \) and \( \gamma_j^f \) are unobserved model parameters, and one can, similar to equation (12), always scale \( \gamma_i^m \) and \( \gamma_j^f \) such that the coefficients on these two parameters sum to one. More precisely, suppose that the coefficients \( \lambda \) and \( 1 - \lambda \) in equation (6) are replaced by \( \lambda_1 \) and \( \lambda_2 \), respectively. Then for any \( \lambda_1 \) and \( \lambda_2 \) such that \( \lambda_1 + \lambda_2 \neq 0 \), there holds

\[
\lambda_1 \gamma_i^m + \lambda_2 \gamma_j^f = \frac{\lambda_1}{\lambda_1 + \lambda_2} \left( (\lambda_1 + \lambda_2) \gamma_i^m \right) + \left( 1 - \frac{\lambda_1}{\lambda_1 + \lambda_2} \right) \left( (\lambda_1 + \lambda_2) \gamma_j^f \right). \tag{13}
\]

Re-interpreting \( (\lambda_1 + \lambda_2) \gamma_i^m \) and \( (\lambda_1 + \lambda_2) \gamma_j^f \) as the new \( \gamma_i^m \) and \( \gamma_j^f \), respectively, and \( \lambda_1 / (\lambda_1 + \lambda_2) \) as \( \lambda \), equation (6) is obtained. Thus, except for the case when \( \lambda_1 + \lambda_2 = 0 \),
without loss of generality the coefficients on $\gamma_i^m$ and $\gamma_j^f$ sum to one. Put another way, the ratio $\lambda_1/\lambda_2 \equiv \lambda/(1 - \lambda)$ is identified, unlike the individual coefficients $\lambda_1$ and $\lambda_2$.

The third source of non-identification arises when the number of funds and managers is too large relative to the number of manager-fund combinations present. In general, not all manager-fund combinations are present, and inference about the fund and manager specific skill components of the intercept, $\gamma_i^m$ and $\gamma_j^f$ in equation (6), respectively, is difficult since their total number may increase rapidly when the cross-section of manager-fund combinations increases. To illustrate this, consider an example with two managers which have both managed the same two funds at different points in time during their careers, resulting in the maximum of four manager-fund combinations. Intuitively it is easy to see that this model is not identified. Although there are five unknown parameters ($\lambda$, two manager $\gamma_i^m$’s and two fund $\gamma_j^f$’s), the model can only identify four $\alpha_p$’s. Therefore the number of manager-fund combinations must be larger than the number of managers plus the number of funds plus one for the model to be identified. If there are multiple clusters of managers and funds that are active only within their own cluster, then to ensure identification, for each of these clusters there must hold that the number of manager-fund combinations is at least as large as the number of managers plus the number of funds. In addition, to identify $\lambda$ there must hold that for at least one cluster the number of manager-fund combinations exceeds the sum of the number of managers and funds active in that cluster.

The fourth and final source of non-identification arises when the number of time periods is smaller than the total number of manager-fund combinations. In this case the variance covariance matrix associated with the vector of regression disturbances in equations (4) and (5) for all manager-fund combinations in a given period $t$ has too many elements in comparison to the number of time periods.

The Bayesian framework developed in the next few subsections lends itself exceptionally well to handle these identification issues. Through economically motivated prior beliefs one can provide additional information and structure to the problem to ensure identification.

B.4 Stochastic setting and likelihood

Suppose there are $i = 1, \ldots, N$ managers, $j = 1, \ldots, M$ funds, and $p = 1, \ldots, P$ manager-fund combinations. In most settings the majority of managers, if not all, have managed less than $M$ funds, and thus the number of manager-fund combinations is smaller than $MN$. Let the earliest date in the sample be indicated by $t = 1$ and the latest date by $t = T$. Let $r$ denote the $T \times P$ matrix containing the $T$ excess return on the $P$ manager-
fund combinations, and let $F$ denote the $T \times S$ matrix containing the $S$ factor returns corresponding to the same periods as the returns in $r$. Let $\epsilon$ be a $T \times P$ matrix whose rows are independent and normally distributed with mean zero and variance-covariance matrix $\Sigma$. The $p$-th element on the diagonal of $\Sigma$ equals $\sigma_p^2$, the variance of $\epsilon_{t,p}$ for all time periods $t = 1, \ldots, T$ (see equation (4)). Having introduced these definitions, the univariate regression relation between the manager-fund combination’s returns and the factor returns in equation (4) can be written into its multivariate equivalent

$$ r = \iota_T \alpha' + F \beta + \epsilon, \quad \text{vec}(\epsilon) \sim N (0, \Sigma \otimes I_T), \quad (14) $$

where “vec” is an operator which stacks the columns of a matrix on top of each other into a vector, “$\otimes$” denotes the Kronecker product, $\iota_T$ is a vector of length $T$ containing ones, $I_T$ is a square matrix of size $T$ with ones on the main diagonal and “~” is read as “is distributed as.” $\alpha$ is the $P \times 1$ vector of intercepts and $\beta$ is the $S \times P$ matrix of factor loadings, where the $p$-th element of $\alpha$ is $\alpha_p$ and the $p$-th column of $\beta$ is $\beta_p$. Thus the manager-fund returns conditional on the factor returns are normally distributed and have a standard factor structure. I assume that the factor data $F$ does not depend on $\alpha$, $\beta$, or $\Sigma$, so that the exact specification of the factor likelihood is not necessary for the analysis.

Let $\delta$ be a $P \times 1$ vector with typical elements $\delta_p$, defined in Section 4.B.1. Then one can express (5) into its multivariate equivalent

$$ \alpha \sim N \left( \delta, \sigma_{\alpha}^2 \frac{\Sigma}{s^2} \right). \quad (15) $$

It is assumed that return likelihood in equation (14) and the cost structure likelihood in equation (15), or equivalently, $\epsilon$ and $\alpha$, are independent.

Finally, let $\gamma^m$ denote the $N \times 1$ vector with typical element $\gamma^m_i$, the parameter associated with the amount of skill of manager $i$, and let $\gamma^f$ denote the $M \times 1$ vector with typical element $\gamma^f_j$, the parameter associated with the amount of skill of fund $j$. Then one can express (6) into its multivariate equivalent

$$ \alpha = \lambda G \gamma^m + (1 - \lambda) H \gamma^f, \quad (16) $$

where $G$, of size $P \times N$, and $H$ of size $P \times M$, are matrices that select the appropriate manager and fund from the vectors $\gamma^m$ and $\gamma^f$, respectively, such that their linear combination results in the $P \times 1$ vector $\alpha$. For example, if all possible manager-fund combinations are present, or $P = MN$, then $G = I_N \otimes \iota_M$ and $H = \iota_N \otimes I_M$, where $I_N$ and $I_M$ are square-matrices of size
and $M$ with ones on their main diagonal, respectively, and $\iota_N$ and $\iota_M$ are column-vectors of size $N$ and $M$ containing ones, respectively.

For notational convenience, let $\gamma$ denote the stacked vector of manager and fund contributions, that is $\gamma \equiv \left( \gamma^m \quad \gamma^f \right)'.$ In addition let the unknown parameters in the model be denoted by $\theta \equiv (\lambda, \gamma, \beta, \Sigma)$.

### B.5 Prior beliefs

The next step is to specify the prior beliefs for the unknown parameters in equations (14), (15) and (16). I assume that elements of $\beta$, $\lambda$, $\gamma$, and $\Sigma$ are independently distributed in the prior, that is,

$$p(\lambda, \gamma, \beta, \Sigma) = p(\gamma) p(\beta) p(\lambda) p(\Sigma),$$

(17)

and that the prior beliefs on the factor loadings $\beta$, and the weight on the manager $\lambda$, are diffuse (see Zellner (1971)):

$$p(\beta) \propto 1, \quad p(\lambda) \propto 1,$$

(18)

where the notation \textquotedblleft$\propto$\textquotedblright{} is read as \textquotedblleft is proportional to\textquotedblright. The choice of a diffuse prior for $\beta$ and $\lambda$ is motivated by the fact that it simplifies the model. Also, a diffuse prior on $\beta$ is a reasonable starting point when analyzing mutual funds, where factor loadings can be estimated relatively precisely (as compared to individual stocks). The choice of a diffuse prior for $\lambda$ is natural, since ex ante there appears to be no economic information available about the relative importance of managers versus funds.

The prior beliefs for $\gamma$ are motivated by the identification problems indicated in Section 4.B.3. That section shows that the model can only identify $\alpha$, and not the individual components that comprise $\alpha$. One can interpret this as saying that the levels and units in which one expresses the contributions of the managers and funds, $(\gamma^m$ and $\gamma^f$, respectively) are known only up to a constant. There are multiple ways to resolve this identification problem, and to choose these constants. For example, one could impose an economic restriction on the mean and variance of $\gamma$. Alternatively, the Bayesian framework is uniquely equipped to deal with this identification problem by specifying an economically motivated prior belief for the manager and fund specific contributions $\gamma^m$ and $\gamma^f$. These prior beliefs are chosen such that the level and units of the manager and fund contributions correspond to the level and units used for $\alpha$. Specifically,

$$p(\gamma) = N(\delta \iota_{M+N}, \sigma^2_{\gamma} I_{M+N}).$$

(19)
Equation (19) expresses the prior belief, that before observing any data, one expects the manager and fund contributions to be independent, the variance of each manager or fund contribution to equal $\sigma^2_\gamma$, and the average manager or fund’s contribution to equal $\bar{\delta}$, which is defined as minus the average fees and costs of a “typical” manager or fund. Since one does not observe fees and costs of either managers nor funds, the parameter $\bar{\delta}$ is specified using an empirical Bayes approach and set to equal the mean of the cross-section of observed costs and fees of all manager-fund combinations, i.e. $\bar{\delta} \equiv 1/P \sum \delta_p$. The normal distribution is chosen for analytic tractability. Although the individual elements of $\gamma$ are statistically independent in the prior, they are not independent in the posterior in the sense that they are all shrunk to the grand mean $\bar{\delta}$. Similar to the interpretation of $\sigma_\alpha$, $\sigma_\gamma$ represents the a priori belief in the possibility of “skill” among managers and funds. Alternatively, $\sigma_\gamma$ can be interpreted as the a priori belief about the possible differences between manager and fund contributions. Since the units of $\gamma$ are chosen such that they match those of $\alpha$, I will frequently consider the situation where $\sigma_\alpha = \sigma_\gamma$ in the remainder of the paper. The use of only one skill parameter for both managers and funds is motivated by the desire to keep the model parsimonious and reduce the dimensionality of the problem. Finally, observe that the prior belief specified in equation (19) provides more “information” than is necessary to just resolve the first two identification problems outlined in Section 4.B.3.

