On the Performance of Mutual Fund Managers

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November 2001

Abstract

This paper 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. One never observes performance outcomes of managers and funds independently but only in conjunction with each other. This paper recognizes that fact and treats managers, funds, and "manager-fund combinations" as separate entities. I investigate performance from three perspectives. First, I examine performance persistence among managers and find some support for persistence. 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 develop a Bayesian framework to estimate it. I find that approximately 30 percent of performance can be attributed to managers, and 70 percent to funds. Third, I investigate whether managers can attract fund flows on the basis of their past performance and find scarce evidence that they are able to do so. Contrary to popular perception, this paper concludes that the fund and not the manager primarily determines performance.

*I thank Roger Edelen, Chris Géczy, Craig MacKinlay, Andrew Metrick, David Musto, Rob Stambaugh, John Stroud, and seminar participants at Tilburg University, the Wharton School, and the 2001 SIRIF Conference on Performance of Managed Funds for valuable comments. Please address correspondence to Klaas P. Baks, Department of Finance, The Wharton School, University of Pennsylvania, 2300 SHDH, 3620 Locust Walk, Philadelphia, PA 19104. Email: klaas.baks.wp00@wharton.upenn.edu. Please visit http://assets.wharton.upenn.edu/~kbaks to obtain the latest version of this paper.

I. 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, 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 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's 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

[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.

[2] Hendricks, Patel, and Zeckhauser (1993), Goetzmann and Ibbotson (1994), and Brown and Goetzmann (1995).

evidence that manager performance is persistent. I then ask 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 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. Using the Gibbs sampler in combination with data augmentation and relatively non-informative priors, I obtain the posterior beliefs for the weight on the term associated with the manager. This Bayesian approach avoids a number of computational difficulties that would confront a frequentist approach, such as maximum likelihood. I find that on average approximately 30 percent of performance is determined by the manager and 70 percent by 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 only has to be 25 percent more productive in order to maintain the same alpha. In addition, with a high degree of confidence, the weight on the manager falls between 15 and 50 percent for a reasonable range of prior beliefs. Thus, contrary to popular perception, the fund and not the manager contributes most to the abnormal performance of a manager-fund combination.

If managers are responsible for only a minor part of fund performance, one might ask if investors are aware of this observation, and to what extent they re-allocate their money with career changes of managers. In the second part of the paper I study the change in total net assets under management, or flow, associated with a manager throughout his career. This is perhaps the most direct way to measure an investors appetite for a manager and his track record. Specifically, I examine if managers are able to take investors money with them when they change funds, and test the hypothesis that "star managers," or managers with a good track record, are able to do so. Since profits of a mutual fund are primarily determined by its assets under management, mutual fund companies have an interest in retaining or attracting managers who can generate large inflows. The second part of the paper studies the market for track records and the portability of a manager's track record.

There are several recent papers that examine how fund flows relate to past performance, including Gruber (1996), Sirri and Tufano (1998), Chevalier and Ellison (1997), Chevalier and Ellison (1999b), and Zheng (1999). With the exception of Chevalier and Ellison (1997) and Chevalier and Ellison (1999b), none of these papers studies the importance of manager performance for this relation. However, due to the short time span and the limited number of manager changes in their data, they are able to examine only the effect of turnover on the net flow of investments into mutual funds. This paper's approach to study the market for track records is based upon a methodology used by Sirri and Tufano (1998). They relate fund flows to relative past fund performance, and I include relative past manager performance in this framework to examine if track records of managers matter. Applying this methodology to the data, there is little evidence for the portability of a manager's track record, consistent with the observation that managers are not the primary factor determining fund performance.

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 (2001b) 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 II discusses the construction of the data and gives summary statistics. Section III studies whether manager returns exhibit performance persistence. Section IV develops the Bayesian model to explore the attribution of performance outcomes between managers and funds and discusses the results of this model. Section V examines the relation between flows and performance. Section VI concludes with an interpretation of the results.

II. 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 she has managed during his career. I only consider manager or manager teams who are identified by a specific person(s), to ensure that manager entities stay the same over time. 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 and a low expense ratio suits long-term investors, whereas a share-class with a low load 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 managers of domestic diversified equity funds (henceforth I call this group of managers "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 pace 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 fund-manager 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 she 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. Thus most managers stay within their fund family during these eight years, and if they change funds, they do so within their fund family. The cross-sectional distribution of the these 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 she manages during her 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 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 managers.[3] 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:

$$r_{it} = \alpha_i + \beta_{1i} RMRF_t + \beta_{2i} SMB_t + \beta_{3i} HML_t + \beta_{4i} PR1YR_t + \epsilon_{it}, \qquad (1)$$

where r_{it} is the time t return on asset i in excess of the one month T-bill return, α_i is the performance measure, and $RMRF_t$, SMB_t, HML_t, and $PR1YR_t$ 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 returns and consequently cannot calculate performance for funds or managers, 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

[3] Khorana (1996) and Hu, Hall, and Harvey (2000) find an inverse relation between the probability of managerial replacement and fund performance.

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 her career. In this study I use an equal and value weighted portfolio of manager-fund combinations' returns that one manager manages as the return series for that manager and use the α 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 highly correlated, or in case the manager has only one fund under management, 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 II.B for more details). For each of these groups of managers I investigate the characteristics of average return, α, residual risk and turnover in the year before the manager leaves the fund, where α and residual risk are measured as the intercept and residual standard deviation in the four factor model in equation (1), using a value weighted method to construct manager returns. To do so I rank all managers of domestic diversified equity funds 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. 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 α 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 α, 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 α, whereas managers who are promoted exhibit precisely the opposite performance behavior. Finally, observe that the α characteristics of managers who 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 Panel A to Panel 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 be fired, and in an effort to prevent this, they may gamble and increase the riskiness of the stocks in the portfolios that they manage. 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 she already anticipates to be fired. However, in case of a good return realization the management company may not fire her. This option-like behavior of the manager in anticipation of being replaced manifests itself in increased residual risk and increased turnover before she 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.[4] 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.

[4]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.

Table VI examines fund entry characteristics of domestic diversified equity managers, 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 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 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 no 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.

III. Performance persistence of managers

Previous papers have employed a variety of methodologies to measure the performance of funds.[5] 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

[5] Carlson (1970), Lehman and Modest (1987), Grinblatt and Titman (1988), Grinblatt and Titman (1992), Goetzmann and Ibbotson (1994), Malkiel (1995), Carhart (1997), Wermers (2000).

from 1993 to 1999 I perform a cross-sectional linear regression of the current manager α ($\alpha_{\text{mgr,current}}$) on the past manager α ($\alpha_{\text{mgr,past}}$)

$$\alpha_{\text{mgr,current}} = \rho_0 + \rho_1 \alpha_{\text{mgr,past}} + \xi_{\text{mgr}}. \tag{2}$$

The independent variable in each regression, $\alpha_{\text{mgr,current}}$, 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 $\alpha_{\text{mgr,past}}$ is similarly defined, except for the fact that last year's manager returns are used to calculate α's. Finally, I assume that the error term ϵ of the factor model in equation (1), used to estimate the various α's in equation (2), is independent of ξ_{mgr}, the error term of the regression in equation (2).

To estimate this model one can pool all the data in the seven years, which assumes that the ξ_{mgr}, the disturbance term in equation (2), are independent within each year. 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 ξ. 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 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 motived by the trade-off to estimate α'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.

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" α's instead of estimated α's; however, α'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 ρ_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 ρ_1 not significantly different from zero with caution.

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 $(\alpha_{\mathrm{mgr,past}})$, allowing the persistence coefficient to become significant.

IV. 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, 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 fund performance. In this section I will attempt to answer this question.

Section IV.A starts by showing that a strategy of investing in relatively good managers is not significantly different from a similar strategy of investing in relatively good funds. This suggests that funds and managers are not very different in terms of performance, and motivates the use of a framework in which one simultaneously accounts for manager and fund performance. Section IV.B discusses a frequentist methodology that one may use to disentangle manager and fund performance. Although a frequentist framework is perhaps an intuitive way to approach this problem, I show that such a methodology may not be very powerful and is fraught with econometric problems. This motivates the use of a more structural environment to examine this question, and I develop a Bayesian model to determine to what extent the manager versus the fund is responsible for performance. Sections IV.C and IV.D give an overview and interpretation of the model and Section IV.E examines the identification of the model. Most of the intuition of the model is contained in these three sections, and starting with Section IV.F I will discuss a formal stochastic set up of the model. Sections IV.F through IV.I study the likelihood, the prior beliefs, missing data issues in the model, and the posterior beliefs respectively. Part of the details of the prior and posterior beliefs are discussed in appendices A and B, respectively. Finally, Section IV.J applies the model developed in Sections IV.C through IV.I to the data.

A. Return-sorted manager and fund portfolios

This section examines if a dynamic strategy of selecting past top managers yields superior performance in subsequent years. This methodology mimics Carhart (1997), but applies it to managers instead of funds. At the beginning of each year, from 1993 to 1999, I form ten equal or value weighted portfolios of managers, based on the average monthly manager return during the past year, and estimate next year's performance on the resulting portfolios. These portfolios are held for one year, and subsequently reformed. This yields a time series of monthly returns on each of the ten decile portfolios from 1993 to 1999. When a manager disappears during the course of a year, the portfolio weights are adjusted accordingly.

Panel A of Table VIII reports the mean and standard deviation of the monthly excess returns and the results from estimating a four factor model for each of the ten decile portfolios. The value and equal weighted decile portfolios exhibit a variation in monthly mean excess return ranging from approximately 8 percent per year for the worst performers to 17 percent per year for the best performers. There is some indication that monthly mean excess return is declining with portfolio rank and this evidence is stronger for equal weighted portfolios than for value weighted portfolios. α's exhibit a similar pattern and their spread ranges from -4 to 2.3 percent per year.

To assess the significance of these results, and determine if there are differences between funds and managers, Panel B in Table VIII reports the equivalent of Panel A, but for domestic diversified equity funds instead of managers.[6] Although Panels A and B are similar in spread and pattern, managers seem to have slightly higher mean monthly excess returns, α's, and accompanying t-statistics, than the funds. Finally, in contrast to Carhart (1997), the spread between the bottom two decile portfolios is not anomalously large. Overall, managers do not explain a bigger spread in monthly mean excess returns and α's than funds. This suggests that managers and funds are not very different in terms of performance persistence in returns, and motivates studying the relative importance of funds and managers.

B. Frequentist 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 she 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 she 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 α onto the fund's past α and the manager's past α, or

$$\alpha_{\text{fund,current}} = \kappa_0 + \kappa_1 \alpha_{\text{fund,past}} + \kappa_2 \alpha_{\text{mgr,past}} + \eta_{\text{mgr,fund}}. \tag{3}$$

[6] The difference between panel B of table VIII and the results reported in Carhart (1997) can be attributed to use of a different time period and a different sample of funds. Carhart (1997) studies resturns on return-sorted fund portfolios from 1963 to 1992, whereas I use the period from 1992 to 1999. In addition, Carhart (1997) sample consists of 1,892 funds of which approximately 85 percent is included in my sample.

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 ϵ of the factor model in equation (1), used to estimate the various α's in equation (3), is independent of η, 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 κ_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 κ_1 or κ_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 III, all the variables in the regression 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 II.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.[7] Having established that the managers included

[7] This 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.

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 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 α'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. Only in the latter case exhibits the dependent variable in the regression in equation (3) reversal to the mean, and are the coefficients κ_1 and κ_2 unbiased. For managers who take on a large amount of idiosyncratic risk, the coefficients in the regression in equation (3) are unbiased, but tends to increase the variance of the estimates of κ_1 and κ_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 in 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 cause the coefficient to be biased 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 III, 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. Another 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 α and past fund α. If the number of managers in charge of solely one fund during their career is relatively large, this correlation is potentially high.

C. Overview of the framework

The problems with the frequentist methodology 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 frequentist framework with its associated measurement problems, a Bayesian methodology is uniquely equipped to deal with uncertainty regarding the unobserved performance of managers and funds. In addition, since the performance of funds and managers are treated as unknown parameters, this approach, unlike Sections III, IV.A, or IV.B, does not rely upon an "artificial" return series of the manager or fund.

