Essays on Delegated Portfolio Management

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Abstract

In Chapter I, we examine the performance of stocks that represent mutual fund managers' "best ideas". The stock that active managers display the most conviction towards ex-ante, significantly outperforms the market, as well as the other stocks in those managers' portfolios.
In Chapter II, I explicitly show that managers, who concentrate their portfolios into a small number of stocks, consistently beat their benchmarks and their more diversified peers. This performance gap can be explained by differing portfolio exposures towards priced risk factors as well as stronger abilities of concentrated managers when investing in stocks with high uncertainty of information.
In Chapter III, I study the information content of portfolio rebalances by mutual fund managers and show that their recent trading decisions predict future stock returns. While purchases by skilled managers are associated with positive future abnormal performance, unskilled managers systematically commit errors in the selection and trading of stocks.

Keywords: Mutual funds, market efficiency, portfolio choice, performance persistence, portfolio concentration.

Resumen

En el capitulo I, se examina el rendimiento de los activos financieros que representan las "mejores ideas" de los gestores de los fondos de inversión. Las inversiones para las que un gestor activo augura un buen rendimiento obtienen mejor retorno de mercado, asi como el resto de inversiones en sus carteras.
En el capitulo II, se muestra explicitamente que los gestores que concentran sus carteras en un número reducido de activos, superan reiteradamente sus benchmarks y otros fondos más diversificados. Esta diferencia de rendimiento se puede explicar gracias a las diferencias en la exposición a factores de riesgo valorados por el mercado y al mayor talento de los gestores que se centran en invertir en activos de alta incertidumbre.
En el capitulo III, se estudia la información contenida en las transacciones de activos y se muestra que las decisiones recientes de los gestores predicen el rendimiento futuro de las inversiones. Mientras que las compras llevadas a cabo por gestores con una habilidad superior se asocian a un rendimiento futuro anormalmente positivo, los gestores poco hábiles cometen errores de forma sistemática en la selección y en las transacciones de activos.

Palabras clave: Fondos de inversión, eficiencia de mercado, elección de carteras, rendimiento continuado, concentración de cartera.

Foreword

The efficiency of global stock markets is one of the central topics in modern financial theory. Since Eugene Fama Fama (1970) provided a clear formulation of this idea, the testing for its validity has become one of the main pursuits of empirical finance. Two methodological avenues are offered to researchers when testing for the informational efficiency of asset markets. First, identifying asset characteristics that are systematically associated with higher than average returns to investors, without being explained by any commonly understood notion of risk, provides evidence against the Efficient Market Hypothesis. Second, the question can be tackled indirectly by testing whether sophisticated investors consistently identify and trade assets with such characteristics.

The research presented in this thesis pursues the second methodological approach, by evaluating the portfolio choice of equity mutual fund managers over the last three decades. The availability of complete historic data on their performance and portfolio choices makes them ideal objects of empirical research. Traditional mutual fund performance studies were based on historical portfolio returns. For the most part they conclude that active managers neither possess stock selection nor market timing abilities. More recent research paints a somewhat brighter picture on the value of active fund management. On the one hand, this is a result of improved econometric techniques to measure abnormal management performance. On the other hand, it is a consequence of the increased use of mutual fund holdings data, which allows for a more granular view on the investment behaviour of fund managers.

The research presented in this thesis takes this question a step further. We argue that it is highly unlikely to detect abnormal performance of mutual fund portfolios, even if their managers possess the abilities to select assets that consistently beat the market. Our hypothesis is based on the fact that fund mangers face a number of constraints and incentives, besides the identification of benchmark-beating investments. In Chapter I, we show how the incentive of fund managers to maximize the mean-variance performance of their portfolios can lead them to excessively diversify their holdings with assets they have no strong conviction about. By inverting the portfolio choice problem of fund managers' we are able to extract the subset of their investments that constitute their best ideas and show that these stocks clearly outperform their benchmark as well as the rest of fund managers' portfolios.

In Chapter II, I test whether fund portfolios concentrated in a small number of stocks generally outperform portfolios that are highly diversified. I find that less diversified fund managers perform significantly better than their more diversified peers. The performance differences can be attributed to differences in stock selection ability, particularly when investing in companies for which information is scarce and uncertain.