As indicated in Section 4.B.3, $\Sigma$ is unidentified if $T < P$. Therefore, instead of using a non-informative prior on $\Sigma$, I use an inverted Wishart prior on $\Sigma$ so that the posterior beliefs are defined in case the data alone do not identify $\Sigma$. Thus

$$\Sigma^{-1} \sim W \left( A^{-1}, \nu \right),$$

where $W \left( A^{-1}, \nu \right)$ is a Wishart distribution with a $P \times P$ scale matrix $A^{-1}$ and $\nu$ degrees of freedom. The parameters of the Wishart distribution are chosen such that the prior distribution on $\Sigma$ is essentially non-informative. Let $\nu = P + 3$, and $A = s^2 (\nu - P - 1) I_P$, so that the prior expectation of $\Sigma$ is given by $E(\Sigma) = A/ (\nu - P - 1) = s^2 I_P$. These prior beliefs on $\Sigma$ indicate that, ex ante, the disturbance term of the factor model in equation (14) is dependent across manager-fund combinations and independent over time. In addition, the ex ante residual variance is the same across manager-fund combinations and equal to $s^2$. The posterior does in general not exhibit these properties since sample evidence updates the prior information. Following an empirical Bayes procedure, $s^2$ is set equal to the average of the diagonal elements of a frequentist estimate of $\Sigma$.

Finally, I assume that the parameters of the (unspecified) factor prior are independent of $\theta$. 

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B.6 Posterior beliefs

To derive the posterior density of the parameter of interest $\lambda$, one has to update the prior beliefs specified in equations (17) through (20) with the return likelihood specified in equation (14) and the cost structure likelihood specified in equation (15).

The marginal posterior beliefs are difficult to obtain analytically, if not impossible. However, one can approximate them by employing the Gibbs sampler, a Markov chain Monte Carlo procedure. Appendices A and B contain the details of the Gibbs sampler and its associated conditional distributions.

B.7 Missing data, survivor bias, and data augmentation

When a manager leaves a fund the investor only observes a fraction of the total possible return data series for that manager-fund combination. That is, if a manager switches to another fund at time $t$, that manager has no data available at his old fund after time $t$. And thus, unless all managers have managed a fund from the beginning of the sample, $t = 1$, until the end of the sample, $t = T$, the return series for that manager-fund combination is truncated and there are missing values in the matrix $r$. One can think of $r$ as an incomplete panel. The missing and observed return data are denoted by $r^{mis}$ and $r^{obs}$, respectively.

To simplify the analysis, I have proceeded thus far as if I have the full return matrix $r$, effectively augmenting the observed return data, $r^{obs}$, with unobserved auxiliary variables $r^{mis}$. The missing data is assumed to be generated by equation (14). I treat the missing return data as another set of unknown “parameters” in the model, and derive their marginal posterior distributions alongside those of the regression parameters. These auxiliary variables can easily be accounted for by the Gibbs sampler, which is employed in the next section to derive the posterior beliefs of the regression parameters and the auxiliary variables $r^{mis}$.

Partially observed return series on certain manager-fund combinations imply that there is potential source survivor bias in the analysis. The evidence in Section 2.C shows that the mere fact of a manager switching to another fund may reveal something about the parameters associated with that manager and fund. The question is whether or not survival of a manager at a fund changes the inference problem for the manager-fund combination returns that are observed.

Following Baks, Metrick, and Wachter (2001), under the assumption that survival of a manager at a fund depends only on realized returns, and not on unobserved model parameters

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8See Tanner and Wong (1987) for an introduction to data augmentation.
generating those returns, this type of survivor bias is not a problem. Conditional on realized returns, the manager-fund combination’s skill does not affect the probability of survival. Realized returns are, of course observable, whereas the regression parameters are unknown. It is quite plausible that survival depends on observed returns, not on unobserved skill.

B.8 Estimating the importance of managers and funds

This section examines the weight on the manager, $\lambda$, defined in equation (16) by applying the methodology developed in the previous sections to the data. As explained in Section 4.B.3, to ensure identification I require that the number of manager-fund combinations is larger than the sum of the number of managers and funds. If there are multiple clusters of managers and funds that are active only within their own cluster, then this condition must hold for each cluster. When the data is limited according to this condition, a sample consisting of 135 managers, 204 funds, and 365 manager-fund combinations remains. There are 49 clusters in the data, implying that a cluster consists on average of seven funds and managers. Among all clusters, the maximum difference between the number of manager-fund combinations and the sum of the number of managers and funds is six. There are 96 months of data in the sample, and thus there are $96 \times 365$ returns, of which 68 percent is missing. The fees are recorded in the CRSP database, and vary across time and manager-fund combination. The average fee equals twelve basispoints per month. Transaction costs are not reported in the CRSP database, and as a result, I use a single value, six basispoints per month, as the cost for every manager.\(^9\) Thus the prior constant $\bar{\delta}$ equals approximately $-18$ basispoints per month.

Figure 1 examines the contribution of the manager to output for a range of values of $\sigma_\alpha$ and $\sigma_\gamma$, which are set equal to each other. In this figure the median (solid line), the 5th and the 95th percentile (dashed line) of the posterior distribution of $\lambda$ are plotted. For $\sigma_\alpha = \sigma_\gamma$ in the range of 18 to 30 basispoints per month $\lambda$ does not vary much and approximately equals 0.53. For more skeptical prior beliefs about the ability of managers, funds, and manager-fund combinations to generate abnormal excess returns, the importance of the manager drops rapidly to approximately 0.10 for $\sigma_\alpha = \sigma_\gamma = 4$ basispoints per month. More importantly, $\lambda$’s standard deviation is relatively small, in the order of 0.04 basispoints per month. The density is asymmetric, and the mass in the tails of the distribution is higher than that of a normal distribution. Using the production function framework interpretation of $\lambda$, this is implies that, on average, if a new manager arrives who is half as productive\(^9\)This value roughly corresponds to the average monthly transactions costs for mutual funds and large institutions found in other studies; see Carhart (1997) for turnover rates and implied trading costs, Keim and Madhavan (1997) for per-trade costs, and Perold (1988) for the methodology behind these calculations.

\[\begin{align*}
\text{Figure 1}
\end{align*}\]
as the previous manager, then, depending on one’s prior beliefs, the fund organization only needs to be approximately 5 to 55 percent more productive in order to maintain the same level of expected abnormal excess returns.

To generate this plot, and subsequent plots in this section, 15,000 Gibbs samples are drawn of which the first 1000 are discarded, so that the influence of the starting values of the Gibbs chain is negligible. Moreover, only every 25th draw is retained to ensure that draws from $\lambda$ are independent.\(^{10}\) Regardless of the starting values, the Gibbs sequence for $\lambda$ mixes well, and converges rapidly to its steady state.

Since there are two likelihoods that determine the posterior beliefs for $\lambda$, it is interesting to see what the influence of each likelihood is. Figures 2 and 3, which are similar to Figure 1, examine the importance of the return likelihood and the cost structure likelihood for $\lambda$. More precisely, Figures 2 and 3 use the entire model in equations (14) through (20), except for equations (14) and (15), respectively, to conduct inference about $\lambda$. Interestingly, it appears that the posterior distribution of $\lambda$ in Figure 1 is built up of two opposite forces. For $\sigma_\alpha = \sigma_\gamma$ larger than 14 basispoints per month, the manager’s contribution to $\alpha$ based on the return likelihood is smaller than the manager’s contribution to $\alpha$ based on the cost structure likelihood. This suggests that in this range of prior beliefs managers are more important in determining the costs of a mutual fund, whereas the funds are more important in determining returns of a mutual fund. This result may at first seem to be counter-intuitive. However, in a model based only on the cost structure likelihood, $\alpha$ does not have the usual interpretation of excess abnormal returns. Rather, $\alpha$ is interpreted as the expected costs incurred by a manager-fund combination. Moreover, given that a fixed transaction cost is used in this analysis, the costs of a manager-fund combination are largely determined by the manager’s compensation, which is usually specified as a fixed fraction of the assets under management. Under the reasonable premise that managers will demand to be compensated with the same fraction of assets under management when they switch mutual funds, costs are mostly associated with the manager.

For $\sigma_\alpha = \sigma_\gamma$ smaller than 14 basispoints per month, the effects of the return and cost structure likelihood switch. That is, the importance of the manager is greater based on the return likelihood than on the cost structure likelihood. This suggests that, the manager contributes most to the manager-fund combination’s returns and the fund organization to the manager-fund combination’s costs. Thus, in this range of prior beliefs, the results imply

\(^{10}\)To determine the number of draws one needs to skip to generate an independence chain, I use a procedure outlined in Raftery and Lewis (1992). Their method, suggests that to estimate the median correctly with a level of precision of 0.01 and with a probability of 95%, every 23th draw in the chain for $\lambda$ is an independent draw.
that the cost structures within the fund, such as the analysts, administrative procedures, etc., determine most of the expenses of a mutual fund. As before the standard deviation of $\lambda$ is relatively small.

As pointed out before, without the assumption that contributions of managers and funds are measured on the same scale and level, as expressed by $\gamma$‘s prior beliefs specified in equation (19), examining the posterior beliefs of $\gamma$ is non-sensible, since $\gamma$‘s level and scale are unidentified (see section 4.B.3). However, after assuming that $\gamma$ and $\alpha$‘s scale and levels are identical, it is interesting to investigate the average levels of contribution of managers and funds to $\alpha$. Figure 4 shows the median (solid line), the 5th percentile and 95th percentile (dashed line) of $\gamma^m$‘s and $\gamma^f$‘s mean and standard deviation when $\sigma_\alpha = \sigma_\gamma$. Both the average contribution of the manager and fund are negative and approximately equal to $\tilde{\delta}$. Moreover, as one believes that managers, funds, and manager-fund combinations have an increasing amount of “skill” (i.e. increasing $\sigma_\alpha = \sigma_\gamma$), the average contribution of managers and funds stays approximately constant. At the same time, the variation of $\gamma^m$ and $\gamma^f$ increases. This last observation is not surprising since the parameter $\sigma_\gamma$ also governs the heterogeneity of the elements in the vector $\gamma$.

A complimentary approach to assess the importance of the manager besides examining $\lambda$, is to study the cross-sectional variance decomposition of the expected abnormal excess return $\alpha$. To do this, I reinterpret the model for $\alpha$ in equation (16) by considering only the two terms on the right hand side of this equation and not the individual elements that each of these terms consists of. Thus, this is a simple additive model of $\alpha$ where $\lambda G\gamma^m$ is the manager term and $(1 - \lambda) H\gamma^f$ is the fund term. Figure 5 shows the decomposition of $\alpha$‘s variance into the manager’s part (solid lines), the fund’s part (dashed lines), and the covariance between the two (dotted lines), as a function of $\sigma_\alpha = \sigma_\gamma$. More precisely, the posterior median, 5th and 95th percentile of the variances and covariance of the two terms on the right hand side of equation (16), $\lambda G\gamma^m$ and $(1 - \lambda) H\gamma^f$, are plotted as a fraction of $\alpha$‘s variance. Most of the cross-sectional variance of $\alpha$ is due to variation associated with the fund, although for $\sigma_\alpha = \sigma_\gamma > 20$ basispoints per month the fund and the manager play an equally important role in explaining $\alpha$‘s cross-sectional variance. This suggests that to maximize abnormal performance one should track fund performance, since they determine most of $\alpha$‘s variation.

Figures 6 and 7 explore the importance of the return likelihood and cost structure likelihood, respectively, for $\alpha$‘s cross-sectional variance decomposition. Similar to Figure 1, it appears that Figure 5 is build up of two opposite forces. Although the result is not as rigid, Figures 6 and 7 suggest that for $\sigma_\alpha = \sigma_\gamma > 15$ basispoints per month, the manager determines most of $\alpha$‘s cross-sectional variation due to costs, whereas funds determine most of $\alpha$‘s
cross-sectional variation due to returns. For $\sigma_{\alpha} = \sigma_{\gamma} \leq 15$ both the return likelihood and the cost structure likelihood suggest that the fund is more important for $\alpha$’s cross-sectional variation than the manager.