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

$$r_{t,p} = \alpha_p + F_t \beta_p + \epsilon_{t,p}, \qquad (4)$$

where α_p is an indicator of skill associated with manager-fund combination p, and $\epsilon_{t,p}$ is a mean-zero regression disturbance at time t, with variance σ_p^2. I assume that disturbance term is independent over time, and dependent across different manager-fund combinations.

I interpret α_p as the performance measure associated with manager-fund combination p. However, as pointed out by Pástor and Stambaugh (2001a) and Pástor and Stambaugh (2001b) 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 α_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.

Next I specify how the intercept in this model relates to the manager and the fund. As pointed out in the previous sections, both manager and fund are likely to play a role in determining the abnormal returns of a manager-fund combination. I model this feature by dividing the intercept of the model, which is interpreted as the skill associated with a specific manager-fund combination, 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 λ 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 fund she works for. I make a similar assumption for the fund, and let 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 variance-covariance structure of the disturbance term in equation (4) the cross-section of returns is related through the non-zero covariance structure of the α_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 allow me to write the intercept of the model in equation (4) as

$$\alpha_p = \lambda\gamma_i^m + (1-\lambda)\,\gamma_j^f, \tag{5}$$

where γ_i^m is a parameter associated with the "skill" of the manager and γ_j^f is a parameter associated with the "skill" of the fund.

The intercept in equation (5) is modeled as the sum of two unknown parts. One learns about managers and funds through the cross-sectional variation in α_p. Intuitively, if one observes a high α_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 she is active.

D. Interpretation of the model

All parameters on the right hand side of equation (5) are unknown, and as result understanding their economic meaning is difficult. This subsection illustrates these interpretation problems, and shows that (5) can be interpreted as a production function, with "manager skill" and "fund skill" as the factors of production.

The fact that the coefficients on γ_i^m and γ_j^f in equation (5) sum to one is not restrictive. Since γ_i^m and γ_j^f are unobserved model parameters, one can always scale γ_i^m and γ_j^f such that the coefficients on these two parameters sum to one. More precisely, suppose that the coefficients λ and $1-\lambda$ in equation (5) are replaced by λ_1 and λ_2, respectively. Then for any λ_1 and λ_2 such that $\lambda_1+\lambda_2 \neq 0$, there holds

$$\lambda_1\gamma_i^m + \lambda_2\gamma_j^f = \frac{\lambda_1}{\lambda_1+\lambda_2}\left(\left(\lambda_1+\lambda_2\right)\gamma_i^m\right) + \left(1-\frac{\lambda_1}{\lambda_1+\lambda_2}\right)\left(\left(\lambda_1+\lambda_2\right)\gamma_j^f\right). \tag{6}$$

Re-interpreting $(\lambda_1+\lambda_2)\,\gamma_i^m$ and $(\lambda_1+\lambda_2)\,\gamma_j^f$ as the new γ_i^m and γ_j^f, respectively, and $\lambda_1/\left(\lambda_1+\lambda_2\right)$ as λ, equation (5) is obtained. Thus, except for the case when $\lambda_1+\lambda_2=0$, without loss of generality the coefficients on γ_i^m and γ_j^f sum to one. Put another way, the ratio $\lambda_1/\lambda_2 \equiv \lambda/\left(1-\lambda\right)$ is identified, unlike the individual coefficients λ_1 and λ_2.

The goal of this section is to characterize the quantities λ and $\lambda/\left(1-\lambda\right)$ and to derive their posterior distributions. What economic meaning can one attach to these quantities? To answer this question I interpret equation (5) 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,

$$1+\alpha_p = \left(1+\gamma_i^m\right)^{\lambda}\left(1+\gamma_j^f\right)^{1-\lambda} \tag{7}$$

approximately equals equation (5) – that is, applying the "log" operator to both sides of equation (7) and using the approximation that $\log\left(1+x\right) \approx x$ for small x gives equation (5). 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 $1+\alpha_p$ dollar, not $\exp(\alpha_p)$ dollar. The error of this approximation roughly equals one half of the variance of α_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, $L_i \equiv 1 + \gamma_i^m$ denotes the production factor associated with manager, and $K_j \equiv 1 + \gamma_j^f$ denotes the production factor associated with the fund, then equation (7) can be written as

$$Y_p = L_i^{\lambda} K_j^{1-\lambda}, \tag{8}$$

which is the familiar Cobb-Douglas production function encountered in the theory of the firm. Observe that identification problem illustrated by equation (6) implies that the model is not able to identify whether the production function has decreasing, constant, or increasing returns to scale.

In this setting λ is interpreted as the elasticity of "output" with respect to the manager input. Alternatively λ is the fraction of output contributed by the manager, or

$$\lambda = \frac{MPL_i \times L_i}{Y_p}, \tag{9}$$

where MPL_i is the marginal productivity of the production factor associated with the manager. 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

$$\frac{\lambda}{1-\lambda} = \frac{MPL_i}{MPK_j} \times \frac{L_i}{K_j} = - \left. \frac{d \log K_i}{d \log L_j} \right|_{Y_p}, \tag{10}$$

where MPK_j is the marginal productivity of the production factor associated with the fund. 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 $\lambda/(1-\lambda)$.

E. Identification of fund and manager gamma's

In this model there are three sources of non-identification. The first source of non-identification arises from the fact that γ_i^m and γ_j^f are known up to a constant. This can easily be seen by rewriting the intercept of the factor model defined in equation (5) as

$$\lambda\gamma_i^m + (1-\lambda)\,\gamma_j^f = \lambda\left(\gamma_i^m + (1-\lambda)\,c\right) + (1-\lambda)\left(\gamma_j^f - \lambda c\right), \tag{11}$$

which holds for any constant c. Equation (11) indicates that for a given λ there are multiple values of γ_i^m and γ_j^f that result in the same value of α_p, and thus the intercept of the model is not identified. Put another way, c changes the fund alpha, γ_j^f, and manager alpha, γ_i^m, but does not impact λ or α_p. Expressing equation (11) in terms of the production function given in equation (8), indicates that the inputs in the production function are unobservable, and unidentified up to a constant. As a result one needs to make an assumption about the level of the two factors of production in order to be able to estimate λ.

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). Thus I need as many restrictions as there are disjoint clusters of managers and funds.

Another way of interpreting equations (11), is to observe that the first moments of γ_i^m and γ_j^f are unidentified. Intuitively, since one only observes returns and α'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 γ_i^m and γ_j^f. The statistical power to conduct inference on λ depends on the cross-sectional variance in α_p. The empirical Section IV.I studies the cross-sectional variance decomposition of equation (5) more closely.

In general, not all manager-fund combinations are present, and inference about the fund and manager specific skill components of the intercept, γ_i^m, and γ_j^f respectively, in equation (5) is difficult since their total number may increase rapidly when the cross-section of fund-manager combinations increases. This observation points to a second source of non-identification which arises when the number of funds and managers is too large relative to the number of manager-fund combinations present. To illustrate this, consider an example with two managers which have both managed the same two funds at different points in time during their career, 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 (λ, two manager γ^m's and two fund γ^f's), the model can only identify four α_p's. Therefore the number of manager-fund combinations must be larger than the sum of the number of managers and 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 fund-manager combinations is at least as large number of managers plus the number of funds, and to identify λ there must hold that for at least one cluster the number of manager-fund combinations exceeds the sum of the number of manager and funds active in that cluster.

The third and final source of non-identification arises when number of time periods is smaller than the total number of manager-fund combinations. In this case the variance covariance matrix associated with the regression disturbance term in equation (4) 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 that I will develop 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.

F. Stochastic setting and the 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 fund-manager 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 L factor returns corresponding to the same periods as the returns in r. Let ϵ be a $T \times P$ matrix whose rows are independent and normally distributed with mean zero and variance-covariance matrix Σ. The p-th element on the diagonal of Σ equals σ_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:

$$r = \iota_T \alpha' + F\beta + \epsilon, \ \text{vec}(\epsilon) \sim N(0, \Sigma \otimes I_T), \tag{12}$$

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, ι_T is a vector of length T containing ones and "$\sim$" is read as "is distributed as". α is the $P \times 1$ vector of intercepts and β is the $S \times P$ matrix of factor loadings, where the p-th element of α is α_p and the p-th column of β is β_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 α, β, or Σ, so that the exact specification of the factor likelihood is not necessary for the analysis.

Let γ^m denote the $N \times 1$ vector with typical element γ_i^m, the parameter associated with the amount of skill of manager i, and let γ^f denote the $M \times 1$ vector with typical element γ_j^f, the parameter associated with the amount of skill of fund j. Then one can express (5) into its multivariate equivalent

$$\alpha = \lambda G \gamma^m + (1 - \lambda) H \gamma^f, \tag{13}$$

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 γ^m and γ^f, respectively, such that their linear combination results in the $P \times 1$ vector α. 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 N and M with ones on their main diagonal, respectively, and ι_N and ι_M are column-vectors of size N and M containing ones, respectively.

To shorten notation let the regression parameters be denoted by $\theta \equiv \left(\lambda, \gamma^m, \gamma^f, \beta, \Sigma\right)$. Given the above assumptions and notation, the likelihood function for the regression parameters θ can be written as:

$$p(r \mid \theta, F) \propto |\Sigma|^{-T/2} \exp\left\{-\frac{1}{2} tr\left(r - (\iota_T \alpha' + F\beta)\right)' \left(r - (\iota_T \alpha' + F\beta)\right) \Sigma^{-1}\right\}, \tag{14}$$

where the notation "$\propto$" is read as "is proportional to."

G. Prior Beliefs

The next step is to specify the prior beliefs for the unknown parameters in equations (12) and (13). I assume that elements of β, λ, Σ are independently distributed in the prior, that is,

$$p(\beta, \lambda, \Sigma) = p(\beta)\, p(\lambda)\, p(\Sigma)\,, \tag{15}$$

and that the prior beliefs on the factor loadings β, and the weight on the manager λ, are diffuse (see Zellner (1971)):

$$p(\beta) \propto 1,\ \ p(\lambda) \propto 1. \tag{16}$$

The choice of a diffuse prior for β and λ is motivated by the fact that it simplifies the model. Also, a diffuse prior on β 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 λ is natural, since ex ante there appears to be no economic information available about the importance of managers versus the importance of funds.

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

$$\Sigma^{-1} \sim W\left(A^{-1}, \nu\right), \tag{17}$$

where $W(A^{-1}, \nu)$ is a Wishart distribution with a $P \times P$ scale matrix A^{-1} and ν degrees of freedom. The parameters of the Wishart distribution are chosen as such that the prior distribution on Σ is essentially non-informative about Σ. Let $\nu = P + 3$, and $A = s^2(\nu - P - 1)\, I_P$, so that the prior expectation of Σ is given by $E(\Sigma) = A/(\nu - P - 1) = s^2 I_P$. These prior beliefs on Σ indicate that, ex ante, the disturbance term of the factor model in equation (12) 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. Finally, following an empirical Bayes procedure, s^2 is set equal to the average of the diagonal elements of a frequentist estimate of Σ.

The prior on $\gamma \equiv \begin{pmatrix} \gamma^{m\prime} & \gamma^{f\prime} \end{pmatrix}^{\prime}$ is specified to be normal with mean zero and variance-covariance matrix V,

$$\gamma \sim N(0, V), \tag{18}$$

where V is a diagonal matrix with large elements on the diagonal. This choice of V implies that the prior on γ is essentially non-informative. There are two parts of information to update the prior in equation (18). This section discusses these two parts of information, and Appendix A contains the details of how to incorporate them into the prior for γ in equation (18).

First, as outlined in Section IV.E, γ is not identified, and only known up to a scalar constant. Moreover, if there are multiple clusters of funds and managers who are active only within their own cluster, then each of these clusters lacks identification. To circumvent this problem one of the manager or fund alpha's in each cluster is assigned a given value; that is, c in equation (11) is specified for each cluster. I require that the difference between cross-sectional average of the γ_j^f (denoted by $\bar{\gamma}^f$) and the cross-sectional average of γ_i^m (denoted by $\bar{\gamma}^m$) is constant in each cluster. For example, one could require that $\bar{\gamma}^f$ equals $\bar{\gamma}^m$, implying that $c = \bar{\gamma}^f - \bar{\gamma}^m = 0$ in equation (11). Since this restriction only identifies $\bar{\gamma}^f$ and $\bar{\gamma}^m$ the value of c is irrelevant for the posterior of λ.