Chapter III presents the results of studying the information content of mutual fund portfolio rebalances. Transaction costs constrain the turnover of mutual fund portfolios to a significant extent. The decision to trade a stock is therefore likely to represent stronger management opinion about value than the passive decision to hold the stock in the portfolio. Concentrating on the performance of stocks that are actively traded by mutual funds rather than fund performance overall is thus likely to provide a clearer picture on the viability of valuation-driven decisions by fund managers. In Chapter III, I study the informational content of trading decisions by mutual fund managers and show that they contain information that can be used to predict future stock returns.

Contents

1 Best Ideas (joint with Randolph Cohen and Christopher Polk)

1.1 Introduction

When asked to talk about his portfolio, the typical investment manager will identify a position therein and proceed to describe the opportunity and the investment thesis with tremendous conviction and enthusiasm. Frequently the listener is overwhelmed by the persuasiveness of the passionate presentation. This leads to a natural follow-up question: how many investments make up the portfolio. Informed that the answer is, e.g., 150, the questioner will often wonder how anyone could possess such depth of knowledge and passion for so many disparate companies. Pressed to answer, investment managers often confess that their portfolio contains a few core high-conviction positions – the "best ideas" – and then a large number of additional positions which may have less expected excess return but which serve to "round out" the portfolio.

This chapter attempts to identify ex ante which of the investments in managers' portfolios were their best ideas and to evaluate the performance of those investments. We find that best ideas not only generate statistically and economically significant risk-adjusted returns over time but that they also systematically outperform the rest of the positions in managers' portfolios. We find this result across all combinations of specifications: different benchmarks, different risk models, different definitions of best ideas. The level of outperformance varies depending on the specification, but for our primary tests falls in the range of one to four percent per quarter.

These findings have powerful implications for our understanding of stock market efficiency. Previous research has generally found that money managers do not outperform benchmarks net of fees. Rubinstein (2001) referred to this fact as the efficient-markets faction's "nuclear bomb" against the "puny rifles" of those who argue risk-adjusted returns are forecastable. Subsequent work has shown quite modest outperformance of around one percent per year for the stocks selected by managers (ignoring all fees and costs). We believe this paper is the first to show evidence that the typical active manager can select stocks that deliver economically large risk-adjusted returns.

This research also has strong implications for the optimal behavior of investors in managed funds. Our findings suggest that while the typical manager has a small number of good investment ideas that provide positive alpha in expectation, the remaining ideas in the typical managed portfolio add no alpha at all. Managers have understandable incentives to include these zero-alpha positions. Without them, the portfolio would contain only a few names, leading to increased volatility, price impact, illiquidity, and regulatory risk. Adding additional stocks to the portfolio can not only reduce volatility but also increase the portfolio's Sharpe Ratio. Perhaps most importantly, adding names enables the manager to take in more assets, and thus draw greater management fees. But while the manager gains from diversifying the portfolio, it is likely that typical investors are made worse off. We suggest that investors who put only a modest fraction of their assets into each managed fund can have substantial gains if managers choose less-diversified portfolios.

The rest of the chapter is structured as follows. In section 1.2 we briefly discuss related literature. In section 1.3 we provide motivation and our methodology. In section 1.4 we summarize the dataset. In section 1.5 we describe the results and their implications. Section 1.6 concludes.

1.2 Related literature

There are several plausible reasons why examining total portfolio performance may be misleading concerning stock-picking skills. First, manager compensation is often tied to the size of the fund's holdings. As a consequence, managers may have in-