Finally note that, given $\gamma$’s prior beliefs which assign equal importance to managers and funds in determining $\alpha$ and that nor the return data nor the cost structure data provides any information on the division of the “level” of $\alpha$ into the manager part and the fund part, the posterior mean of $\lambda G \gamma^m$ equals the posterior mean of $(1 - \lambda) H \gamma^f$. Thus as outlined in Section 4.B.2 the ability to estimate the model comes from the cross-sectional variance in $\alpha$.

5 Conclusion

Most previous studies on mutual fund performance do not differentiate between mutual fund managers and the fund organization at which they work. Moreover, they infer fund attributes by combining the information in different manager-fund combinations, and treat these attributes as if they belong to the fund. This study explicitly distinguishes between funds, managers and manager-fund combinations by employing a newly constructed database that tracks 2,086 managers of domestic diversified equity mutual funds during their careers from 1992 to 1999.

The first part of the paper examines manager performance and its relation to fund performance. Although manager performance is somewhat persistent, this does not necessarily imply that managers are important for determining a manager-fund combination’s performance. In the second part of the paper I develop a Bayesian model to investigate the relative importance of funds and managers for a manager-fund combination’s performance. The model separates abnormal returns into a linear convex combination of two terms: one term associated with the manager and one term associated with the fund. This setup is interpreted as a log-linearized Cobb-Douglas production function, where abnormal returns, or output by a manager-fund combination is a function of two unobserved inputs: one input associated with the manager, and one associated with the fund. In this framework, I find that the fraction of abnormal returns contributed by the fund ranges from approximately 90 to 50 percent, depending on one’s prior beliefs. The remaining 10 to 50 percent is contributed by the manager. That is, if a new manager who is half as productive as the previous manager commences at a fund, then that fund only has to be 5 to 50 percent more productive in order to maintain the same alpha.

Although the results in this paper are perhaps surprising, there might be a few explanations. The findings in the second part of the paper, that managers are less important than
funds for performance, could be explained by an imperfect labor-market for managers. In fact, in a perfect market a manager’s contribution to a manager-fund combination would be zero, since his compensation would exactly reflect his “value added” to the manager-fund combination. The relative importance of a fund for alpha suggests that this market is working fairly well.\textsuperscript{11}

The methodologies developed in this paper are a first step toward understanding the relative importance of managers and funds for performance. As a rule of thumb, the results in this study indicate that performance is mainly driven by the fund. While mutual fund companies will undoubtedly continue to create star-managers and advertise their past track-record, investors should focus on fund performance.

\textsuperscript{11}Berk and Green (2002) provide a theoretical framework that relates fund flows to performance. In their model a competitive market for capital provision, combined with decreasing returns to scale in active portfolio management, ensures that economic rents of a mutual fund flow through to the managers, not to the investors. Their conclusions correspond to the manager results in my model. However, their framework does not apply to funds in my model, since, arguably, the costs of running an organization decrease when fund flows increase, implying increasing returns to scale in portfolio management for fund organizations.
Appendix A. Prior beliefs

Using equations (17), (18), (19), and (20), the prior density of $\theta \equiv (\lambda, \gamma, \beta, \Sigma)$ can be written as

$$p(\theta) = p(\Sigma) p(\gamma) = W^{-1}(A, \nu) \times N(\delta_{M+N} \nu, \sigma^2_\gamma I_{M+N})$$

$$\propto |\Sigma|^{-1/2(\nu+P+1)} \exp \left\{ -\frac{1}{2} trA\Sigma^{-1} \right\} \times \exp \left\{ -\frac{(\gamma - \delta_{M+N})'(\gamma - \delta_{M+N})}{2\sigma^2_\gamma} \right\}, \quad (A1)$$

where as before the notation “$\propto$” is read as “is proportional to,” “$tr$” denotes the trace operator, $\nu_{M+N}$ is a vector of length $M+N$ containing ones, and $I_{M+N}$ is a square matrix of size $M+N$ with ones on the main diagonal. The choice of $A$ and $\nu$ in Section 4.B.5 implies that the prior density of $\Sigma$, is non-informative. The informativeness of $\gamma$’s prior density depends on the value of $\sigma_\gamma$. Small values of $\sigma_\gamma$ represent strongly informed prior beliefs, whereas large values of $\sigma_\gamma$ represent relatively uninformative prior beliefs.

The assumed distributional properties of $\lambda$ and $\gamma$ in section 4.B.5 imply that $\alpha$ has a non-standard density. To see this rewrite $\alpha$ as a function of $\gamma$:

$$\alpha \equiv Z\gamma, \quad (A2)$$

where $Z$ is a $P \times (M+N)$ matrix defined as $\left( \begin{array}{c} \lambda G \\ (1-\lambda) H \end{array} \right)$. Given the relation between $\alpha$ and $\gamma$ in equation (A2) and that $\gamma$ is normally distributed, the density of $\alpha$ conditional on $\lambda, G$ and $H$ is given by

$$\alpha \mid \lambda, G, H \sim N(\delta Z\nu_{M+N}, \sigma^2_\gamma ZZ') \quad (A3)$$

The mean and variance of the density in equation (A3) can be rewritten as $\tilde{\delta}_P$ and $\sigma^2_\gamma (\lambda^2G' + (1-\lambda)^2 HH')$, respectively. Since the variance-covariance matrix of $\alpha \mid \lambda$ is a second degree polynomial in $\lambda$, deriving the unconditional prior beliefs for $\alpha$ by integrating out $\lambda$ in the density in equation (A3) is difficult. Although the entire distribution is difficult to derive, using the law of iterated expectations, the unconditional prior mean of $\alpha$ is given by $\tilde{\delta}_P$. The unconditional variance-covariance matrix of $\alpha$ is improper which can be verified by combining $\lambda$’s uninformative prior beliefs with the variance decomposition for conditional random variables.\textsuperscript{12}

\textsuperscript{12}If one approximates $\lambda$’s improper prior density by $\lim_{x \to -\infty} p(\lambda) = 1/(2x)$ for $-x \leq \lambda \leq x$, then it is straightforward to see that $\alpha$’s variance-covariance matrix is improper:

$$Var(\alpha) = \lim_{x \to -\infty} Var(\lambda) (E(\alpha \mid \lambda)) = E(\lambda (Var(\alpha \mid \lambda))) = \lim_{x \to -\infty} \sigma^2_\gamma \left( \frac{x^2}{3} (GG' + HH') + HH' \right).$$
Observe that conditioning on $G$ and $H$ may not be trivial. Beliefs that incorporate the knowledge which manager-fund combinations occur (i.e. knowing $G$ and $H$), may be different from those that do not, or mathematically $p(\theta | \cdot) \neq p(\theta | \cdot, G, H)$. The prior and posterior beliefs specified in Section 4.B are all formulated conditional on $G$ and $H$. For notational convenience I omit the conditioning on the manager and fund selection matrices $G$ and $H$ throughout the appendix.

Appendix B. Posterior beliefs

This appendix examines the construction of the posterior beliefs for $\theta$. There are two independent likelihoods to update $\theta$; the cost structure likelihood and return likelihood, both discussed in Section 4.B.4. Appendix B.1 examines $\theta$’s posterior density based on both likelihoods. Appendices B.2 and B.3 then examine $\theta$’s posterior density based on each individual likelihood.

B.1. Posterior based on the cost structure likelihood and the return likelihood

In this appendix I derive $\theta$’s posterior distribution based on the cost structure likelihood and the return likelihood, given in equations (14) and (15), respectively. Following Stambaugh (2001), the information about $\alpha$ in equation (15) is incorporated into the prior by re-interpreting $\delta$ in that equation as a realization of a multivariate normal with mean $\alpha$ and variance covariance matrix $\sigma^2\Sigma/s^2$:

$$\delta \mid \gamma, \lambda, \Sigma \sim N\left(\alpha, \sigma^2\Sigma/s^2\right).$$

(B1)

Applying Bayes rule to update the prior density in equation (A1) with the information contained in the cost structure likelihood in equation (B1), and the return likelihood in equation (14) gives the posterior density of all parameters:

$$p(\theta \mid \delta, r, F) \propto p(r \mid \theta, F) \times p(\delta \mid \theta) \times p(\theta).$$

(B2)

Given the “sparse” structure of $G$ and $H$, some off-diagonal elements of $\alpha$’s variance-covariance matrix are zero, whereas other elements are not defined.
Note that the cost likelihood and return likelihood are assumed to be independent. Since the posterior distribution in equation (B2) has a non-trivial dependence on the parameters $\lambda$ and $\gamma$, the Gibbs sampler is used to generate draws from this distribution.\(^\text{13}\)

As pointed out in Section 4.B.7 I have proceeded as if I have the full return matrix $r$, effectively augmenting the observed return data $r^{obs}$, with the unobserved auxiliary variables $r^{mis}$. These auxiliary variables are easily accounted for by the Gibbs sampler. By alternating draws between $\theta \mid r^{mis}, r^{obs}, F, \delta$ and $r^{mis} \mid \theta, r^{obs}, F, \delta$ one obtains a sample of the distribution of interest, $\theta \mid r^{obs}, F, \delta$. Since the Gibbs sampler is also used to draw from $\theta \mid r, F, \delta$, integrating out the missing data only amounts to one additional draw from the appropriate conditional distribution.

Given an initial estimate of $\theta$, the Gibbs sampler cycles through the following conditional densities

- $r^{mis} \mid \delta, \theta, r^{obs}, F$
- $\gamma \mid \lambda, \beta, \Sigma, \delta, r, F$
- $\lambda \mid \gamma, \beta, \Sigma, \delta, r, F$
- $\Sigma \mid \gamma, \lambda, \beta, \delta, r, F$
- $\beta \mid \gamma, \lambda, \Sigma, \delta, r, F$

The next five subsections examine these densities.