The second part of prior information pertains to α defined in equation (13). Similar to Baks, Metrick, and Wachter (2001), I model the prior beliefs for α as a normal

$$\alpha \mid \Sigma, \delta \sim N\left(\delta, \sigma_\alpha^2 \frac{\Sigma}{s^2}\right), \tag{19}$$

where σ_α represents the prior belief in the possibility of skill, and s^2 is the average level of residual risk among all manager-fund combinations. δ is a $P \times 1$ vector with typical elements $\delta_p = (-fee_p - cost_p) < 0$, which implies that ex ante one expects the performance of manager-fund combination p, α_p, before transactions costs ($cost_p$) and total fees (fee_p) to be zero. The normal distribution in equation (19) is chosen for analytic tractability. To understand why the conditional prior covariance matrix of α is proportional to Σ consider a fully invested manager-fund combination which has a skill level α_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 α_p would fall to $\alpha_p/2$. Equation (19) recognizes this relation, and incorporates the fact that a skilled manager-fund combination can control the expected α_p through the strategic use of leverage. The ratio Σ/s^2 effectively links the posterior distributions of Σ and α.

The prior link between α and Σ 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 (2001a), and Pástor and Stambaugh (2001b). Mathematically, the link in (19) is identical to theirs, although their motivation is somewhat different. In these papers σ_α 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.

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

H. 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, $t = T$, 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

Partially observed return series on certain manager-fund combinations imply that there is potential source survivor bias in the analysis. The evidence in Section II.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. Under reasonable assumptions given below, I will show that this type of survivor bias is not a problem.

Following Baks, Metrick, and Wachter (2001), I represent the presence of manager-fund combination returns using a "presence indicator matrix" Ψ, which is a matrix of the same dimensions as r with each element equal to 1 if the corresponding component of r is observed and 0 if it is missing. The question is whether

$$p\left(\theta \mid r^{obs}, F\right) = p\left(\theta \mid r^{obs}, F, \Psi\right). \tag{20}$$

That is, does inference on θ change if conditioned on Ψ. Under the following reasonable assumption on the conditions for survival the answer is "no:"

$$p\left(\Psi \mid r^{obs}, F, \theta\right) = p\left(\Psi \mid r^{obs}, F\right) \tag{21}$$

This assumption states that survival of a manager at a fund depends only on realized returns. 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.

Under the assumption in equation (21), it follows that survivor bias is not a problem for the analysis. In particular by Bayes rule:

$$\begin{aligned} p\left(\theta \mid r^{obs}, F, \Psi\right) &= \frac{p\left(\Psi \mid r^{obs}, F, \theta\right) p\left(\theta \mid r^{obs}, F\right)}{p\left(\Psi \mid r^{obs}, F\right)} \\ &= p\left(\theta \mid r^{obs}, F\right) \end{aligned} \tag{22}$$

The intuition behind this result is that the returns are already observed, so there is no additional information in return-based survival. Note that in general

$$p\left(r^{obs} \mid \theta, F, \Psi\right) \neq p\left(\theta \mid r^{obs}, F\right). \tag{23}$$

That is, the likelihood conditional on survival is not the same as the likelihood without conditioning on survival. The prior on θ conditional on survival also differs from the unconditional prior; in particular, values of θ that increase the likelihood of survival would receive greater weight in the prior. Equation (22) demonstrates that the effect on the prior and the likelihood must exactly cancel, and thus the posterior remains the same.[8]

I have just shown that under reasonable assumptions, the survival of a manager at a fund does not alter the posterior beliefs for the parameters in the model. However, when a manager switches to a different fund, the return series for that manager-fund combination is truncated, and part of the data is missing. To simplify the analysis in this section, I proceed 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 (12). 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}.[9]

I. Posterior Beliefs

The goal of this section is to calculate the posterior of λ, the fraction of manager-fund output generated by the manager. The marginal posterior beliefs are impossible to obtain analytically, but one can approximate them by employing the Gibbs sampler, a Markov chain Monte Carlo procedure. Briefly, the Gibbs sampler is a technique for generating random variables from a (marginal) distribution indirectly, without having to calculate the density. Although the marginal distributions of the regression parameters and the missing data are difficult to obtain, the full conditional distributions are relatively straightforward to calculate. The Gibbs sampler cycles through these full conditionals to generate a sequence of random variables. Under mild regularity conditions the random variables in this sequence converge to the true marginal and joint distributions.[10]

Appendix B contains the details of the Gibbs sampler, and its associated conditional distributions.

[8]Little and Rubin (1987) give a more formal and detailed treatment of inference in settings with missing data.

[9]See Tanner and Wong (1987).

[10]Casella and George (1992) give an excellent introduction to the Gibbs Sampler.

J. Estimating the importance of managers and funds

This section examines the weight on the manager, λ, defined in equation (13) by applying the methodology developed in the previous sections to the data. As explained in Section IV.E, 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 an average cluster consists of a total of seven funds and managers. Among all clusters, the maximum difference between the number of fund-manager 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 96×365 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 – therefore, I use a single value, six basispoints per months, as the *cost* for every manager.[11]

Figure 1 shows a histogram and a nonparametric density estimate of the posterior of λ, the weight on the manager for $\sigma_\alpha = 30$ basispoints per month. The mean of the posterior density of λ is approximately 0.32 and 95 percent of the observations fall between 0.25 and 0.40. The maximum and minimum value of λ are 0.22 and 0.44, respectively. The density is nearly symmetrical, and the mass in the tails of the distribution is slightly less than that of a normal distribution. To generate this plot 50,500 Gibbs samples are drawn of which the first 500 are discarded, so that the influence of the starting values of the Gibbs chain is negligible. Also, only every 50th draw is retained to ensure that draws from λ are independent.[12] Regardless of the starting values, the Gibbs sequence for λ mixes well, and converges rapidly to its steady state.

[11] 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.

[12] 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 46th draw in the chain for λ is an independent draw.

Figure 2 examines the relation between the fraction of income generated by the manager, λ, and σ_α, the ex ante amount of "skill" a manager-fund combination has. Since this model is about the attribution of skill among managers and funds, one would not expect the amount of skill to be very relevant. This is partially confirmed in Figure 2. Although the mean of the distribution of λ does not vary for a reasonable range of σ_α, the uncertainty about the attribution of performance outcomes between funds and managers increases when one decreases σ_α. Figure 3 shows a transformation of Figure 2 and examines the relation between, σ_α and the marginal rate of technical substitution between the input associated with the manager and the input associated with the fund, or $\lambda / (1-\lambda)$. On average, if a new manager arrives who is only half as productive as the previous manager, then the fund organization only needs to be 25 percent more productive in order to maintain the same level of expected abnormal returns.

As outlined in Section IV.E, the ability to estimate equation (5), comes from the cross-sectional variance in α_p's. Figure 4 shows the decomposition of this variance into a manager part, a fund part, and the covariance between the two. More precisely, the variance and covariance of the two terms on the right hand side of equation (13), $\lambda G \gamma^m$ and $(1-\lambda) H \gamma^f$, are plotted as a fraction of the total variance of α. Most of the cross-sectional variance of α is due to variation associated with the fund.

V. The flow-performance relation

If managers are responsible for only a minor part of fund performance, one may ask if investors are aware of this observation. A direct way to answer this question is to examine to what extent investors re-allocate their money with career changes of managers. As discussed briefly in the introduction, the appetite of investors for a manager and his track-record can perhaps best be measured by examining the relation between fund flows and past performance of managers. The methodology to examine the portability of a manager's track record is based upon Sirri and Tufano (1998), who use a piecewise linear regression framework to examine the relation between past fund performance and fund flows. I extend their framework by including past manager performance.

In each year from 1993 to 1999 I perform a cross-sectional regression of fund flow over the coming year on past relative performance of funds and managers. I define net flows as the net growth in fund assets beyond reinvested dividends, and is calculated using the following formula

$$\frac{TNA_{t+1} - TNA_t\,(1 + r_{t+1})}{TNA_t}, \tag{24}$$

where TNA_t is the total net assets of the fund at the beginning of period t, and r_{t+1} is the fund's return during period t. The relative past performance of a manager is defined as the fraction of managers of domestic diversified equity funds that has a lower average raw return over the past year than the manager under consideration. This definition reflects the fact that investors make decisions based on the relative ranking of managers, not on their absolute performance. The relative ranking of a fund is defined similarly and represents the fraction of domestic diversified equity funds that has a lower average raw return over the past year than the fund under consideration. Both relative raw-return ranking measures range from zero to one. Previous studies have shown that flow reacts in a non-linear fashion to relative performance, and that good performers receive relative larger inflows than the outflows that poor performers experience. To reflect this, I follow Sirri and Tufano (1998) and employ a piecewise linear regression framework for both the manager ranking and the fund ranking, where the support of these rank-variables is divided into quintiles. This framework allows the sensitivity of fund flows to relative past performance of manager and funds to vary for each quintile.

To control for the fact that funds with a relatively small amount of assets under management have larger relative flows, I include past total net assets in the regression. Moreover, to control for risk assumed by a fund I also include the standard deviation of monthly returns over the past year. As final control variable I include average monthly expense ratio over the past year. Holding everything else constant, investors would prefer funds with a low expense ratios over funds with a high expense ratios.

Column five in Table VII reports the regression of fund flow on past relative fund raw return ranking. Similar to what has been documented in the literature, I find that top performing funds attract subsequent large inflows. For example, consider a fund in the 85th relative raw return percentile. If this fund improves its performance such that it rises to the 95th percentile, its inflows over the next year will increase by approximately 30 percent. Column one and three show a similar regression of fund flow on past manager performance, where the past manager raw return ranking is based upon a value and equal weighted portfolio, respectively. Although less convincingly than the results for funds, managers who performed relatively well over the past year and fell in the top quintile of the average relative raw return ranking are able to generate significant inflows.

Finally, in the second and fourth column of Table VII I include both past fund and manager performance and find that the results are less clear. For example, in the value weighted case in column two, flows react positively to funds that fell in top quintile of the average relative raw return ranking. However, the regression also suggests that fund flows react positively to poor manager performance. These surprising results may be the result of the correlation among relative manager and fund ranking.

The results in Table VII are robust to a number of changes. Measuring past performance over the past two or three years instead of the past year, or using α as a performance measure instead of raw returns, does not qualitatively change the results. Also, using other break points to divide the support instead using of quintiles, does not impact the results, as long as there is a sufficiently small "top bin" to capture the sensitivity of fund flows to these extreme performers.

The lack of evidence indicating that managers are relevant for fund flows, may be due to the fact that investors are only able to distinguish between the fund and the manager when the two have a significant performance difference. Thus only when the manager performs well relative to the fund, would an investor be able to distinguish between fund and manager and re-allocate their investments with manager changes. The regression in Table VIII captures this idea, and examines the relation between fund flows and the difference between the fund and manager ranking. The difference in fund and manager ranking ranges from minus one to one. Only a few managers manage a large number of funds simultaneously, and thus large performance differences between funds and managers are relatively rare. To ensure a sufficient number of observations in each part of the support of the rank difference variable, I construct only three bins with boundaries -0.2 and 0.2. As in Table VII, I control for past assets under management, the standard deviation of monthly returns and the past expense ratio.

The results in Table VIII are ambiguous, and there is no significant evidence that fund flows are sensitive to relatively good performing managers. Again, the results are robust to changing the break points of the bins, using α's instead of raw returns, and using different time periods to calculate fund and manager raw return rankings.

VI. 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. 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 the 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 manager is approximately only 30 percent. The remaining 70 percent is contributed by 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 only has to be 25 percent more productive in order to maintain the same alpha.

The second part of the paper investigates whether managers can attract fund flows on the basis of their past performance. Consistent with the finding that funds primarily determine performance, I find that there is only scarce evidence for the ability of a manager to capitalize on his track record, and attract fund flows.