centives to continue investing fund capital after their supply of alpha-generating ideas has run out. This tension has been the subject of recent analysis, highlighted by the work of Berk and Green (2004). Second, the very nature of fund evaluation may cause managers to hold some or even many stocks on which they have neutral views concerning future performance. In particular, since managers may be penalized for exposing investors to idiosyncratic risk, diversification may cause managers to hold some stocks not because they increase the mean return on the portfolio but simply because these stocks reduce overall portfolio volatility. Third, open end mutual funds provide a liquidity service to investors. Edelen (2002) provides strong evidence that liquidity management is a major concern for fund managers and that performance evaluation methods should take it into account. Alexander, Cici and Gibson (2007) show explicitly that fund managers trade-off liquidity against valuation motives, when making investment decisions. Finally, even if managers were to only hold stocks that they expect to outperform, it is likely that they believe that some of these bets are better than others.
Recent theoretical work by VanNieuwerburgh and Veldkamp (2008) has highlighted the importance of specialization in managerial information acquisition. They show that returns to specialization in information acquisition imply that investors should not hold diversified portfolios. Our results may help to shed some light on Van Nieuwerburgh and Veldkamp's conclusions.
There are several empirical papers with findings related to ours. Evidence that managers select stocks well can be found in Wermers (2000) and in Cohen, Gompers and Vuolteenaho (2002). Evidence that managers who focus on a limited area of expertise outperform more than the typical manager can be found in Kacperczyk, Sialm and Zheng (2006). Baks, Busse and Green (2006) document that managers who select more concentrated portfolios outperform. Cremers and Petajisto (forthcoming) demonstrate that the share of portfolio holdings that differ from the benchmark (what they define as active share) forecasts a fund's

abnormal return – this forecastability could be due to managerial focus or portfolio concentration or both. Concurrent research suggests that extracting managers' beliefs about expected returns from portfolio holdings might be useful. In particular, Shumway, Szefler and Yuan (2009) show that the precision of the implied beliefs from a manager's holdings concerning expected returns helps to identify sucessful managers. Pomorski (2009) shows that when multiple funds that belong to the same company trade the same stock in the same direction, that stock outperforms. Wermers, Yao and Zhao (2007) document that trading strategies based on portfolio holdings generate returns exceeding seven percent during the following year, adjusted for the size, book-to-market, and momentum characteristics of stocks. Their result depends on weighting those holdings by past fund performance.

1.3 Methodology

To formally motivate how we extract the best ideas of portfolio managers, we first consider a simple portfolio optimization problem. Consider a linear factor model for the returns on N given assets. Let r_t be the vector of returns on those N assets at time t, with mean μ and covariance matrix Ω. Returns are in excess of the risk-free rate, unless the asset is a zero-investment portfolio. For a set of K factor portfolios, we assume that the following relation holds

$$\begin{aligned} r_t &= \alpha + B r_{Kt} + \varepsilon_t \\ E[\varepsilon_t] &= 0, E[\varepsilon_t \varepsilon_t'] = \Sigma, Cov[r_{Kt,}\varepsilon_t] = 0 \\ r_{Kt} &= \omega_{Kt}^{'} r_t \end{aligned}$$

where B is a NxK matrix of factor sensitivities, r_{Kt} is the K-vector of factor portfolio returns in period t, ω_{Kt} is the matrix of stock weights resulting in these factor returns, and α and ε_t are the N-vectors of mispricings and disturbances, respectively. Finally, Σ is assumed to be of full rank.

An exact K-factor pricing relation implies that α is a vector of zeros. If pricing is not exact, then α is non-zero and related to the residual covariance matrix Σ as described in MacKinlay (1995). MacKinlay shows how the optimal orthogonal portfolio is the unique portfolio that can be constructed from these N assets to be uncorrelated with the factor portfolios and, in conjunction with the factor portfolios, forms the tangency portfolio. For example, when K=1 and the residual covariance matrix Σ is diagonal and proportional to the identity matrix, the orthogonal portfolio weights in the N assets and in the factor portfolio are

$$c \begin{bmatrix} \alpha \\ -\beta'\alpha \end{bmatrix}$$

where c is a normalizing constant and β is the vector of loadings on the factor. The weights on the N assets are proportional to the mispricing vector while the weight on the factor portfolio makes the portfolio orthogonal with respect to the factor. With less restrictive assumptions about Σ, the weights in the orthogonal portfolio then become proportional to $\Sigma^{-1}\alpha$. For example, if Σ is diagonal but stocks differ in the level of residual variance, the weight in each stock is proportional to $\frac{\alpha_i}{\sigma_i^2}$.