**B.1.1. Conditional posterior distribution of $\gamma$**

To derive $\gamma$’s posterior distribution conditional on $\Sigma, \lambda, r, F$ and $\delta$, rearrange the factor model in equation (14) as follows

\[
\text{vec} \left( r - F\beta \right) = (I_P \otimes \iota_T) Z\gamma + \text{vec} \left( \epsilon \right), \quad (B3)
\]

\(^{\text{13}}\)Casella and George (1992) give an excellent introduction to the Gibbs Sampler.
where $Z$ is defined in equation (A2), and, as before, “vec” is an operator which stacks the columns of a matrix on top of each other into a vector and “$\otimes$” denotes the Kronecker product. Then it follows that the return likelihood can be written as

$$p(r | \theta, F) \propto \exp \left\{ -\frac{1}{2} (\text{vec}(r - F\beta) - (I_P \otimes \iota_T) Z\gamma)' \right.$$ 

$$\left. (\Sigma \otimes I_T)^{-1} (\text{vec}(r - F\beta) - (I_P \otimes \iota_T) Z\gamma) \right\}. \quad (B4)$$

Multiplying the prior density in equation (A1), the cost structure likelihood in equation (B1), and the return likelihood in equation (B4), as in equation (B2), gives the distribution of $\gamma$ conditional on $\lambda, \beta, \Sigma, \delta, r,$ and $F$. After collecting the terms involving $\gamma$, and twice completing the square on $\gamma$ it follows that this conditional posterior distribution can be written as

$$p(\gamma | \lambda, \beta, \Sigma, \delta, r, F) \propto \exp \left\{ -\frac{1}{2} (\gamma - \hat{\gamma})' V^{-1} (\gamma - \hat{\gamma}) \right\}, \quad (B5)$$

where

$$V = \left( \frac{1}{\sigma_\gamma^2} I_{M+N} + \left( \frac{s^2}{\sigma_\alpha^2} \right) Z'\Sigma^{-1} Z \right)^{-1}$$

$$\equiv (V_0^{-1} + V_c^{-1} + V_r^{-1})^{-1}, \quad (B6)$$

and

$$\hat{\gamma} = V \left( \frac{\bar{\delta}}{\sigma_\gamma^2} I_{M+N} + Z'\Sigma^{-1} \left( \frac{s^2}{\sigma_\alpha^2} \delta + (r - F\beta)' \iota_T \right) \right)$$

$$\equiv V (V_0^{-1}\hat{\gamma}_0 + V_c^{-1}\hat{\gamma}_c + V_r^{-1}\hat{\gamma}_r). \quad (B7)$$

Thus $\gamma | \lambda, \beta, \Sigma, \delta, r, F$ is normally distributed with mean $\hat{\gamma}$ and variance-covariance matrix $V$. Common to Bayesian analysis and illustrated in equation (B7) the posterior mean of $\gamma | \Sigma, \beta, \lambda, \delta, r, F$ is the weighted average of $\gamma$’s prior mean given by $\hat{\gamma}_0 \equiv \bar{\delta} I_{N+M}$, the cost structure likelihood mean of $\gamma$ given by $\hat{\gamma}_c \equiv (Z'\Sigma^{-1} Z)^{-1} Z'\Sigma^{-1} \delta$, and the return likelihood mean of $\gamma$ given by $\hat{\gamma}_r \equiv (Z'\Sigma^{-1} Z)^{-1} Z'\Sigma^{-1} (r - F\beta)' \iota_T / T$, where the weights are proportional to $\gamma$’s prior precision given by $V_0^{-1} = I_{M+N}/\sigma_\gamma^2$, $\gamma$’s cost structure likelihood precision given by $V_c^{-1} = s^2/\sigma_\alpha^2 Z'\Sigma^{-1} Z$, and $\gamma$’s return likelihood precision given by $V_r^{-1} = T Z'\Sigma^{-1} Z$, respectively. Similarly, $\gamma$’s posterior precision $V^{-1}$ is the sum of $\gamma$’s prior precision $V_0^{-1}$, $\gamma$’s cost structure likelihood precision $V_c^{-1}$, and $\gamma$’s return likelihood precision $V_r^{-1}$.
Note that the identification problems outlined in Section 4.B.3 imply that \( Z'\Sigma^{-1}Z \) is singular. The prior beliefs for \( \gamma \) resolve these identification problems by including \( V_0 \) in the total variance \( V \) in equation (B6).

### B.1.2. Conditional posterior distribution of \( \lambda \)

To derive \( \lambda \)'s posterior distribution conditional on \( \gamma, \beta, \Sigma, \delta, r, \) and \( F \), rewrite the factor model in equation (14) as a function of \( \lambda \),

\[
\text{vec} \left( r - F\beta - \nu_T (H\gamma^f)' \right) = (W \otimes \nu_T) \lambda + \text{vec} (\epsilon), \tag{B8}
\]

where \( W \equiv G\gamma^m - H\gamma^f \). Then it follows that the return likelihood can be written as

\[
p(r | \theta, F) \propto \exp \left\{ -\frac{1}{2} \left( \text{vec} \left( r - F\beta - \nu_T (H\gamma^f)' \right) - (W \otimes \nu_T) \lambda \right)' \right. \\
\left. \times \left( \Sigma \otimes I_T \right)^{-1} \left( \text{vec} \left( r - F\beta - \nu_T (H\gamma^f)' \right) - (W \otimes \nu_T) \lambda \right) \right\} \tag{B9}
\]

Multiplying the prior density in equation (A1), the cost structure likelihood in equation (B1) and the return likelihood in equation (B9), as in equation (B2), and collecting the terms involving \( \lambda \), gives the distribution of \( \lambda \) conditional on \( \gamma, \Sigma, \delta, r, \) and \( F \). After completing the square on \( \lambda \), it follows that this conditional posterior distribution can be written as

\[
\lambda | \gamma, \beta, \Sigma, \delta, r, F \sim N \left( \hat{\lambda}, \sigma^2_\lambda \right), \tag{B10}
\]

where

\[
\sigma^2_\lambda = \left( \left( \frac{s^2}{\sigma^2_\alpha} + T \right) W'\Sigma^{-1}W \right)^{-1} \\
\equiv \left( \frac{1}{\sigma^2_{c,\lambda}} + \frac{1}{\sigma^2_{r,\lambda}} \right)^{-1}, \tag{B11}
\]

and

\[
\hat{\lambda} = \sigma^2_\lambda W'\Sigma^{-1} \left( r - F\beta - \nu_T (H\gamma^f)' \right)' \nu_T + \frac{s^2}{\sigma^2_\alpha} (\delta - H\gamma^f) \\
\equiv \sigma^2_\lambda \left( \frac{1}{\sigma^2_{c,\lambda}} \hat{\lambda}_c + \frac{1}{\sigma^2_{r,\lambda}} \hat{\lambda}_r \right). \tag{B12}
\]
Thus $\lambda \mid \gamma, \beta, \Sigma, \delta, r, F$ is normally distributed with mean $\hat{\lambda}$ and variance $\sigma^2_\lambda$. Common to Bayesian analysis, and illustrated in equation (B12), $\lambda$’s posterior mean is the weighted average of $\lambda$’s cost structure likelihood mean $\hat{\lambda}_c = (W'\Sigma^{-1}W)^{-1} \times W'\Sigma^{-1} (\delta - H \gamma f)$, and $\lambda$’s return likelihood mean $\hat{\lambda}_r = (W'\Sigma^{-1}W)^{-1} \times (r - F\beta - H\gamma f)' \frac{\nu_T}{T}$, where the weights are proportional to $\lambda$’s cost likelihood precision, given by $1/\sigma^2_{c,\lambda} = s^2/\sigma^2_\alpha W'\Sigma^{-1}W$, and $\lambda$’s return likelihood precision, given by $1/\sigma^2_{r,\lambda} = TW'\Sigma^{-1}W$, respectively. Similarly, $\lambda$’s posterior precision $1/\sigma^2_\lambda$ is the sum of $\lambda$’s cost structure likelihood precision $1/\sigma^2_{c,\lambda}$ and $\lambda$’s return likelihood precision $1/\sigma^2_{r,\lambda}$.

**B.1.3. Conditional posterior distribution of $\Sigma$**

To derive the posterior distribution of $\Sigma$ conditional on $\gamma, \lambda, \beta, \delta, r, F$ and $\delta$, rewrite the cost structure likelihood in equation (B1) as

$$p(\delta \mid \theta) = |\Sigma|^{-1/2} \exp \left\{ -\frac{1}{2} \text{tr} \left( \frac{s^2}{\sigma^2_\alpha} (\alpha - \delta) (\alpha - \delta)' \Sigma^{-1} \right) \right\} \tag{B13}$$

and the return likelihood in equation (14) as

$$p(r \mid \theta, F) \propto |\Sigma|^{-T/2} \exp \left\{ -\frac{1}{2} \text{tr} \left( (r - (\nu_T \alpha' + F\beta))' (r - (\nu_T \alpha' + F\beta)) \Sigma^{-1} \right) \right\}. \tag{B14}$$

Substituting equations (A1), (B13) and (B14) into equation (B2), and collecting all the terms involving $\Sigma$, gives the posterior density of $\Sigma$ conditional on $\gamma, \lambda, \beta, \delta, r, F$

$$p(\Sigma \mid \gamma, \lambda, \beta, \delta, r, F) \propto |\Sigma|^{-(\nu+P+2)/2} \exp \left\{ -\frac{1}{2} \text{tr} \left( Q + A \right) \Sigma^{-1} \right\}, \tag{B15}$$

where

$$Q = \frac{s^2}{\sigma^2_\alpha} (\alpha - \delta)' (\alpha - \delta)' + (r - (\nu_T \alpha' + F\beta))' (r - (\nu_T \alpha' + F\beta))$$

$$\equiv Q_c + Q_r. \tag{B16}$$

That is, $\Sigma \mid \gamma, \lambda, \beta, \delta, r, F$ has an inverted Wishart distribution with precision matrix $Q + A$ and $\nu + T + 1$ degrees of freedom. Note that if $P > 1$, $Q_c \equiv s^2/\sigma^2_\alpha (\alpha - \delta)' (\alpha - \delta)'$ is singular, and if $P > T$, $Q_r \equiv (r - (\nu_T \alpha' + F\beta))' (r - (\nu_T \alpha' + F\beta))$ is singular. If $Q$ is singular the conditional density of $\Sigma$ is identified through $\Sigma$’s prior density, and in particular through the non-singular matrix $A$. 


B.1.4. Conditional posterior distribution of $\beta$

First recognize that the cost structure likelihood in equation (B1) is non-informative about $\beta$, and thus only the return likelihood is relevant for $\beta$’s posterior distribution. To derive the conditional distribution of $\beta$ given $\lambda, \gamma, \delta, r$, and $F$, rewrite the factor model in equation (14) as

$$r - \iota T \alpha' = F \beta + \epsilon.$$  \hspace{1cm} (B17)

This is a standard multivariate normal model, and combined with the $\beta$’s flat prior this gives (see e.g. Zellner (1971))

$$\text{vec } (\beta) \mid \alpha, \Sigma, r, F \sim N \left( \text{vec } \left( \hat{\beta} \right), \Sigma \otimes (F'F)^{-1} \right),$$ \hspace{1cm} (B18)

where

$$\hat{\beta} = (F'F)^{-1} F' (r - \iota T \alpha').$$ \hspace{1cm} (B19)

B.1.5. Conditional posterior distribution of the missing return data

To derive the posterior density of the missing return data $r^{mis}$ conditional on $\alpha, \beta, \Sigma, \delta, r^{obs}$, and $F$ recognize that the error term in the factor model in equation (14) is only correlated in the cross-section, and thus only observed returns in period $t$ are relevant for inference about missing return values in period $t$. In addition, similar to the derivation of $\beta$’s posterior beliefs, the cost structure likelihood in equation (B1) is non-informative about the missing return data. Consequently the conditional posterior for the missing return data is the product of $T$ independent distributions, one for each period in the sample, or

$$p \left( r^{mis} \mid r^{obs}, \alpha, \beta, \delta, \Sigma, F \right) = p \left( r^{mis} \mid r^{obs}, \alpha, \beta, \Sigma, F \right)$$

$$= \prod_{t=1}^{T} p \left( r^{mis}_t \mid r^{obs}_t, \alpha, \beta, \Sigma, F \right).$$ \hspace{1cm} (B20)