Although the results in this paper are perhaps surprising, there might be a few explanations. The findings in the first part of the paper, that funds primarily determine performance, could be a result of the fact that the manager's compensation decreases the abnormal performance of a manager-fund combination. 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 finding in the second part of the paper that managers cannot attract fund flows on the basis of their past performance, could be not only a reflection of the previous finding that the fund organization primarily determines the performance of manager-fund combinations. It could also indicate that investors are making decisions on the basis of factors other than performance. The average investor is confronted with a confusing choice of thousands of different mutual funds, all offering a slightly different "product." Qualities such as brand name are likely to play an important role in an investment decision. Unless the manager is a star-manager and highly publicized in the media, the average investor is unlikely to follow precisely the manager's career moves. Sometimes the fund's brand name and manager coincide, such as for Peter Lynch and the Fidelity Magellan Fund, but in most cases they do not. As a result investors might not pay much attention to the manager.

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 article indicate that performance is mainly driven by the fund. While mutual fund management companies will undoubtedly continue to create star-managers and advertise their past track-record, investors should focus on fund performance.

Appendix A. Prior beliefs

This appendix examines the construction of the prior beliefs for θ. First I discuss the prior distribution on $\gamma \equiv \begin{pmatrix} \gamma^{m\prime} & \gamma^{f\prime} \end{pmatrix}^{\prime}$. Then I derive the prior beliefs on all parameters.

There are two pieces of information that need to be included into the prior for γ conditional on λ and Σ: the restrictions $\bar{\gamma}^m = \bar{\gamma}^f$ (see Section IV.G for more details), and the relation given in equation (19). To incorporate this information, the construction of this prior is split up in two stages, much like conventional Bayesian inference where prior beliefs are updated with observed data to result in the posterior beliefs. One starts out with an unconditional (that is, not conditioned on any observable quantities) prior on γ,[13] given in equation (18), and updates this prior with the restrictions and the relation given in equation (19) resulting in the new prior for γ.

As indicated in Section IV.G, if there are multiple cluster of funds and managers who are active only within their own cluster, then each of these clusters lacks identification for γ. If D denotes the number of clusters in the data, I impose the restriction that $\bar{\gamma}^m = \bar{\gamma}^f$ for each cluster, or in matrix notation

$$R\gamma = q, \tag{A1}$$

where R is a $D \times (M + N)$ matrix and q is a column-vector of length D.

Following Stambaugh (2001), the information about α in equation (19) is incorporated into the prior for γ by re-interpreting δ in equation (19) as a realization of a multivariate normal with mean α and variance covariance matrix $\sigma_\alpha^2 \Sigma / s^2$:

$$\delta \mid \gamma^m, \gamma^f, \lambda, \Sigma \sim N\left(\alpha, \sigma_\alpha^2 \frac{\Sigma}{s^2}\right). \tag{A2}$$

Using Bayes rule I update the prior distribution on γ in equation (18) with the restrictions $R\gamma = q$ and the information in equation (A2):

$$\begin{aligned} p\left(\gamma^m, \gamma^f \mid \Sigma, \lambda, \delta, P\gamma = q\right) &\propto p\left(\delta \mid \gamma^m, \gamma^f, \lambda, \Sigma\right) p\left(\gamma^m, \gamma^f \mid P\gamma = q\right) \\ &= N\left(\alpha, \sigma_\alpha^2 \frac{\Sigma}{s^2}\right) \times N\left(\gamma_0, V_0\right), \end{aligned} \tag{A3}$$

[13]In statistical theory this type of prior is also known as a "hyperprior."

where the distribution of $\left(\gamma^m, \gamma^f\right)$ conditional on $R\gamma = q$ is derived using standard results from the normal distribution. Thus $\gamma_0 \equiv Bq$, $V_0 \equiv V - BRV$, and $B \equiv VR' \left(RVR'\right)^{-1}$. Observe that V_0 is symmetric and singular by construction. For notational convenience I omit the conditioning on δ in the remainder of this appendix and in Appendix B.

Using equations (15), (16), (17), and (A3), the prior density can be written as

$$p(\theta) = W\left(A^{-1}, \nu\right) \times N\left(\alpha, \sigma_\alpha^2 \frac{\Sigma}{s^2}\right) \times N\left(\gamma_0, V_0\right). \tag{A4}$$

Appendix B. Gibbs sampler

In this appendix I will derive the conditionals necessary for the Gibbs sampler. Multiplying the prior density in equation (A4) and the likelihood in equation (14) gives the joint posterior density of the regression parameters and the missing data, which can be written as

$$\begin{aligned} p\left(\theta, r^{mis} \mid r^{obs}, F\right) &\propto p\left(r \mid \theta, F\right) p(\theta) \\ &\propto |\Sigma|^{-T/2} \exp\left\{-\frac{1}{2} tr\left(r - \left(\iota_T \alpha' + F\beta\right)\right)' \left(r - \left(\iota_T \alpha' + F\beta\right)\right)\Sigma^{-1}\right\} \times \\ &\quad |\Sigma|^{-1/2(\nu+P+1)} \exp\left\{-\frac{1}{2} tr A\Sigma^{-1}\right\} \times \exp\left\{-\frac{1}{2}\left(\gamma - \gamma_0\right)' V_0 \left(\gamma - \gamma_0\right)\right\} \\ &\quad \times |\Sigma|^{-1/2} \exp\left\{-\frac{1}{2}\left(\delta - \alpha\right)' \left(\sigma_\alpha^2 \frac{\Sigma}{s^2}\right)^{-1} \left(\delta - \alpha\right)\right\}. \end{aligned} \tag{B5}$$

Given an initial estimate of θ, the Gibbs sampler cycles through the following conditional densities

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

- $\lambda \mid \gamma^m, \gamma^f, \beta, \Sigma, r, F$

In the next few subsections I will derive the distribution of each of these conditional random variables.

B.1. Conditional distribution of (γ^m, γ^f)

To derive the posterior distribution of the $N+M$ elements of γ conditional on $\lambda, \beta, \Sigma, r, F$ and $R\gamma = q$, recognize that one only needs to derive the posterior for $M+N-D$ elements of γ, and that the posterior beliefs for the remaining elements of γ can be derived using the D restrictions in $R\gamma = q$. Mathematically this relation can be expressed as

$$\begin{aligned} p\left(\gamma \mid \lambda, \beta, \Sigma, P\gamma = q, r, F\right) &= p\left(\gamma^{\text{elim}} \mid \lambda, \beta, \Sigma, R\gamma = q, r, F, \gamma^{\text{keep}}\right) p\left(\gamma^{\text{keep}} \mid \lambda, \beta, \Sigma, r, F\right) \\ &= p\left(\gamma^{\text{keep}} \mid \lambda, \beta, \Sigma, r, F\right), \end{aligned} \quad \text{(B6)}$$

where γ^{elim} is a $D \times 1$ vector containing the elements of γ that are eliminated using the D restrictions in $R\gamma = q$, and γ^{keep} is a $(M + N - D) \times 1$ vector containing the remaining elements of γ. Thus γ^{elim} and γ^{keep} are defined by the following equation

$$R\gamma = R_1\gamma^{\text{elim}} + R_2\gamma^{\text{keep}} = q, \quad \text{(B7)}$$

where R_1 is a square, non-singular matrix of size D, and R_2 is a $D \times (M + N - D)$ matrix. From equation (B7) it follows that one can express γ^{elim} in terms of γ^{keep}:

$$\gamma^{\text{elim}} = R_1^{-1}q - R_1^{-1}R_2\gamma^{\text{keep}}. \quad \text{(B8)}$$

Next, let α defined in equation (13) be written as

$$\alpha = Z\gamma, \quad \text{(B9)}$$

where Z is a $P \times (M + N)$ matrix defined as $\lambda G + (1 - \lambda) H$. Partitioning Z into Z^{keep} and Z^{elim} corresponding to γ^{elim} and γ^{keep} allows one to rewrite α as

$$\begin{aligned} \alpha &= Z^{\text{keep}}\gamma^{\text{keep}} + Z^{\text{elim}}\gamma^{\text{elim}} && \text{(B10)} \\ &= \tilde{Z}\gamma^{\text{keep}} + \tilde{q}, && \text{(B11)} \end{aligned}$$

where the equation (B11) is obtained by substituting equation (B8) into (B10), and thus $\tilde{Z} \equiv Z^{\text{keep}} - Z^{\text{elim}} R_1^{-1} R_2$ and $\tilde{q} \equiv Z^{\text{elim}} R_1^{-1} q$.

To derive the prior beliefs on γ^{keep}, substitute α in equation (B11) into the conditional prior in equation (A3), and eliminate γ^{elim}:

$$p\left(\gamma^{\text{keep}} \mid \Sigma, \lambda, \delta, R\gamma = q\right) = N\left(\tilde{Z}\gamma^{\text{keep}} + \tilde{q}, \sigma_\alpha^2 \frac{\Sigma}{s^2}\right) \times N\left(\tilde{\gamma}_0, \tilde{V}_0\right), \tag{B12}$$

where $\tilde{V}_0$ is square matrix of size $M + N - D$ that only contains the rows and columns of V_0 that correspond to γ^{keep}, and $\tilde{\gamma}_0$ is a vector of size $M + N - D$ that only contains the rows of γ_0 that correspond to γ^{keep}. Similarly, to derive the likelihood of γ^{keep}, substitute α in equation (B11) into the factor model in equation (12) and rearrange

$$vec\left(r - F\beta - \iota_T \tilde{q}'\right) = \left(\tilde{Z} \otimes \iota_T\right) \gamma^{\text{keep}} + \epsilon. \tag{B13}$$

Multiplying the prior for γ^{keep} in equation (B12) and the likelihood implied in equation (B13) gives the posterior for γ^{keep} conditional on $\lambda, \beta, \Sigma, r$, and F. After aggregating the terms involving γ^{keep} by twice completing the square on γ^{keep}, it follows that the conditional posterior can be written as

$$p\left(\gamma^{\text{keep}} \mid \lambda, \beta, \Sigma, r, F\right) \propto \exp\left\{\left(\gamma^{\text{keep}} - \hat{\gamma}\right)' \Omega^{-1} \left(\gamma^{\text{keep}} - \hat{\gamma}\right)\right\}, \tag{B14}$$

where

$$\Omega = \tilde{V}_0^{-1} + \left(T + \frac{s^2}{\sigma_\alpha^2}\right) \tilde{Z}'\Sigma^{-1}\tilde{Z}, \tag{B15}$$

and

$$\hat{\gamma} = \Omega^{-1}\left(\tilde{Z}'\Sigma^{-1}\left(\left(r - F\beta - \iota_T\tilde{q}'\right)' \iota_T + \frac{s^2}{\sigma_\alpha^2}\left(\delta - \tilde{q}\right)\right) + \tilde{V}_0^{-1}\tilde{\gamma}_0\right). \tag{B16}$$

Hence the conditional posterior distribution of γ^{keep} given $\lambda, \beta, \Sigma, r$, and F is normally distributed with mean $\hat{\gamma}^{\text{keep}}$ and variance covariance matrix Ω^{-1}. Common to Bayesian analysis, the mean of the conditional posterior distribution of γ^{keep}, $\hat{\gamma}$ in equation (B16), is the weighted average of the prior mean of γ^{keep} and the sample estimate of γ^{keep}, where the weights are the prior precision of γ^{keep}, given by $\tilde{V}_0^{-1} + s^2/\sigma_\alpha^2 \tilde{Z}'\Sigma^{-1}\tilde{Z}$, and the data precision of γ^{keep} given by $T\tilde{Z}'\Sigma^{-1}\tilde{Z}$.