Without loss of generality reorder the vector of returns in period $t$, $r_t$, such that the missing values are at the top ($r^{mis}_t$) and the observed values at the bottom ($r^{obs}_t$). Also, reorder the parameters $\alpha, \beta, \Sigma$ in the same fashion, where parameters of manager-fund combinations that have a missing return in period $t$ get the superscript $mis$ and those that have an observed return in period $t$ get the superscript $obs$. Because I assume that both the
missing data and observed data are generated by the factor model in equation (14) (see also Section 4.B.7), the distribution of this re-ordered vector is given by

\[
\begin{pmatrix}
    r_{t}^{mis} \\
    r_{t}^{obs}
\end{pmatrix}
\sim N\left(\begin{pmatrix}
    \alpha_{mis}^{\prime} + F_{t}\beta_{mis}^{\prime} \\
    \alpha_{obs}^{\prime} + F_{t}\beta_{obs}^{\prime}
\end{pmatrix}, \begin{pmatrix}
    \Sigma_{mis,mis} & \Sigma_{mis,obs} \\
    \Sigma_{obs,mis} & \Sigma_{obs,obs}
\end{pmatrix}\right)
\] (B21)

Using the properties of the normal distribution, for each vector of missing returns in period \(t\) there holds:

\[
p \left( r_{t}^{mis} \mid r_{t}^{obs}, \alpha, \beta, \Sigma, F \right) \sim N \left( \mu_{t}^{mis}, \Phi_{t}^{mis} \right),
\] (B22)

where

\[
\mu_{t}^{mis} = \alpha_{mis}^{\prime} + F_{t}\beta_{mis}^{\prime} + \Sigma_{mis,obs} \left( \Sigma_{obs,obs} \right)^{-1} \left( r_{t}^{obs} - \left( \alpha_{obs}^{\prime} + F_{t}\beta_{obs}^{\prime} \right) \right)
\] (B23)

and

\[
\Phi_{t}^{mis} = \Sigma_{mis,mis} - \Sigma_{mis,obs} \left( \Sigma_{obs,obs} \right)^{-1} \Sigma_{obs,mis}.
\] (B24)

**B.2. Posterior based on the cost structure likelihood**

The derivation of \(\theta\)'s posterior density based on the cost structure likelihood is similar to the derivation of \(\theta\)'s posterior density based on both the cost structure likelihood and the return likelihood described in Appendix B.1. Since the cost structure likelihood does not provide information on \(r^{mis}\) or \(\beta\), the Gibbs sampler skips the two steps associated with the distributions of these parameters and instead will only cycle through the following three conditional densities: \(p(\gamma \mid \lambda, \Sigma, \delta)\), \(p(\lambda \mid \gamma, \Sigma, \delta)\), and \(p(\Sigma \mid \gamma, \lambda, \delta)\).

Because \(\theta\)'s posterior density based on the cost structure likelihood does not consider the information in the return likelihood, the three conditional distributions that constitute the Gibbs sampler are slightly different from the ones discussed in sections B.1.1, B.1.2 and B.1.3. Simply leaving out the parts associated with the return likelihood yields the new results. Thus, the posterior for \(\gamma \mid \lambda, \Sigma, \delta\) is normally distributed with mean \(\hat{\gamma}_{0c} \equiv V_{0c} \left( V_{0}^{-1} \hat{\gamma}_{0} + V_{c}^{-1} \hat{\gamma}_{c} \right)\), and variance-covariance matrix \(V_{0c} \equiv \left( V_{0}^{-1} + V_{c}^{-1} \right)^{-1}\), where \(V_{0}, V_{c}^{-1}\), and \(\hat{\gamma}_{c}\) are defined as in Section B.1.1. The posterior for \(\lambda \mid \gamma, \Sigma, \delta\) is normally distributed with mean \(\hat{\lambda}_{c}\) and variance \(\sigma_{\lambda}^{2}\), both defined in Section B.1.2. Finally \(\Sigma \mid \gamma, \lambda, \delta\) has an inverted Wishart distribution with precision matrix \(Q_{c} + A\) and \(\nu + 1\) degrees of freedom, where \(Q_{c}\) is defined in Section B.1.3.
B.3. Posterior based on the return likelihood

As in the previous subsection, the derivation of \( \theta \)’s posterior density based on the cost structure likelihood is similar to the derivation of \( \theta \)’s posterior density based on both the cost structure likelihood and the return likelihood described in Appendix B.1. As in that appendix, the Gibbs sampler cycles through five conditional densities: 

\[
p(r_{mis} \mid \theta, r_{obs}, F), \quad p(\gamma \mid \lambda, \beta, \Sigma, r, F), \quad p(\gamma \mid \lambda, \beta, \Sigma, r, F), \quad p(\Sigma \mid \gamma, \lambda, \beta, r, F), \quad \text{and} \quad p(\beta \mid \gamma, \lambda, \Sigma, r, F).
\]

Because the cost structure likelihood does not provide any information about \( \beta \) and \( r_{mis} \), the conditional densities \( p(\beta \mid \gamma, \lambda, \Sigma, r, F) \) and \( p(r_{mis} \mid \theta, r_{obs}, F) \) do not change by conditioning on \( \delta \), and thus these densities are the same as in Appendices B.1.4 & B.1.5, and given in equations (B18) and (B20), (B22), respectively. Similar to Appendix B.2, to obtain the remaining three densities in the Gibbs sampler one needs to slightly modify the densities in sections B.1.1, B.1.2 and B.1.3 by leaving out the parts associated with the cost structure likelihood. Thus, the posterior for \( \gamma \mid \lambda, \Sigma, r, F \) is normally distributed with mean \( \hat{\gamma}_0 \equiv V_0 r^{-1} (V_0^{-1} \hat{\gamma}_0 + V_r^{-1} \hat{\gamma}_r) \), and variance-covariance matrix \( V_0 r \equiv (V_0^{-1} + V_r^{-1})^{-1} \), where \( V_0, \hat{\gamma}_0, V_r^{-1} \), and \( \hat{\gamma}_r \) are defined as in Section B.1.1. The posterior for \( \lambda \mid \gamma, \Sigma, r, F \) is normally distributed with mean \( \hat{\lambda}_r \) and variance \( \sigma_r^2 \), both defined in Section B.1.2. Finally \( \Sigma \mid \gamma, \lambda, r, F \) has an inverted Wishart distribution with precision matrix \( Q_r + A \) and \( \nu + T \) degrees of freedom, where \( Q_r \) is defined in Section B.1.3.
References


CRSP, 2000, CRSP survivor bias free US mutual fund database file guide.


Table I: Career characteristics of domestic diversified equity managers

Table I reports the career characteristics of mutual fund managers of domestic diversified equity funds in the period from January 1992 to December 1999. A manager is defined as an individual or group whose names are explicitly known. A group of people managing a fund is treated as a single manager. A manager change is defined as a manager leaving a fund or starting at a new fund. A manager disappears from the data if he leaves a fund and does not manage any other fund in the period after he leaves and before January 2000. A manager is defined to “reappear in the data managing greater total assets” if the monthly average total assets under management by that manager in the year following a change, are greater than the monthly average total assets under management by the manager in the year prior to the change, adjusted for the average growth rate of total net assets of all domestic diversified equity funds. “Number of funds” in year \( t \) is defined as the number of funds under management by all managers active in year \( t \).

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Fund years</td>
<td>6,287</td>
<td>351</td>
<td>483</td>
<td>592</td>
<td>694</td>
<td>800</td>
<td>977</td>
<td>1,149</td>
<td>1,241</td>
</tr>
<tr>
<td>No. of manager-fund combinations</td>
<td>2,118</td>
<td>420</td>
<td>581</td>
<td>710</td>
<td>826</td>
<td>1,002</td>
<td>1,174</td>
<td>1,351</td>
<td>1,386</td>
</tr>
<tr>
<td>No. of managers</td>
<td>2,086</td>
<td>403</td>
<td>521</td>
<td>586</td>
<td>680</td>
<td>769</td>
<td>857</td>
<td>922</td>
<td>927</td>
</tr>
<tr>
<td>Total manager changes</td>
<td>2,610</td>
<td>140</td>
<td>235</td>
<td>262</td>
<td>308</td>
<td>443</td>
<td>451</td>
<td>450</td>
<td>321</td>
</tr>
<tr>
<td>Manager change in which manager disappears</td>
<td>441</td>
<td>10</td>
<td>39</td>
<td>38</td>
<td>65</td>
<td>69</td>
<td>62</td>
<td>67</td>
<td>91</td>
</tr>
<tr>
<td>Manager change in which the manager appears for the first time in the data</td>
<td>899</td>
<td>73</td>
<td>115</td>
<td>108</td>
<td>110</td>
<td>124</td>
<td>145</td>
<td>139</td>
<td>85</td>
</tr>
<tr>
<td>Manager change in which the manager reappears in the data, managing fewer total assets</td>
<td>264</td>
<td>5</td>
<td>15</td>
<td>20</td>
<td>24</td>
<td>55</td>
<td>47</td>
<td>58</td>
<td>40</td>
</tr>
<tr>
<td>Manager change in which the manager reappears in the data, managing more total assets</td>
<td>250</td>
<td>5</td>
<td>15</td>
<td>23</td>
<td>23</td>
<td>41</td>
<td>55</td>
<td>65</td>
<td>23</td>
</tr>
<tr>
<td>No. of funds</td>
<td>1,602</td>
<td>410</td>
<td>546</td>
<td>662</td>
<td>758</td>
<td>906</td>
<td>1,069</td>
<td>1,225</td>
<td>1,264</td>
</tr>
<tr>
<td>Instances in which fund disappears</td>
<td>229</td>
<td>7</td>
<td>12</td>
<td>10</td>
<td>32</td>
<td>33</td>
<td>40</td>
<td>46</td>
<td>49</td>
</tr>
<tr>
<td>Instances in which fund appears for the first time</td>
<td>969</td>
<td>63</td>
<td>111</td>
<td>107</td>
<td>86</td>
<td>142</td>
<td>190</td>
<td>185</td>
<td>85</td>
</tr>
</tbody>
</table>
Table II: Domestic diversified equity manager style transitions

Table II reports the style transitions of managers of domestic diversified equity funds when they start managing a new or additional fund. The entries in the table indicate the number of transitions from a style of the current fund(s) under management to the style of a new fund. If a manager has multiple funds under management when he starts managing a new fund, all entries in the table that represent a transition from a style associated with the funds already under management to the style of the new fund are increased by one. A manager is defined to belong to a certain style category when all the funds he managed during his career belong to that same category. The “other” style category consists of managers that could either not be classified, or had multiple funds under management with different styles.

<table>
<thead>
<tr>
<th>Style new fund</th>
<th>Small company growth</th>
<th>Other aggressive growth</th>
<th>Growth</th>
<th>Income</th>
<th>Growth &amp; income</th>
<th>Maximum capital gains</th>
<th>Other</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Small company growth</td>
<td>99</td>
<td>8</td>
<td>27</td>
<td>0</td>
<td>13</td>
<td>0</td>
<td>0</td>
<td>147</td>
</tr>
<tr>
<td>Other aggressive growth</td>
<td>11</td>
<td>21</td>
<td>20</td>
<td>1</td>
<td>3</td>
<td>4</td>
<td>0</td>
<td>60</td>
</tr>
<tr>
<td>Style growth current fund(s)</td>
<td>35</td>
<td>21</td>
<td>150</td>
<td>1</td>
<td>20</td>
<td>1</td>
<td>2</td>
<td>230</td>
</tr>
<tr>
<td>Income</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>Growth &amp; income</td>
<td>14</td>
<td>5</td>
<td>26</td>
<td>0</td>
<td>68</td>
<td>1</td>
<td>0</td>
<td>114</td>
</tr>
<tr>
<td>Maximum capital gains</td>
<td>1</td>
<td>4</td>
<td>11</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>18</td>
</tr>
<tr>
<td>Other</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Total</td>
<td>161</td>
<td>59</td>
<td>235</td>
<td>2</td>
<td>105</td>
<td>6</td>
<td>3</td>
<td>571</td>
</tr>
</tbody>
</table>
Table III reports cross-sectional moments of attributes of managers of domestic diversified equity funds in the period from January 1992 to December 1999. The last five columns report the mean and standard deviation (in parentheses) of (i) the total number of funds under management during the manager’s career, (ii) the total time worked in years, (iii) the time spent in between funds in years, (iv) the average time spent at one fund in years, and (v) the number of management companies worked for, respectively. A manager is defined to belong to a certain style category when all the funds he managed during his career belong to that same category. The “other” style category consists of managers that could either not be classified, or had multiple funds under management with different styles. Active managers are those who manage a fund at the end of the sample, December 1999. Retired managers are those who appear in the sample but are not active at this date.

<table>
<thead>
<tr>
<th>Group</th>
<th>Total number</th>
<th>No. of funds under mgmt.</th>
<th>Time worked (years)</th>
<th>Time spent in between funds (years)</th>
<th>Time spent at one fund (years)</th>
<th>No. of mgmt. comp. worked for</th>
</tr>
</thead>
<tbody>
<tr>
<td>Domestic diversified equity managers</td>
<td>2,086</td>
<td>1.67</td>
<td>3.60</td>
<td>0.02</td>
<td>3.06</td>
<td>1.16</td>
</tr>
<tr>
<td></td>
<td>(1.29)</td>
<td>(2.36)</td>
<td>(0.22)</td>
<td>(2.11)</td>
<td>(0.44)</td>
<td></td>
</tr>
<tr>
<td>By manager style</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Small company growth</td>
<td>359</td>
<td>1.47</td>
<td>3.25</td>
<td>0.01</td>
<td>2.87</td>
<td>1.10</td>
</tr>
<tr>
<td></td>
<td>(1.04)</td>
<td>(2.19)</td>
<td>(0.10)</td>
<td>(1.92)</td>
<td>(0.33)</td>
<td></td>
</tr>
<tr>
<td>Other aggressive growth</td>
<td>119</td>
<td>1.22</td>
<td>3.07</td>
<td>0.01</td>
<td>2.78</td>
<td>1.05</td>
</tr>
<tr>
<td></td>
<td>(0.61)</td>
<td>(2.14)</td>
<td>(0.07)</td>
<td>(1.86)</td>
<td>(0.22)</td>
<td></td>
</tr>
<tr>
<td>Growth</td>
<td>804</td>
<td>1.41</td>
<td>3.48</td>
<td>0.01</td>
<td>3.17</td>
<td>1.12</td>
</tr>
<tr>
<td></td>
<td>(0.94)</td>
<td>(2.35)</td>
<td>(0.16)</td>
<td>(2.24)</td>
<td>(0.37)</td>
<td></td>
</tr>
<tr>
<td>Income</td>
<td>12</td>
<td>1</td>
<td>2.94</td>
<td>0</td>
<td>2.94</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>(0)</td>
<td>(0.99)</td>
<td>(0)</td>
<td>(0.99)</td>
<td>(0)</td>
<td></td>
</tr>
<tr>
<td>Growth and income</td>
<td>371</td>
<td>1.35</td>
<td>3.61</td>
<td>0.00</td>
<td>3.37</td>
<td>1.11</td>
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<tr>
<td></td>
<td>(0.82)</td>
<td>(2.46)</td>
<td>(0.01)</td>
<td>(2.29)</td>
<td>(0.32)</td>
<td></td>
</tr>
<tr>
<td>Maximum capital gains</td>
<td>22</td>
<td>1</td>
<td>5.31</td>
<td>0</td>
<td>5.31</td>
<td>1.08</td>
</tr>
<tr>
<td></td>
<td>(0)</td>
<td>(2.96)</td>
<td>(0)</td>
<td>(2.96)</td>
<td>(0.28)</td>
<td></td>
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<tr>
<td>Other</td>
<td>399</td>
<td>2.73</td>
<td>4.13</td>
<td>0.09</td>
<td>2.74</td>
<td>1.36</td>
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<tr>
<td></td>
<td>(1.85)</td>
<td>(2.35)</td>
<td>(0.40)</td>
<td>(1.81)</td>
<td>(0.64)</td>
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</tr>
<tr>
<td>By current status</td>
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</tr>
<tr>
<td>Active</td>
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<td>2.00</td>
<td>4.24</td>
<td>0.04</td>
<td>3.48</td>
<td>1.21</td>
</tr>
<tr>
<td></td>
<td>(1.66)</td>
<td>(2.54)</td>
<td>(0.29)</td>
<td>(2.27)</td>
<td>(0.53)</td>
<td></td>
</tr>
<tr>
<td>Retired</td>
<td>1,453</td>
<td>1.48</td>
<td>3.05</td>
<td>0.01</td>
<td>2.68</td>
<td>1.13</td>
</tr>
<tr>
<td></td>
<td>(0.97)</td>
<td>(2.04)</td>
<td>(0.13)</td>
<td>(1.89)</td>
<td>(0.36)</td>
<td></td>
</tr>
</tbody>
</table>
Table IV: Manager database time-series summary statistics

Table IV reports cross-sectional averages on annual/monthly time-series average manager attributes for all managers in charge of domestic diversified equity funds from January 1992 to December 1999. Panel A reports annual statistics, panel B splits the sample by manager style, and panel C by current status. SCG stands for small company growth, AG stands for aggressive growth, G&I stands for growth and income, and MCG stands for maximum capital gains. A manager is defined to belong to a certain style category when all the funds he managed during his career belong to that same category. The “other” style category consists of managers that could either not be classified, or had multiple funds under management with different styles. Active managers are those who manage a fund at the end of the sample, December 1999. Retired managers are those who appear in the sample but are not active at this date.

<table>
<thead>
<tr>
<th></th>
<th>No. of Mgrs.</th>
<th>funds with all load over expense turnover maximum load</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No. of mgrs.</td>
<td>under simultaneous net assets</td>
</tr>
<tr>
<td></td>
<td>frequency</td>
<td>(%/year)</td>
</tr>
<tr>
<td>Panel A: Annual characteristics of managers of domestic diversified equity funds</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1992</td>
<td>403</td>
<td>1.15</td>
</tr>
<tr>
<td>1993</td>
<td>521</td>
<td>1.19</td>
</tr>
<tr>
<td>1994</td>
<td>586</td>
<td>1.22</td>
</tr>
<tr>
<td>1995</td>
<td>680</td>
<td>1.26</td>
</tr>
<tr>
<td>1996</td>
<td>769</td>
<td>1.31</td>
</tr>
<tr>
<td>1997</td>
<td>857</td>
<td>1.39</td>
</tr>
<tr>
<td>1998</td>
<td>922</td>
<td>1.43</td>
</tr>
<tr>
<td>1999</td>
<td>927</td>
<td>1.49</td>
</tr>
<tr>
<td>mean</td>
<td>708</td>
<td>1.31</td>
</tr>
<tr>
<td>std</td>
<td>194</td>
<td>0.12</td>
</tr>
<tr>
<td>Panel B: Characteristics of managers of domestic diversified equity funds by manager style</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SCG</td>
<td>359</td>
<td>1.23</td>
</tr>
<tr>
<td>AG</td>
<td>119</td>
<td>1.11</td>
</tr>
<tr>
<td>Growth</td>
<td>804</td>
<td>1.19</td>
</tr>
<tr>
<td>Income</td>
<td>12</td>
<td>1.00</td>
</tr>
<tr>
<td>G&amp;I</td>
<td>371</td>
<td>1.17</td>
</tr>
<tr>
<td>MCG</td>
<td>22</td>
<td>1.00</td>
</tr>
<tr>
<td>Other</td>
<td>399</td>
<td>1.64</td>
</tr>
</tbody>
</table>

Panel C: Characteristics of managers of domestic diversified equity funds by current status

<table>
<thead>
<tr>
<th></th>
<th>Mgrs.</th>
<th>with all load under max. load</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>funds</td>
<td>over turnover load</td>
</tr>
<tr>
<td></td>
<td>mgmt.</td>
<td>(%/year)</td>
</tr>
<tr>
<td></td>
<td>frequency</td>
<td>(%/year)</td>
</tr>
<tr>
<td></td>
<td>(%/year)</td>
<td>(%/year)</td>
</tr>
<tr>
<td>Active</td>
<td>633</td>
<td>1.35</td>
</tr>
<tr>
<td>Retired</td>
<td>1,453</td>
<td>1.21</td>
</tr>
</tbody>
</table>
Table V: Fund exit characteristics of domestic diversified equity managers

Each month from January 1992 to December 1999 I determine which managers leave the sample (panel A), which managers leave a fund without leaving the sample (panel B), and which managers leave a fund and manage fewer / more assets over the next year compared to the previous year, adjusted for the overall growth in total net assets of all domestic diversified equity funds (panel C / D). Next I rank all domestic diversified equity managers who are active in that month in 10 equal-sized portfolios based on four characteristics: average return, $\alpha$, residual risk, and turnover, all measured over the past year. $\alpha$ is defined as the intercept in a four factor model and residual risk is defined as the residual standard deviation in this model. In a month that a manager manages multiple funds I value weight returns and turnover by the fund’s total net assets. Then, for each decile portfolio of a characteristic, an entry in the table represents the sum of the number of managers that leave a fund over all months, expressed as a fraction of the total number of managers that leave in all decile portfolios of that characteristic. For example, the top left entry in panel A indicates that 5.8 percent of all managers that left the sample fell in the decile portfolio that had the highest average returns. Interaction is the value of a statistic designed to test for interaction between a set of managers leaving a fund and a manager characteristic. No interaction would be represented by each cell of a column containing ten percent of the managers that leave. (*) and (**) indicate significant interaction at the 95 and 99 percent level, respectively.