B.2. Conditional distribution of β

To derive the conditional distribution of β given α, Σ, r, and F rewrite the model in equation (12) as

$$r - \iota_T \alpha' = F\beta + \epsilon. \tag{B17}$$

This is a standard multivariate model, and combined with the flat prior for β this gives (see e.g. Zellner (1971))

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

where

$$\hat{\beta} = (F'F)^{-1} F' (r - \iota_T \alpha'). \tag{B19}$$

B.3. Conditional distribution of Σ

To derive the posterior distribution of Σ conditional on α, β, r and F, collect all the terms involving Σ in the full posterior in equation (B5):

$$p(\Sigma \mid \alpha, \beta, r, F) \propto |\Sigma|^{-(T+\nu+P+2)/2} \exp\left\{-\frac{1}{2} tr(Q + A)\Sigma^{-1}\right\}, \tag{B20}$$

where

$$Q = (r - (\iota_T \alpha' + F\beta))' (r - (\iota_T \alpha' + F\beta)) + \frac{s^2}{\sigma_\alpha^2} (\alpha - \delta)(\alpha - \delta)'. \tag{B21}$$

That is, $\Sigma \mid \alpha, \beta, r, F$ has an inverted Wishart distribution with parameter matrix $Q + A$ and $\nu + T + 1$ degrees of freedom. Note that when $T < P$ both terms on the right hand side of (B21) are singular and consequently Q is singular. In that case Σ is identified through the prior density.

B.4. Conditional distribution of λ

To derive the posterior distribution for λ conditional on $\gamma^m, \gamma^f, \beta, \Sigma, r$, and F, rewrite the factor model in equation (12) as a function of λ,

$$vec\left(r - F\beta - \iota_T \left(H\gamma^f\right)'\right) = \left(W \otimes \iota_T\right)\lambda + vec\left(\epsilon\right), \tag{B22}$$

where $W \equiv G\gamma^m - H\gamma^f$. This is a standard univariate normal model, and combined with the prior for λ this gives (see e.g. Zellner (1971))

$$\lambda \mid \gamma^m, \gamma^f, \beta, \Sigma, r, F \sim N\left(\hat{\lambda}, \sigma_\lambda^2\right), \tag{B23}$$

where

$$\sigma_\lambda^2 = \left(\left(T + \frac{s^2}{\sigma_\alpha^2}\right) W'\Sigma^{-1}W\right)^{-1}, \tag{B24}$$

and

$$\hat{\lambda} = \sigma_\lambda^2 W'\Sigma^{-1}\left(\left(r - F\beta - \iota_T\left(H\gamma^f\right)'\right)'\iota_T + \frac{s^2}{\sigma_\alpha^2}\left(\delta - H\gamma^f\right)\right). \tag{B25}$$

Thus $\lambda \mid \gamma^m, \gamma^f, \beta, \Sigma, r, F$ is normally distributed with mean $\hat{\lambda}$ and variance σ_λ^2.

B.5. Conditional distribution of the missing return data

To derive the posterior distribution for r^{mis} conditional on $\alpha, \beta, \Sigma, r^{obs}$, and F recognize that the error term in the factor model in equation (12) is only correlated in the cross-section, and thus only observed returns in period t are relevant for inference about a missing values in period t. Consequently the conditional posterior for the missing return data is the product of T independent distributions, one for each period in the sample, or

$$p\left(r^{mis} \mid r^{obs}, \alpha, \beta, \Sigma, F\right) = \prod_{t=1}^{T} p\left(r_t^{mis} \mid r_t^{obs}, \alpha, \beta, \Sigma, F\right). \tag{B26}$$

Without loss of generality, reorder the vector of returns in period t, r_t, such that the missing values are at the top (r_t^{mis}) and the observed values at the bottom $\left(r_t^{obs}\right)$. Also, reorder the parameters α, β, and Σ 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 the both the missing data and observed data are generated by the factor model in equation (12) (see also Section IV.H), the distribution of this re-ordered vector is given by

$$\begin{pmatrix} r_t^{mis} \\ r_t^{obs} \end{pmatrix} \sim N\left(\begin{pmatrix} \alpha^{mis\prime} + F_t\beta^{mis} \\ \alpha^{obs\prime} + F_t\beta^{obs} \end{pmatrix}, \begin{pmatrix} \Sigma^{mis,mis} & \Sigma^{mis,obs} \\ \Sigma^{obs,mis} & \Sigma^{obs,obs} \end{pmatrix}\right) \tag{B27}$$

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

$$p\left(r_t^{mis} \mid r_t^{obs}, \alpha, \beta, \Sigma, F\right) \sim N\left(\mu_t^{mis}, \Phi_t^{mis}\right), \tag{B28}$$

where

$$\mu_t^{mis} = \alpha^{mis\prime} + F_t\beta^{mis} + \Sigma^{mis,obs}\left(\Sigma^{obs,obs}\right)^{-1}\left(r_t^{obs} - \left(\alpha^{obs\prime} + F_t\beta^{obs}\right)\right) \tag{B29}$$

and

$$\Phi_t^{mis} = \Sigma^{mis,mis} - \Sigma^{mis,obs}\left(\Sigma^{obs,obs}\right)^{-1}\Sigma^{obs,mis}. \tag{B30}$$

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Table I. Career characteristics of domestic diversified equity managers, 1992-1999

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 after a change (period A), are greater than the monthly average total assets under management by the manager in the year prior to the change (period B), multiplied by the average growth rate of total net assets of all domestic diversified equity funds from period B to period A. "Number of funds" in year t is defined as the number of funds under management by all managers active in year t.

Category	Total	1992	1993	1994	1995	1996	1997	1998	1999
Fund years	6,287	351	483	592	694	800	977	1,149	1,241
No. of manager-fund combinations	2,118	420	581	710	826	1,002	1,174	1,351	1,386
No. of managers	2,086	403	521	586	680	769	857	922	927
Total manager changes	2,610	140	235	262	308	443	451	450	321
Manager change in which manager disappears	441	10	39	38	65	69	62	67	91
Manager change in which the manager appears for the first time in the data	899	73	115	108	110	124	145	139	85
Manager change in which the manager reappears in the data, managing fewer total assets	264	5	15	20	24	55	47	58	40
Manager change in which the manager reappears in the data, managing more total assets	250	5	15	23	23	41	55	65	23
No. of funds	1,602	410	546	662	758	906	1,069	1,225	1,264
Instances in which fund disappears	229	7	12	10	32	33	40	46	49
Instances in which fund appears for the first time	969	63	111	107	86	142	190	185	85

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 she managed during her career belong to that same category. The "other" style category contains managers that could either not be classified, or had multiple funds under management with different styles.

		Style new fund							
		Small company growth	Other agg. growth	Growth	Income	Growth and income	Max. capital gains	Other	Total
Style current fund(s)	Small company growth	99	8	27	0	13	0	0	147
	Other agressive growth	11	21	20	1	3	4	0	60
	Growth	35	21	150	1	20	1	2	230
	Income	1	0	1	0	0	0	0	2
	Growth & Income	14	5	26	0	68	1	0	114
	Maximum capital gains	1	4	11	0	1	0	1	18
	Other	0	0	0	0	0	0	0	0
	Total	161	59	235	2	105	6	3	517

Table III. Manager database cross-sectional summary statistics, 1992-1999

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 she managed during her career belong to that same category. The "other" style category contains 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.

		Cross-sectional moments of manager attributes				
Group	Total number	No. of funds under mgmt.	Time worked (years)	Time spent in between funds (years)	Time spent at one fund (years)	No. of mgmt. comp. worked for
Domestic diversified equity managers	2,086	1.67	3.60	0.02	3.06	1.16
		(1.29)	(2.36)	(0.22)	(2.11)	(0.44)
By manager style						
Small company growth	359	1.47	3.25	0.01	2.87	1.10
		(1.04)	(2.19)	(0.10)	(1.92)	(0.33)
Other agressive growth	119	1.22	3.07	0.01	2.78	1.05
		(0.61)	(2.14)	(0.07)	(1.86)	(0.22)
Growth	804	1.41	3.48	0.01	3.17	1.12
		(0.94)	(2.35)	(0.16)	(2.24)	(0.37)
Income	12	1	2.94	0	2.94	1
		(0)	(0.99)	(0)	(0.99)	(0)
Growth and income	371	1.35	3.61	0.00	3.37	1.11
		(0.82)	(2.46)	(0.01)	(2.29)	(0.32)
Maximum capital gains	22	1	5.31	0	5.31	1.08
		(0)	(2.96)	(0)	(2.96)	(0.28)
Other	399	2.73	4.13	0.09	2.74	1.36
		(1.85)	(2.35)	(0.40)	(1.81)	(0.64)
By current status						
Active	633	2.00	4.24	0.04	3.48	1.21
		(1.66)	(2.54)	(0.29)	(2.27)	(0.53)
Retired	1,453	1.48	3.05	0.01	2.68	1.13
		(0.97)	(2.04)	(0.13)	(1.89)	(0.36)

Table IV. Manager database time-series summary statistics, 1992-1999

Table IV reports time-series averages on annual/monthly cross-sectional average manager attributes for all managers in charge of domestic diversified equity funds from January 1992 to December 1999. The eight columns in the table represent (i) the number of managers (monthly frequency), (ii) the number of funds a manager has under simultaneous management (monthly frequency), (iii) the total assets under management (monthly frequency), (iv) the assets per fund under management (monthly frequency), (v) the annual expense ratio (annual frequency), (vi) turnover (annual frequency), (vii) the percentage of managers who only have load funds under management (annual frequency), and (viii) the maximum load charged (annual frequency). Panel A reports the aforementioned statistics for manager of domestic diversified equity funds in each year of the sample. Panel B splits the sample by manager style, and panel C by status. 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 contains 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.

		Cross-sectional average of annual/monthly time-series average manager attributes						
	No. of mgrs	No. of funds under sim. mgmt	Total net assets ($m)	Net assets per fund ($m)	Expense ratio (%/year)	Turn-over (%/year)	Load mgrs. (%)	Maximum load (%/year)
Panel A: Annual characteristics of managers of domestic diversified equity funds								
1992	403	1.15	$334	$296	1.45%	68.0%	8.51%	4.6%
1993	521	1.19	$429	$372	1.38%	66.8%	10.7%	4.6%
1994	586	1.22	$456	$390	1.33%	72.3%	12.0%	4.4%
1995	680	1.26	$553	$464	1.36%	76.0%	13.7%	4.2%
1996	769	1.31	$759	$612	1.39%	78.6%	13.1%	4.0%
1997	857	1.39	$872	$692	1.38%	86.5%	14.7%	4.0%
1998	922	1.43	$994	$784	1.38%	88.8%	17.0%	4.1%
1999	927	1.49	$1,128	$866	1.43%	95.0%	18.5%	4.1%
mean	708	1.31	$691	$559	1.39%	79.0%	13.5%	4.2%
std	194	0.12	$290	$209	0.04%	10.2%	3.2%	0.2%
Panel B: Characteristics of managers of domestic diversified equity funds by manager style								
Small company growth	359	1.23	$239	$211	1.45%	77.5%	10.1%	4.2%
Aggressive growth	119	1.11	$340	$323	1.73%	143.0%	14.3%	3.8%
Growth	804	1.19	$506	$385	1.38%	70.5%	13.9%	4.3%
Income	12	1.00	$138	$138	1.41%	113.0%	1.6%	4.9%
Growth and income	371	1.17	$891	$819	1.17%	57.4%	13.6%	4.1%
Max. capital gains	22	1.00	$4,105	$4,105	1.51%	86.5%	25.7%	4.0%
Other	399	1.64	$1,066	$783	1.44%	91.2%	15.0%	4.3%
Panel C: Characteristics of managers of domestic diversified equity funds by current status								
Active	633	1.35	$792	$643	1.38%	78.2%	11.5%	4.1%
Retired	1,453	1.21	$544	$443	1.41%	79.0%	14.6%	4.3%

Table V. Fund exit characteristics of domestic diversified equity managers

Each month from January 1992 to December 1999 we 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, we rank all domestic diversified equity managers who are active in that month in 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 we value weight returns and turnover by the funds total net assets. For each month we count the number of managers that leave the sample in each of these decile portfolios and sum them up over all months. The entries in the table are then the fraction of managers that leave a fund (panel A, B, C, D) and fall in a particular characteristic decile portfolio. 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 (panel A, B, C, D), 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.