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>Panel A: managers that leave the sample</th>
<th>Panel B: managers that leave a fund without leaving the sample</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>average return</td>
<td>residual risk</td>
</tr>
<tr>
<td>1 (high)</td>
<td>5.8%</td>
<td>4.6%</td>
</tr>
<tr>
<td>2</td>
<td>5.2%</td>
<td>7.9%</td>
</tr>
<tr>
<td>3</td>
<td>8.7%</td>
<td>5.8%</td>
</tr>
<tr>
<td>4</td>
<td>6.7%</td>
<td>8.9%</td>
</tr>
<tr>
<td>5</td>
<td>10.4%</td>
<td>7.3%</td>
</tr>
<tr>
<td>6</td>
<td>11.4%</td>
<td>8.9%</td>
</tr>
<tr>
<td>7</td>
<td>11.4%</td>
<td>11.4%</td>
</tr>
<tr>
<td>8</td>
<td>12.3%</td>
<td>15.0%</td>
</tr>
<tr>
<td>9</td>
<td>13.1%</td>
<td>15.6%</td>
</tr>
<tr>
<td>10 (low)</td>
<td>15.0%</td>
<td>14.6%</td>
</tr>
<tr>
<td>Interaction</td>
<td>50.1**</td>
<td>69.2**</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>Panel C: managers that leave a fund and will manage fewer assets</th>
<th>Panel D: managers that leave a fund and will manage more assets</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>average return</td>
<td>residual risk</td>
</tr>
<tr>
<td>1 (high)</td>
<td>2.5%</td>
<td>2.5%</td>
</tr>
<tr>
<td>2</td>
<td>2.5%</td>
<td>8.7%</td>
</tr>
<tr>
<td>3</td>
<td>5.0%</td>
<td>3.8%</td>
</tr>
<tr>
<td>4</td>
<td>7.5%</td>
<td>16.3%</td>
</tr>
<tr>
<td>5</td>
<td>13.8%</td>
<td>6.3%</td>
</tr>
<tr>
<td>6</td>
<td>13.8%</td>
<td>6.3%</td>
</tr>
<tr>
<td>7</td>
<td>11.3%</td>
<td>7.5%</td>
</tr>
<tr>
<td>8</td>
<td>12.5%</td>
<td>13.8%</td>
</tr>
<tr>
<td>9</td>
<td>13.8%</td>
<td>23.8%</td>
</tr>
<tr>
<td>10 (low)</td>
<td>17.5%</td>
<td>11.3%</td>
</tr>
<tr>
<td>Interaction</td>
<td>23.4**</td>
<td>28.6**</td>
</tr>
</tbody>
</table>
Table VI: Fund entry characteristics of domestic diversified equity managers

Each month from January 1992 to December 1999 I determine which experienced managers start at a fund (panel A), and which experienced managers start at a fund and manage on average fewer / more assets over the next year compared to the previous year, adjusted for the overall growth in total net assets of all domestic diversified equity funds (panel B / C). Next, I rank all domestic diversified equity managers who are active in that month into 10 equal-sized portfolios based on four characteristics: average return, α, residual risk, and turnover, all measured over the past year. α is defined as the intercept in a four factor model and residual risk is defined as the residual standard deviation in this model. In a month that a manager manages multiple funds I value weight returns and turnover by the fund's total net assets. Then, for each decile portfolio of a characteristic, an entry in the table represents the sum of the number of managers that leave a fund over all months, expressed as a fraction of the total number of managers that leave in all decile portfolios of that characteristic. For example, the top left entry in panel A indicates that 13.3 percent of all experienced managers that started at a fund fell in the decile portfolio with the highest average return. Interaction is the value of a statistic designed to test for interaction between a set managers starting at a fund and a manager characteristic. No interaction would be represented by each cell of a column containing ten percent of the managers that leave. (*) and (**) indicate significant interaction at the 95 and 99 percent level, respectively.

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>Panel A: experienced managers that start at a fund</th>
<th>Panel B: exp. managers that start a fund and will manage fewer assets</th>
<th>Panel C: exp. managers that start a fund and will manage more assets</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>average return</td>
<td>residual risk</td>
<td>turnover</td>
</tr>
<tr>
<td>1 (high)</td>
<td>13.3%</td>
<td>14.1%</td>
<td>11.5%</td>
</tr>
<tr>
<td>2</td>
<td>13.6%</td>
<td>11.2%</td>
<td>9.7%</td>
</tr>
<tr>
<td>3</td>
<td>11.7%</td>
<td>11.0%</td>
<td>8.4%</td>
</tr>
<tr>
<td>4</td>
<td>10.7%</td>
<td>10.4%</td>
<td>10.2%</td>
</tr>
<tr>
<td>5</td>
<td>9.1%</td>
<td>11.2%</td>
<td>8.9%</td>
</tr>
<tr>
<td>6</td>
<td>8.6%</td>
<td>9.7%</td>
<td>9.7%</td>
</tr>
<tr>
<td>7</td>
<td>9.1%</td>
<td>8.1%</td>
<td>9.9%</td>
</tr>
<tr>
<td>8</td>
<td>6.5%</td>
<td>6.5%</td>
<td>9.1%</td>
</tr>
<tr>
<td>9</td>
<td>9.4%</td>
<td>8.6%</td>
<td>11.7%</td>
</tr>
<tr>
<td>10 (low)</td>
<td>7.8%</td>
<td>9.1%</td>
<td>11.0%</td>
</tr>
<tr>
<td>Interaction</td>
<td>18.0*</td>
<td>14.9</td>
<td>4.2</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>Panel C: exp. managers that start a fund and will manage more assets</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>average return</td>
</tr>
<tr>
<td>1 (high)</td>
<td>16.9%</td>
</tr>
<tr>
<td>2</td>
<td>14.2%</td>
</tr>
<tr>
<td>3</td>
<td>11.8%</td>
</tr>
<tr>
<td>4</td>
<td>10.8%</td>
</tr>
<tr>
<td>5</td>
<td>9.8%</td>
</tr>
<tr>
<td>6</td>
<td>8.4%</td>
</tr>
<tr>
<td>7</td>
<td>8.8%</td>
</tr>
<tr>
<td>8</td>
<td>7.1%</td>
</tr>
<tr>
<td>9</td>
<td>8.1%</td>
</tr>
<tr>
<td>10 (low)</td>
<td>4.1%</td>
</tr>
<tr>
<td>Interaction</td>
<td>35.6**</td>
</tr>
</tbody>
</table>
Table VII: Annual regressions of manager $\alpha$ on past manager $\alpha$

On January 1 each year from 1993 to 1999 I perform a cross-sectional regression of current manager $\alpha$ on past manager $\alpha$. The dependent variable in each regression, $\alpha_{mgr}$, is the intercept in a four factor model, and is calculated using the monthly returns on an equal or value weighted portfolio of mutual funds which the manager will manage during the coming year. Past manager $\alpha$ ($\alpha_{mgr,past}$) is the intercept in a four factor model and is calculated using the monthly returns on an equal or value weighted portfolio of mutual funds which the manager managed during the previous year. To construct a value weighted portfolio, the fund’s returns are weighted by the total net assets of that fund. Manager promotion/demotion is a dummy variable taking on the value one if the manager started or left a fund (“fund change”) in the previous year and managed on average more/fewer assets over the year after that change in comparison to the year before that change, adjusted for the overall growth in total net assets of all domestic diversified equity funds. The regressions in panel A represent the time-series average of the annual regressions coefficients on the constant, and past manager $\alpha$ as outlined in Fama and MacBeth (1973). Also the number of time-series observations and the time-series average of the annual adjusted $R^2$ are reported. The regressions in panel B exhibits the same regression as the one in panel A, but instead of using the Fama and MacBeth (1973) methodology all the observations used for the annual regressions in panel A are pooled. $t$-statistics are in parentheses. (*) and (**) indicate two-tail significance at the 95 and 99 percent level, respectively.

<table>
<thead>
<tr>
<th>Panel A: Fama and MacBeth (1973) regression of manager $\alpha$ on past manager $\alpha$</th>
</tr>
</thead>
<tbody>
<tr>
<td>value weighted</td>
</tr>
<tr>
<td>constant</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>$\alpha_{mgr,past}$</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>manager</td>
</tr>
<tr>
<td>promoted</td>
</tr>
<tr>
<td>manager</td>
</tr>
<tr>
<td>demoted</td>
</tr>
<tr>
<td>Obs.</td>
</tr>
<tr>
<td>Adj. $R^2$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: Pooled regression of manager $\alpha$ on past manager $\alpha$</th>
</tr>
</thead>
<tbody>
<tr>
<td>value weighted</td>
</tr>
<tr>
<td>constant</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>$\alpha_{mgr,past}$</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>manager</td>
</tr>
<tr>
<td>promoted</td>
</tr>
<tr>
<td>manager</td>
</tr>
<tr>
<td>demoted</td>
</tr>
<tr>
<td>Obs.</td>
</tr>
<tr>
<td>Adj. $R^2$</td>
</tr>
</tbody>
</table>
Table VIII: Regressions of manager $\alpha$ on past fund $\alpha$ and past manager $\alpha$

$\alpha$’s are estimated using Carhart’s (1997) four factor model. Panel A estimates equation (3) using a manager change as the event to define the dependent variables versus the independent variables. Thus current fund performance, $\alpha_{fund, current}$, is calculated using fund returns after a new manager arrives and before he leaves. Past manager performance, $\alpha_{mgr, past}$, and past fund performance, $\alpha_{fund, past}$, are calculated using all manager and fund data before the manager commenced at a fund, respectively. Panel B estimates equation (3) at the beginning of each year from 1993 to 1999 and reports the time-series averages of each of these regressions as outlined in Fama and MacBeth (1973). Current fund performance, $\alpha_{fund, current}$, is calculated using fund returns in the coming year. Past manager performance, $\alpha_{mgr, past}$, and past fund performance, $\alpha_{fund, past}$, are calculated using all manager and fund data over the past year, respectively. Also the time series average of the annual number of observations and the annual adjusted $R^2$ are reported. For both panels I weigh fund returns by the total net assets of that fund to construct a value weighted portfolio of past manager returns. (*) and (**) indicate two-tail significance at the 95 and 99 percent level, respectively. $t$-statistics are in parentheses.

<table>
<thead>
<tr>
<th></th>
<th>Panel A</th>
<th>Panel B</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>event based regressions</td>
<td>annual regressions</td>
</tr>
<tr>
<td></td>
<td>value weighted</td>
<td>equal weighted</td>
</tr>
<tr>
<td>constant</td>
<td>0.0019</td>
<td>0.0021</td>
</tr>
<tr>
<td></td>
<td>(1.78)</td>
<td>(1.92)</td>
</tr>
<tr>
<td>$\alpha_{mgr, past}$</td>
<td>0.16</td>
<td>0.15</td>
</tr>
<tr>
<td></td>
<td>(1.05)</td>
<td>(0.94)</td>
</tr>
<tr>
<td>$\alpha_{fund, past}$</td>
<td>-0.26</td>
<td>-0.25</td>
</tr>
<tr>
<td></td>
<td>(-1.51)</td>
<td>(-1.45)</td>
</tr>
<tr>
<td>Obs.</td>
<td>130</td>
<td>127</td>
</tr>
<tr>
<td>Adj. $R^2$</td>
<td>0.013</td>
<td>0.019</td>
</tr>
</tbody>
</table>
Figure 1: The posterior median (solid), 5th and 95th percentile (dashed) of \( \lambda \) as a function of \( \sigma_\alpha = \sigma_\gamma \), based on the return likelihood and the cost structure likelihood

\( \lambda \) is defined as the weight on the manager’s contribution to manager-fund combination \( p \)'s \( \alpha \), or \( \alpha_p = \lambda \gamma^m_i + (1 - \lambda) \gamma^f_j \), where \( \gamma^m_i \) and \( \gamma^f_j \) are unobserved “skill levels” associated with manager \( i \) and fund \( j \), respectively. Inference about lambda is based on the returns and costs of manager-fund combinations. The return likelihood is defined by Carhart’s (1997) four factor model, where the intercept in the model, \( \alpha_p \), is interpreted as the expected abnormal excess return. The disturbance term of the factor model is temporally independent and normally distributed with mean zero and variance \( \sigma^2_p \). Conditional on \( \sigma^2_p = s^2 \), the cost structure likelihood is defined by \( \alpha_p \mid \sigma^2_p = s^2, \delta_p \sim N(\delta_p, \sigma^2_\alpha) \), where \( \delta_p \) is the “cost” of manager-fund combination \( p \) and \( \sigma_\alpha \) is a measure of “skill” among manager-fund combinations. Except for \( \gamma^m_i \) and \( \gamma^f_j \), there are non-informed prior beliefs on all model parameters. To ensure identification \( \gamma^m_i \) and \( \gamma^f_j \) are a priori normally distributed with mean \( \bar{\delta} \) and variance \( \sigma^2_\gamma \), where \( \sigma_\gamma \) is interpreted as a skill measure of managers and funds. \( \sigma_\alpha \) and \( \sigma_\gamma \) are expressed in basispoints per month. The prior constant \( s^2 \) equals 0.0035. See Section 4.B for more details.
Figure 2: The posterior median (solid), 5th and 95th percentile (dashed) of \( \lambda \) as a function of \( \sigma_\gamma \), based on the return likelihood

\( \lambda \) is defined as the weight on the manager’s contribution to manager-fund combination \( p \)’s \( \alpha \), or

\[
\alpha_p \equiv \lambda \gamma^m_i + (1 - \lambda) \gamma^f_j,
\]

where \( \gamma^m_i \) and \( \gamma^f_j \) are unobserved “skill levels” associated with manager \( i \) and fund \( j \), respectively. Inference about \( \lambda \) is based on the returns of manager-fund combinations. The return likelihood is defined by Carhart’s (1997) four factor model, where the intercept in the model, \( \alpha_p \), is interpreted as the expected abnormal excess return. The disturbance term of the factor model is temporally independent and normally distributed with mean zero and variance \( \sigma^2_p \). Except for \( \gamma^m_i \) and \( \gamma^f_j \), there are non-informed prior beliefs on all model parameters. To ensure identification \( \gamma^m_i \) and \( \gamma^f_j \) are a priori normally distributed with mean \( \delta \) and variance \( \sigma^2_\gamma \), where \( \sigma_\gamma \) is interpreted as a skill measure of managers and funds. \( \sigma_\alpha \) and \( \sigma_\gamma \) are expressed in basispoints per month. The prior constant \( s^2 \) equals 0.0035. See Section 4.B for more details.
Figure 3: Posterior distribution of $\lambda$ as a function of $\sigma_\gamma$, based on the cost structure likelihood

$\lambda$ is defined as the weight on the manager's contribution to manager-fund combination $p$'s $\alpha$, or $\alpha_p \equiv \lambda \gamma^m_i + (1 - \lambda) \gamma^f_j$, where $\gamma^m_i$ and $\gamma^f_j$ are unobserved “skill levels” associated with manager $i$ and fund $j$, respectively. Inference about lambda is based on the costs of manager-fund combinations. Conditional on $\sigma^2_p = s^2$, the cost structure likelihood is defined by $\alpha_p | \sigma^2_p = s^2, \delta_p \sim N(\delta_p, \sigma^2_\alpha)$, where $\delta_p$ is the “cost” of manager-fund combination $p$ and $\sigma_\alpha$ is a measure of “skill” among manager-fund combinations. Except for $\gamma^m_i$ and $\gamma^f_j$, there are non-informed prior beliefs on all model parameters. To ensure identification $\gamma^m_i$ and $\gamma^f_j$ are a priori normally distributed with mean $\bar{\delta}$ and variance $\sigma^2_\gamma$, where $\sigma_\gamma$ is interpreted as a skill measure of managers and funds. $\sigma_\alpha$ and $\sigma_\gamma$ are expressed in basispoints per month. The prior constant $s^2$ equals 0.0035. See Section 4.B for more details.
Figure 4: The mean (solid), 5th and 95th percentile (dashed) of the posterior distribution of the mean and standard deviation of $\gamma^m$ and $\gamma^f$ as a function of $\sigma_\alpha = \sigma_\gamma$, based on the return likelihood and the cost structure likelihood.

$\gamma^m_i$ and $\gamma^f_j$ are unobserved “skill levels” associated with manager $i$ and fund $j$, respectively, and their weighted linear combination equates to $\alpha$ of manager-fund combination $p$, or $\alpha_p = \lambda \gamma^m_i + (1 - \lambda) \gamma^f_j$. Inference about $\gamma^m$ and $\gamma^f$ is based on the returns and costs of manager-fund combinations. The return likelihood is defined by Carhart’s (1997) four factor model, where the intercept in the model, $\alpha_p$, is interpreted as the expected abnormal excess return. The disturbance term of the factor model is temporally independent and normally distributed with mean zero and variance $\sigma^2_p$. Conditional on $\sigma^2_p = s^2$, the cost structure likelihood is defined by $\alpha_p | \sigma^2_p = s^2, \delta_p \sim N(\delta_p, \sigma^2_\alpha)$, where $\delta_p$ is the “cost” of manager-fund combination $p$ and $\sigma_\alpha$ is a measure of “skill” among manager-fund combinations. Except for $\gamma^m_i$ and $\gamma^f_j$, there are non-informed prior beliefs on all model parameters. To ensure identification $\gamma^m_i$ and $\gamma^f_j$ are a priori normally distributed with mean $\bar{\delta}$ and variance $\sigma^2_\gamma$, where $\sigma_\gamma$ is interpreted as a skill measure of managers and funds. $\sigma_\alpha$ and $\sigma_\gamma$ are expressed in basispoints per month. The prior constant $s^2$ equals 0.0035. See Section 4.B for more details.
Figure 5: Cross-sectional variance decomposition of $\alpha$ as a function of $\sigma_\alpha = \sigma_\gamma$, based on the return likelihood and the cost structure likelihood

This figure shows the selected moments of the posterior density of the three terms associated with the variance decomposition of $\alpha$: the variance of the manager term (solid), the variance of fund term (dashed), and the covariance (dotted), all expressed as a fraction of $\alpha$’s variance. The 5th percentile, the median and the 95th percentile are plotted for each of the three posterior densities. $\alpha_p$ is a linear combination of unobserved “skill levels” associated with the manager and fund, respectively, or in matrix notation, $\alpha = \lambda G \gamma^m + (1 - \lambda) H \gamma^f$, where $G$ and $H$ are matrices that select the appropriate elements of $\gamma^m$ and $\gamma^f$, respectively, such that their linear combination results in the vector $\alpha$. Inference is based on the returns and costs of manager-fund combinations. The return likelihood is defined by Carhart’s (1997) four factor model, where the intercept in the model, $\alpha_p$, is interpreted as the expected abnormal excess return. The disturbance term of the factor model is temporally independent and normally distributed with mean zero and variance $\sigma^2_p$. Conditional on $\sigma^2_p = s^2$, the cost structure likelihood is defined by $\alpha_p \mid \sigma^2_p = s^2, \delta_p \sim N(\delta_p, \sigma^2_\alpha)$, where $\delta_p$ is the “cost” of manager-fund combination $p$ and $\sigma_\alpha$ is a measure of “skill” among manager-fund combinations. Except for $\gamma_i^m$ and $\gamma_j^f$, there are non-informed prior beliefs on all model parameters. To ensure identification $\gamma_i^m$ and $\gamma_j^f$ are a priori normally distributed with mean $\bar{\delta}$ and variance $\sigma^2_\gamma$, where $\sigma_\gamma$ is interpreted as a skill measure of managers and funds. $\sigma_\alpha$ and $\sigma_\gamma$ are expressed in basispoints per month. The prior constant $s^2$ equals 0.0035. See Section 4.B for more details.
Figure 6: Cross-sectional variance decomposition of $\alpha$ as a function of $\sigma_\gamma$, based on the return likelihood

This figure shows the selected moments of the posterior density of the three terms associated with the variance decomposition of $\alpha$: the variance of the manager term (solid), the variance of fund term (dashed), and the covariance (dotted), all expressed as a fraction of $\alpha$'s variance. The 5th percentile, the median and the 95th percentile are plotted for each of the three posterior densities. $\alpha_p$ is a linear combination of unobserved “skill levels” associated with the manager and fund, respectively, or in matrix notation, $\alpha = \lambda G \gamma^m + (1 - \lambda) H \gamma^f$, where $G$ and $H$ are matrices that select the appropriate elements of $\gamma^m$ and $\gamma^f$, respectively, such that their linear combination results in the vector $\alpha$. Inference is based on the returns of manager-fund combinations. The return likelihood is defined by Carhart’s (1997) four factor model, where the intercept in the model, $\alpha_p$, is interpreted as the expected abnormal excess return. The disturbance term of the factor model is temporally independent and normally distributed with mean zero and variance $\sigma^2_p$. Except for $\gamma^m_i$ and $\gamma^f_j$, there are non-informed prior beliefs on all model parameters. To ensure identification $\gamma^m_i$ and $\gamma^f_j$ are a priori normally distributed with mean $\bar{\delta}$ and variance $\sigma^2_{\gamma}$, where $\sigma_\gamma$ is interpreted as a skill measure of managers and funds. $\sigma_\alpha$ and $\sigma_\gamma$ are expressed in basispoints per month. The prior constant $s^2$ equals 0.0035. See Section 4.B for more details.
Figure 7: Cross-sectional variance decomposition of $\alpha$ as a function of $\sigma_\alpha$, based on the cost structure likelihood

This figure shows the selected moments of the posterior density of the three terms associated with the variance decomposition of $\alpha$: the variance of the manager term (solid), the variance of fund term (dashed), and the covariance (dotted), all expressed as a fraction of $\alpha$’s variance. The 5th percentile, the median and the 95th percentile are plotted for each of the three posterior densities. $\alpha_p$ is a linear combination of unobserved “skill levels” associated with the manager and fund, respectively, or in matrix notation, $\alpha = \lambda G \gamma_m + (1 - \lambda) H \gamma_f$, where $G$ and $H$ are matrices that select the appropriate elements of $\gamma_m$ and $\gamma_f$, respectively, such that their linear combination results in the vector $\alpha$. Inference is based on the costs of manager-fund combinations. Conditional on $\sigma_p^2 = s^2$, the cost structure likelihood is defined by $\alpha_p \mid \sigma_p^2 = s^2, \delta_p \sim N(\delta_p, \sigma_\alpha^2)$, where $\delta_p$ is the “cost” of manager-fund combination $p$ and $\sigma_\alpha$ is a measure of “skill” among manager-fund combinations. Except for $\gamma_m^i$ and $\gamma_f^j$, there are non-informed prior beliefs on all model parameters. To ensure identification $\gamma_m^i$ and $\gamma_f^j$ are a priori normally distributed with mean $\delta$ and variance $\sigma_\gamma^2$, where $\sigma_\gamma$ is interpreted as a skill measure of managers and funds. $\sigma_\alpha$ and $\sigma_\gamma$ are expressed in basispoints per month. The prior constant $s^2$ equals 0.0035. See Section 4.B for more details.