	Panel A: managers that leave the sample				Panel B: managers that leave a fund without leaving the sample			
portfolio	average return	α	residual risk	turn-over	average return	α	residual risk	turn-over
1 (high)	5.8%	4.6%	11.2%	11.4%	4.3%	6.7%	11.0%	14.2%
2	5.2%	7.9%	10.2%	11.1%	10.4%	9.2%	12.3%	13.5%
3	8.7%	5.8%	11.2%	10.0%	10.4%	10.4%	7.4%	10.1%
4	6.7%	8.9%	9.1%	10.0%	8.6%	14.1%	12.3%	12.8%
5	10.4%	7.3%	10.4%	9.5%	11.7%	8.6%	11.0%	11.5%
6	11.4%	8.9%	10.0%	10.0%	12.3%	7.4%	6.1%	10.1%
7	11.4%	11.4%	11.0%	9.3%	6.7%	8.0%	12.9%	6.8%
8	12.3%	15.0%	10.2%	9.3%	12.9%	9.8%	10.4%	11.5%
9	13.1%	15.6%	9.1%	9.7%	12.9%	17.2%	7.4%	5.4%
10 (low)	15.0%	14.6%	7.5%	9.7%	9.8%	8.6%	9.2%	4.1%
interaction	50.1**	69.2**	5.81	1.87	13.0	14.2	8.66	17.8*

	Panel C: managers that leave a fund and will manage fewer assets				Panel D: managers that leave a fund and will manage more assets			
portfolio	average return	α	residual risk	turn-over	average return	α	residual risk	turn-over
1 (high)	2.5%	2.5%	11.3%	18.4%	10.4%	14.6%	10.4%	12.5%
2	2.5%	8.7%	12.5%	15.8%	22.9%	8.3%	12.5%	7.5%
3	5.0%	3.8%	3.8%	9.2%	16.7%	14.6%	16.7%	5.0%
4	7.5%	16.3%	11.3%	14.5%	8.3%	14.6%	12.5%	12.5%
5	13.8%	6.3%	15.0%	11.8%	10.4%	14.6%	8.3%	15.0%
6	13.8%	6.3%	5.0%	10.5%	12.5%	6.3%	4.2%	10.0%
7	11.3%	7.5%	13.8%	5.3%	0.0%	8.3%	10.4%	10.0%
8	12.5%	13.8%	16.3%	6.6%	10.4%	6.3%	4.2%	17.5%
9	13.8%	23.8%	7.5%	5.3%	8.3%	6.3%	8.3%	5.0%
10 (low)	17.5%	11.3%	3.8%	2.6%	0.0%	6.3%	12.5%	5.0%
interaction	23.4**	28.6**	17.3*	19.0*	27.4**	6.9	7.1	7.1

Table VI. Fund entry characteristics of domestic diversified equity managers

Each month from January 1992 to December 1999 we 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, we 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 we value weight returns and turnover by the funds total net assets. For each month we count the number of managers that leave the sample in each of these decile portfolios and sum them up over all months. The entries in the table are then the fraction of managers that leave a fund (panel A, B, C) and fall in a particular characteristic decile portfolio. 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 (panel A, B, C), 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.

	Panel A: experienced managers that start at a fund				Panel B: experienced managers that start a fund and will manage fewer assets			
portfolio	average return	α	residual risk	turn-over	average return	α	residual risk	turn-over
1 (high)	13.3%	14.1%	11.5%	10.1%	1.9%	3.8%	13.5%	11.8%
2	13.6%	11.2%	9.7%	8.0%	11.5%	11.5%	15.4%	19.6%
3	11.7%	11.0%	8.4%	11.3%	7.7%	7.7%	5.8%	11.8%
4	10.7%	10.4%	10.2%	12.8%	7.7%	5.8%	11.5%	17.6%
5	9.1%	11.2%	8.9%	9.2%	9.6%	9.6%	7.7%	13.7%
6	8.6%	9.7%	9.7%	14.0%	7.7%	3.8%	9.6%	11.8%
7	9.1%	8.1%	9.9%	5.1%	9.6%	9.6%	1.9%	0.0%
8	6.5%	6.5%	9.1%	6.5%	3.8%	7.7%	17.3%	0.0%
9	9.4%	8.6%	11.7%	10.4%	15.4%	23.1%	9.6%	5.9%
10 (low)	7.8%	9.1%	11.0%	12.5%	25.0%	17.3%	7.7%	7.8%
interaction	18.0*	14.9	4.2	26.2**	18.4*	15.9	11.1	28.9**

	Panel C: experienced managers that start a fund and will manage more assets			
portfolio	average return	α	residual risk	turn-over
1 (high)	16.9%	17.2%	10.8%	10%
2	14.2%	11.8%	8.1%	5.6%
3	11.8%	10.8%	9.1%	11.2%
4	10.8%	11.5%	10.1%	10.4%
5	9.8%	10.1%	9.5%	9.2%
6	8.4%	11.1%	9.5%	14.4%
7	8.8%	7.8%	11.1%	6.4%
8	7.1%	6.8%	8.1%	7.2%
9	8.1%	5.4%	11.8%	11.6%
10 (low)	4.1%	7.4%	11.8%	14.0%
interaction	35.6**	29.3**	5.1	20.8*

Table VII. Annual regressions of manager α on past manager α

On January 1 each year from 1993 to 1999 we perform a cross-sectional regression of current manager α on past manager α. The dependent variable in each regression, α_{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 α ($\alpha_{\text{mgr, past}}$) 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 we weigh the fund returns 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 each of the annual regressions coefficients on the constant, and past manager α as outlined in Fama and MacBeth (1973). For each of these cross-sectional regressions we also report the number of observations and the time-series average of the annual adjusted R^2. 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 we pool all the observations used for the annual regressions in panel A. t-statistics are in parentheses. (*) and (**) indicate two-tail significance at the 95 and 99 percent level, respectively.

Panel A: Fama-McBeth regression of manager α on past manager α				
	value weighted		equal weighted	
constant	-0.0009	-0.0010	-0.0007	-0.0009
	(-0.57)	(-0.83)	(-0.49)	(-0.78)
$\alpha_{\text{mgr,past}}$	0.15	0.17*	0.17	0.19*
	(1.69)	(2.63)	(1.95)	(3.14)
manager		-0.0002		0.0005
promoted		(-0.22)		(0.39)
manager		0.0002		0.00006
demoted		(-0.27)		(0.02)
Obs.	7	7	7	7
Adj. R^2	0.033	0.039	0.037	0.040

Panel B: Pooled regression of fund α on past manager α				
	value weighted		equal weighted	
constant	0.0011**	-0.0011**	-0.0010**	-0.0010**
	(-7.91)	(-6.76)	(-6.63)	(-6.02)
$\alpha_{\text{mgr,past}}$	0.13**	0.13**	0.16**	0.16**
	(8.33)	(8.30)	(10.6)	(10.4)
manager		-0.007		-0.0001
promoted		(-1.52)		(-0.32)
manager		0.0002		0.0003
demoted		(0.29)		(0.47)
Obs.	4,751	4,486	4,882	4,553
Adj. R^2	0.014	0.015	0.022	0.023

Table VIII. Portfolios of domestic diversified equity funds and managers formed on lagged returns

On January 1 each year from 1992 to 1999 we sort managers of domestic diversified equity funds (panel A) and domestic diversified equity funds themselves (panel B) into decile portfolios based on their previous calender year's average return, where manager return is defined as the return on an equal or value weighted portfolio of the funds under management by that manager. The decile portfolios are equal or value weighted and the weights are readjusted whenever a fund or manager disappears. Managers and funds with the highest past return comprise decile one and managers and funds with the lowest past return comprise decile ten. For each of the decile portfolios we report the mean and standard deviation of the monthly excess return and estimate a 4-factor model. α is the intercept of the 4-factor model (expressed in bp), $t(\alpha)$ is the t-statistic associated with this estimate and R^2 is the adjusted R-squared for this regression. (*) and (**) indicate two-tail significance at the 95 and 99 percent level, respectively.

Panel A: manager portfolios

port	value weighted					equal weighted				
folio	mean	std	α	$t(\alpha)$	R^2	mean	std	α	$t(\alpha)$	R^2
1 (high)	1.13	4.52	3.96	0.22	0.88	1.29	4.55	18.59	1.50	0.94
2	1.13	3.65	1.20	0.11	0.94	1.18	3.88	7.92	0.90	0.96
3	1.23	3.59	-0.75	-0.09	0.96	1.18	3.76	1.34	0.19	0.97
4	1.16	3.65	-1.68	-0.17	0.95	1.12	3.66	-1.06	-0.18	0.98
5	0.95	3.54	-12.25	-1.26	0.94	0.95	3.59	-11.20	-2.16	0.98
6	1.16	3.70	-0.56	-0.06	0.95	0.98	3.63	-9.89	-1.61	0.98
7	0.89	3.94	-28.91*	-2.95	0.95	0.94	3.82	-16.47	-2.11	0.97
8	0.93	3.99	-20.85	-2.24	0.96	0.87	3.91	-20.32*	-2.61	0.97
9	0.89	4.31	-32.57*	-2.38	0.92	0.79	4.07	-29.33	-2.22	0.92
10 (low)	0.86	4.35	-23.73	-1.29	0.86	0.66	4.10	-30.50	-2.08	0.90
1-10 spread	0.27	2.71	27.68	0.91	0.05	0.62	2.12	49.09	2.35	0.26

Panel B: fund portfolios

port-	value weighted					equal weighted				
folio	mean	std	α	$t(\alpha)$	R^2	mean	std	α	$t(\alpha)$	R^2
1 (high)	1.24	4.37	5.22	0.38	0.92	1.25	4.43	12.12	1.01	0.94
2	1.19	3.68	3.44	0.35	0.94	1.21	3.88	7.56	0.82	0.96
3	1.16	3.55	0.30	0.05	0.97	1.10	3.72	-4.57	-0.62	0.97
4	1.10	3.47	-4.76	-1.09	0.99	1.07	3.62	-4.44	-0.81	0.98
5	1.04	3.51	-7.89	-1.01	0.96	0.99	3.61	-11.36	-2.58	0.99
6	1.01	3.55	-7.38	-0.95	0.96	0.99	3.68	-9.26	-1.89	0.99
7	1.03	3.80	-15.7	-1.64	0.95	0.87	3.75	-20.9	-2.91	0.97
8	0.92	3.87	-20.3	-2.10	0.95	0.91	3.79	-17.7	-2.24	0.97
9	0.87	4.15	-33.4*	-2.37	0.91	0.79	3.95	-28.2*	-2.44	0.93
10 (low)	0.70	4.35	-42.8*	-2.66	0.90	0.58	4.05	-41.8*	-2.93	0.91
1-10 spread	0.54	2.48	48.0	1.92	0.22	0.67	2.16	53.9*	2.54	0.27

Table IX. The effect of relative manager and fund raw return performance on fund flows

On January 1 each year from 1992 to 1999 we perform a cross-sectional regression of fund flow over the coming year on the log of the fund's assets under management, the fund's standard deviation of monthly returns, the fund's average expense ratio, the fund's raw return ranking, and the manager's raw return ranking, where all the dependent variables are measured over the last year. Fund flow is defined as the relative change in assets under management from year t to year $t+1$, adjusted for the fund's raw return during that year: $(TNA_{t+1} - TNA_t\,(1 + R_{t+1}))\,/TNA_t$. A manager's/fund's raw return ranking is a number between zero and one that indicates the fraction of all domestic diversified equity managers/funds that had a lower average raw return than the manager/fund under consideration. Manager raw returns are calculated using the monthly raw returns on an equal or value weighted portfolio of mutual funds which the manager has under management. To construct a value weighted portfolio we weigh the fund returns by the total net assets of that fund. We employ a piecewise linear regression framework for the fund's and manager's relative raw return ranking, where we divide the support of these variables in quintiles. The coefficients on each of the quintiles indicate the sensitivity of fund flow to the fund's or manager's past raw return ranking over that range of the support. The regressions represent the time-series average of each of the annual regressions coefficients as outlined in Fama and MacBeth (1973). For each of these cross-sectional regressions we also report the sum of the number of observations in each year and the time-series average of the annual adjusted R^2. t-statistics are in parentheses. (*) and (**) indicate two-tail significance at the 95 and 99 percent level, respectively.

	value weighted		equal weighted		
Intercept	1.03	0.90*	1.49*	1.29*	1.31
	(2.28)	(2.51)	(2.50)	(2.36)	(2.03)
Log lag TNA	-0.39**	-0.27**	-0.42**	-0.32**	-0.31**
	(4.80)	(-5.40)	(-4.64)	(-4.49)	(-3.44)
Std of monthly returns	8.98	3.66	5.44	0.97	1.26
	(0.99)	(1.41)	(0.61)	(0.38)	(0.39)
Lag expense ratio	-274	-187*	354	-263*	-258
	(-1.87)	(-2.61)	(-2.15)	(-2.53)	(-2.02)
Breakdown of fund rank					
Bottom performance quintile		-0.45		1.07	2.35
		(-0.35)		(0.59)	(1.40)
4th performance quintile		-1.55*		-0.80	1.07
		(-2.42)		(-0.75)	(1.64)
3rd performance quintile		1.39		-0.29	-0.70
		(1.04)		(-0.27)	(-0.76)
2nd performance quintile		0.88		1.48	1.06
		(0.74)		(1.71)	(0.93)
Top performance quintile		6.20*		1.46	3.12*
		(2.33)		(0.71)	(3.31)
Breakdown of manager rank					
Bottom performance quintile	3.11	3.02*	2.78	1.82	
	(1.89)	(2.99)	(1.33)	(0.93)	
4th performance quintile	0.90	2.47**	1.49	2.38	
	(1.21)	(3.43)	(1.60)	(2.02)	
3rd performance quintile	0.43	-1.55	-0.83	-1.53	
	(0.30)	(-1.73)	(-1.08)	(-2.27)	
2nd performance quintile	1.11	0.06	1.84	0.45	
	(0.88)	(0.12)	(2.01)	(0.94)	
Top performance quintile	3.74*	-3.65	4.19	1.80	
	(2.81)	(-1.36)	(2.29)	(0.95)	
Obs.	3,911	3,774	3,946	3,808	4,207
Adj. R^2	0.10	0.09	0.09	0.09	0.09

Table X. The effect of relative rank difference between manager and fund raw return performance on fund flows, 1992-1999

On January 1 each year from 1992 to 1999 we perform a cross-sectional regression of fund flow over the coming year on the log of the fund's assets under management, the fund's standard deviation of monthly returns, the fund's expense ratio, and the difference between the fund's raw return ranking and the manager's raw return ranking, where all the dependent variables are measured over the last year. Fund flow is defined as the relative change in assets under management from year t to year $t+1$, adjusted for the fund's raw return during that year: $(TNA_{t+1} - TNA_t(1 + R_{t+1}))/TNA_t$. A manager's/fund's raw return ranking is a number between zero and one that indicates the fraction of all domestic diversified equity managers/funds that had a lower average raw return than the manager/fund under consideration. Manager raw returns are calculated using the monthly raw returns on an equal or value weighted portfolio of mutual funds which the manager has under management. To construct a value weighted portfolio we weigh the fund returns by the total net assets of that fund. We employ a piecewise linear regression framework for the difference between the fund's and manager's relative raw return ranking, where we divide the support of this variable, ranging from minus one to one, into three pieces. The coefficients on each of these pieces indicate the sensitivity of fund flow to the difference between the fund's and the manager's past raw return ranking over the piece of the support. The regressions represent the time-series average of each of the annual regressions coefficients as outlined in Fama and MacBeth (1973). For each of these cross-sectional regressions we also report the sum of the number of observations in each year and the time-series average of the annual adjusted R^2. t-statistics are in parentheses. (*) and (**) indicate two-tail significance at the 95 and 99 percent level, respectively.

	value weighted	equal weighted
Intercept	1.32	2.45*
	(1.47)	(2.50)
Log lag TNA	-0.27*	-0.32*
	(-3.67)	(-3.07)
Std of monthly returns	4.68	2.21
	(1.45)	(0.69)
Lag expense ratio	-225	-318
	(-2.05)	(-2.07)
Breakdown of fund rank minus manager rank		
Difference between -1 and -0.2	-0.89	1.72
	(-0.28)	(0.83)
Difference between -0.2 and 0.2	0.50	-0.30
	(0.44)	(-0.90)
Difference between 0.2 and 1	0.42	0.73
	(0.22)	(0.42)
Obs.	3,774	3,808
Adj. R^2	0.06	0.05

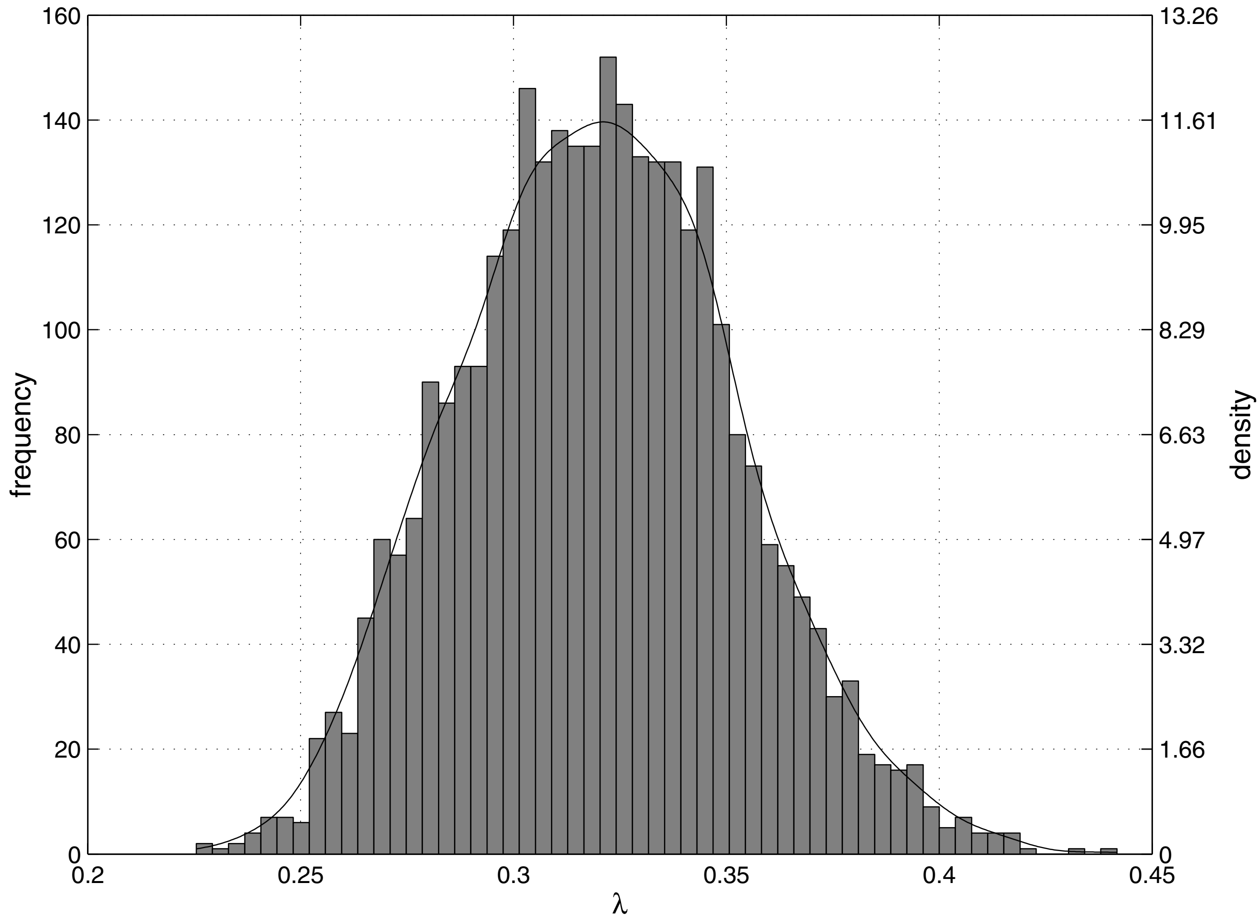

Figure 1.

Posterior density of λ for $\sigma_\alpha = 30$ bp

This figure shows a histogram and a nonparametric estimate of the posterior density of λ, the weight on the manager which is defined by the following four factor model (Carhart (1997)): $r_{t,p} = \alpha_p + F_t\beta_p + \epsilon_{t,p}$, where the intercept in the model, α_p, is a linear combination of γ_i^m, the "skill" associated with manager i and γ_j^f, the "skill" associated with fund j:

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

p is an index that runs over all manager-fund combinations. The disturbance term $\epsilon_{t,p}$, is normally distributed with mean zero and variance σ_p^2. In addition the error term is correlated across manager-fund combinations, but not across time. $r_{t,p}$ denotes the return at time t by manager i at fund j. F_t are the known factor returns at time t, and β_p are the factor loadings of manager-fund combination p. Except for $\left(\gamma^m, \gamma^f\right)$, there are uninformed priors on all model parameters. To ensure identification we require the average fund γ to equal the average manager γ, or $\bar{\gamma}^m = \bar{\gamma}^f$. Finally, conditional on $\sigma_p^2 = s^2$ there holds that the composite intercept in the model, α_p, is normally distributed with mean δ and variance σ_α^2, where δ is the expected abnormal return for manager-fund combination p. The prior constant s^2 equals 0.0035. See section IV for more details.

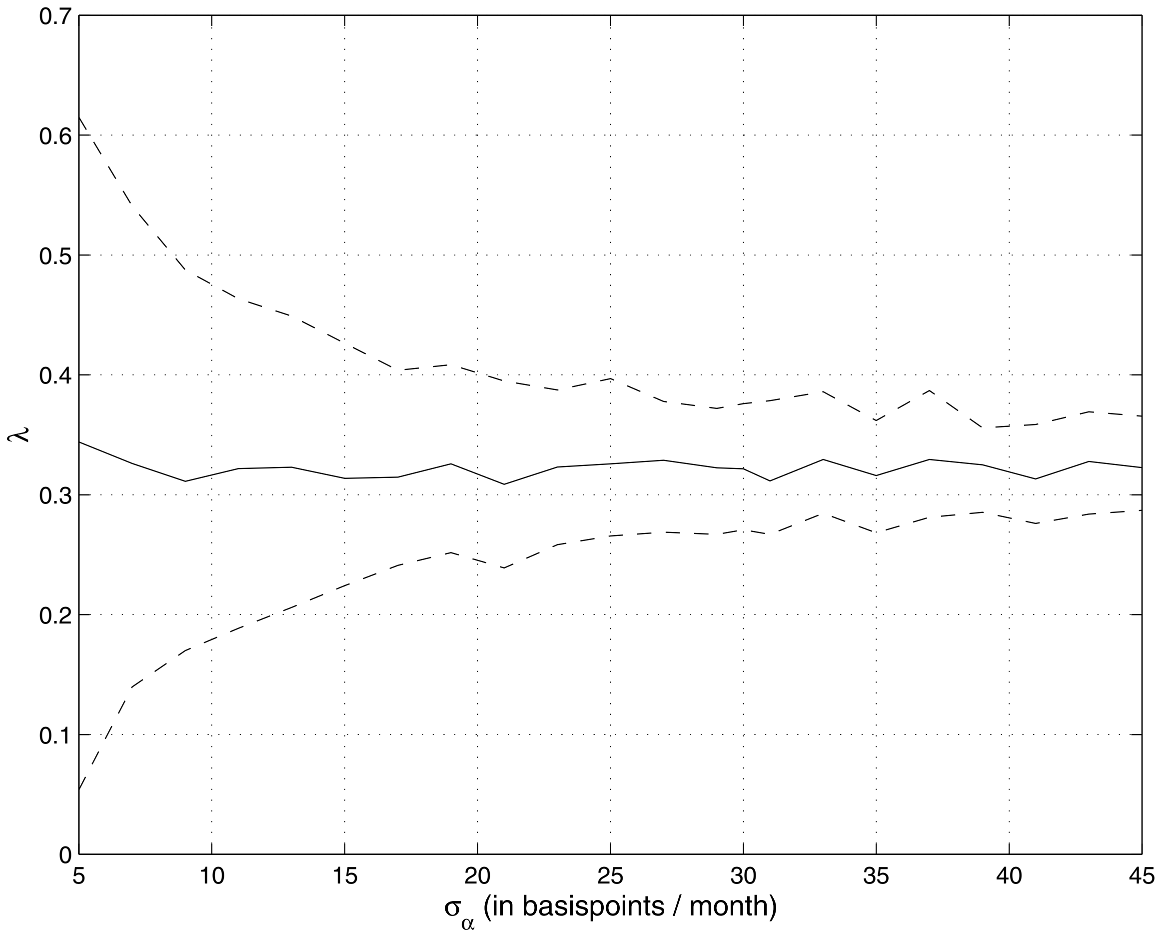

Figure 2.

Posterior distribution of λ as a function of σ_α

This figure shows selected moments of the posterior density of λ as a function of σ_α. The median (solid line), 5th and 95th percentile (dashed) of the distribution of λ are plotted. λ is the weight on the manager which is defined by the following four factor model (Carhart (1997)): $r_{t,p} = \alpha_p + F_t\beta_p + \epsilon_{t,p}$, where the intercept in the model, α_p, is a linear combination of γ_i^m, the "skill" associated with manager i and γ_j^f, the "skill" associated with fund j:

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

p is an index that runs over all manager-fund combinations. The disturbance term $\epsilon_{t,p}$, is normally distributed with mean zero and variance σ_p^2. In addition the error term is correlated across manager-fund combinations, but not across time. $r_{t,p}$ denotes the return at time t by manager i at fund j. F_t are the known factor returns at time t, and β_p are the factor loadings of manager-fund combination p. Except for $\left(\gamma^m, \gamma^f\right)$, there are uninformed priors on all model parameters. To ensure identification we require the difference between the average fund γ to equal the average manager γ, or $\bar{\gamma}^m = \bar{\gamma}^f$. Finally, conditional on $\sigma_p^2 = s^2$ there holds that the composite intercept in the model, α_p, is normally distributed with mean δ and variance σ_α^2, where δ is the expected abnormal return for manager-fund combination p. The prior constant s^2 equals 0.0035. See section IV for more details.

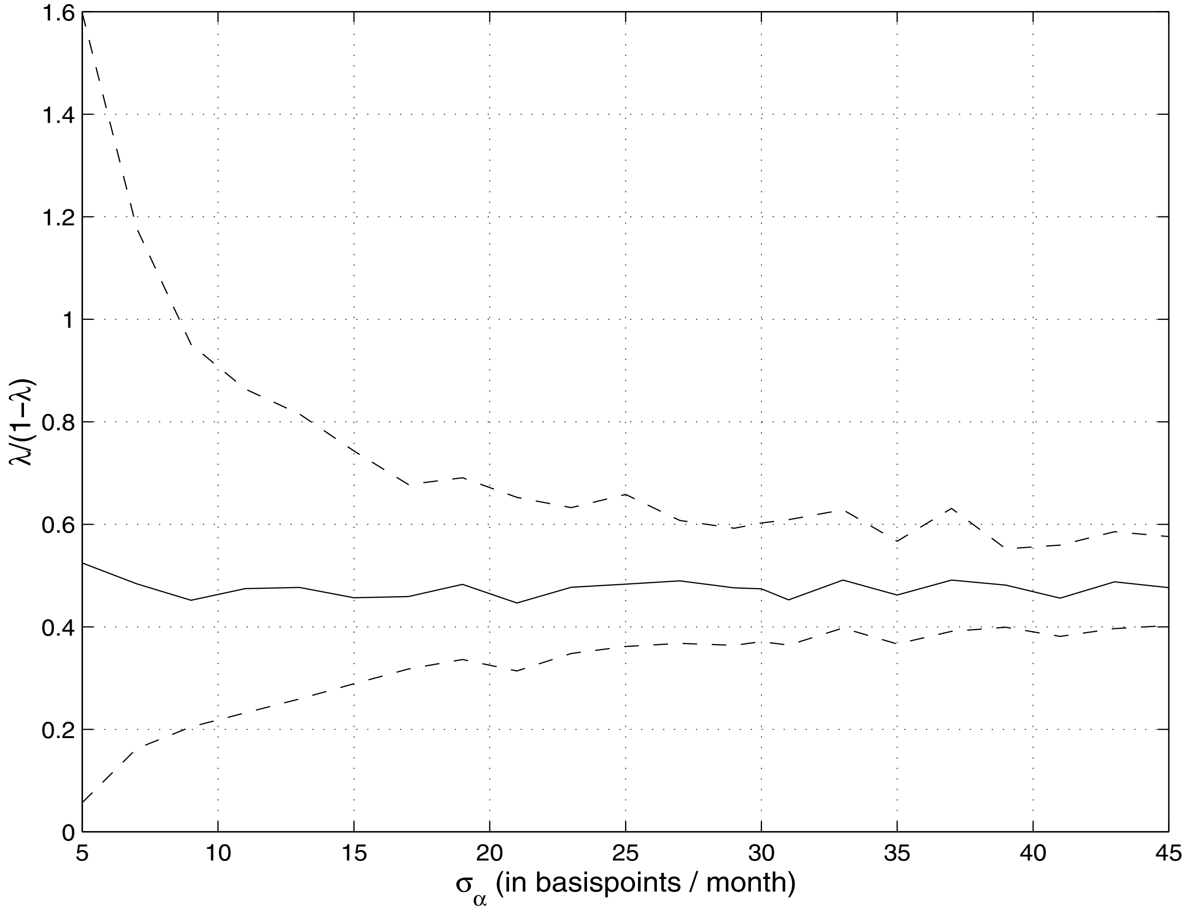

Figure 3.

Posterior distribution of $\lambda/(1-\lambda)$ as a function of σ_α

This figure shows selected moments of the posterior density of $\lambda/(1-\lambda)$ as a function of σ_α. The median (solid line), 5th and 95th percentile (dashed) of the distribution of $\lambda/(1-\lambda)$ are plotted. λ is the weight on the manager which is defined by the following four factor model (Carhart (1997)): $r_{t,p} = \alpha_p + F_t\beta_p + \epsilon_{t,p}$, where the intercept in the model, α_p, is a linear combination of γ_i^m, the "skill" associated with manager i and γ_j^f, the "skill" associated with fund j:

$$\alpha_p \equiv \lambda\gamma_i^m + (1-\lambda)\gamma_j^f.$$

p is an index that runs over all manager-fund combinations. The disturbance term $\epsilon_{t,p}$, is normally distributed with mean zero and variance σ_p^2. In addition the error term is correlated across manager-fund combinations, but not across time. $r_{t,p}$ denotes the return at time t by manager i at fund j. F_t are the known factor returns at time t, and β_p are the factor loadings of manager-fund combination p. Except for $\left(\gamma^m, \gamma^f\right)$, there are uninformed priors on all model parameters. To ensure identification we require the difference between the average fund γ to equal the average manager γ, or $\bar{\gamma}^m = \bar{\gamma}^f$. Finally, conditional on $\sigma_p^2 = s^2$ there holds that the composite intercept in the model, α_p, is normally distributed with mean δ and variance σ_α^2, where δ is the expected abnormal return for manager-fund combination p. The prior constant s^2 equals 0.0035. See section IV for more details.

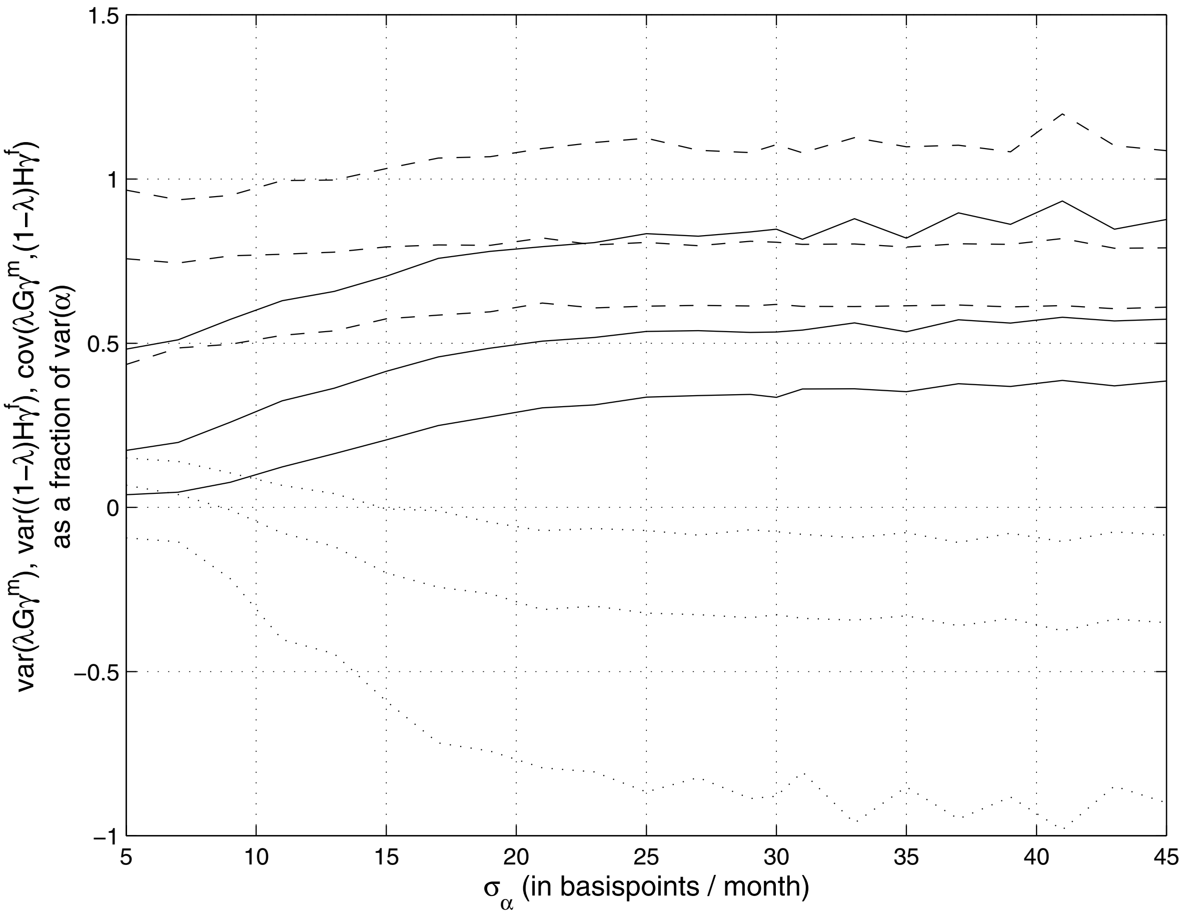

Figure 4.

Cross-sectional varaince decomposition of α as a function of σ_α

This figure shows the selected moments of the posterior density of the three terms associated with the variance decomposition of α: the variance of the manager term (solid), the variance of fund term (dashed), and the covariance (dotted), all expressed as a fraction of the total variance of α. The 5th percentile, the median and the 95th percentile are plotted of each of the three posterior densities are plotted. More precisely, α is defined as the intercept in a four factor model (Carhart (1997)): $r_{t,p} = \alpha_p + F_t\beta_p + \epsilon_{t,p}$, and is a linear combination with weights λ and $1-\lambda$ of γ_i^m, the "skill" associated with manager i and γ_j^f, the "skill" associated with fund j: $\alpha_p \equiv \lambda\gamma_i^m + (1-\lambda)\,\gamma_j^f$, where p is an index that runs over all manager-fund combinations. 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 γ^m and γ^f, respectively, such that their linear combination results in the vector α. The disturbance term $\epsilon_{t,p}$, is normally distributed with mean zero and variance σ_p^2. In addition the error term is correlated across manager-fund combinations, but not across time. $r_{t,p}$ denotes the return at time t by manager i at fund j. F_t are the known factor returns at time t, and β_p are the factor loadings of manager-fund combination p. Except for $\left(\gamma^m, \gamma^f\right)$, there are uninformed priors on all model parameters. To ensure identification we require the difference between the average fund γ to equal the average manager γ, or $\bar{\gamma}^m = \bar{\gamma}^f$. Finally, conditional on $\sigma_p^2 = s^2$ there holds that the composite intercept in the model, α_p, is normally distributed with mean δ and variance σ_α^2, where δ is the expected abnormal return for manager-fund combination p. The prior constant s^2 equals 0.0035. See section IV for more details.