This textbook theory motivates benchmark-adjusted weights as appropriate measures of managers' views on mispricing. Practically speaking, we adjust the weights we observe in holdings data in one of four ways. Our basic approach is to identify best ideas as those which the manager overweights the most relative to some benchmark weighting scheme. In order to show robustness of the result, we use several different weighting schemes motivated by theory as well as simplicity and intuition. The simplest approach we consider is to compare the weights in the portfolio to the market capitalization weights of the stocks. That is, if Microsoft makes up 2 percent of the U.S. stock market, and Merck makes up 1 percent, we identify Microsoft's overweight as its portfolio weight minus 2 percent while Merck's overweight is its portfolio weight minus 1 percent. Of course, it is quite possible that every stock in a manager's portfolio is viewed as overweighted by this metric. This is especially true for the portfolios of small-cap managers, where a typical stock might have a market weight that is quite small, and each stock in the portfolio may have weights greater than 2 percent, for example. However, this is not a problem because we are only interested in the relative overweights of each stock - there is no need for the overweights to add to zero or to anything else. Therefore, our most intuitive approach is to define manager j's tilt in stock i as the difference between the fund's portfolio weight in i, λ_{ijt}, and the weight of stock i in the market portfolio, λ_{iMt}

$$market\_tilt_{ijt} \equiv \lambda_{ijt} - \lambda_{iMt}$$

While intuitive, the weighting scheme discussed above is not clearly motivated by theory. A scheme that does follow from theory represents our second approach. For simplicity we select the Capital Asset Pricing Model to capture the return generating process of equity returns.[1] Using this model, we estimate the idiosyncratic risk component of each stock in the CRSP universe. Our estimate is simply the mean square error obtained by regressing a daily time series of stock i 's excess returns over the risk-free rate on market excess returns over the previous 250-day period.[2] We then need to add two strong assumptions: first, the model we have selected captures the factor structure of returns, so that the idiosyncratic risk components of stocks relative to this model are independent. Second, the goal of each manager is to create a portfolio with maximum information ratio - that is, he wishes to maximize excess return relative to volatility by combining the set of stocks that he has selected. Given that the Sharpe Ratio is probably the most widely cited performance statistic of mutual fund managers our second assumption does not appear to be very restrictive. Under these conditions, the manager's weight in each stock relative to the benchmark will be

[1]In unreported results we repeat the analysis using the Fama-French Model (Fama and French (1993)) as the underlying asset pricing model. We found that this does not influence our results significantly.

[2]We exclude stocks with stock prices less than five dollars when calculating tilts based on the interaction with idiosyncratic volatility.

given by its expected risk adjusted return divided by the stock's idiosyncratic variance. Each stock is viewed as being an equally good investment on a risk vs. expected return basis. Therefore, we thus modify the above tilt by scaling it with our estimate of the stock's idiosyncratic variance,

$$CAPM\_tilt_{ijt} \equiv \sigma_{it}^2(\lambda_{ijt} - \lambda_{iMt})$$

However, not all managers are benchmarked against the market. Ideally, we would subtract the portfolio weights of the benchmark relevant to the specific manager. One very general way to achieve this is to construct the benchmark as the market-capitalization-weighted portfolio of stocks contained in the manager's portfolio. To clarify: suppose that the appropriate benchmark portfolio consisted of Stocks A and B, each of which makes up only a very tiny fraction of the stock market (i.e., they are micro-cap stocks). Further, suppose that stock A has twice the market capitalization of Stock B. Then, in this weighting scheme, Stock A would have a benchmark weight of 66.67%, and Stock B a benchmark weight of 33.33%. If the portfolio held equal dollar amounts of Stock A and Stock B, Stock A would be viewed as being underweight by 16.67%, while Stock B as being overweight by 16.67%. Using this scheme, the summed tilts sum to zero. Regardless, it is the relative tilt within each portfolio that matters for our approach: in this example, Stock B would be the best idea, and Stock A would be the worst idea. Formally we define the portfolio tilt measures as,

$$portfolio\_tilt_{ijt} \equiv \lambda_{ijt} - \lambda_{ijtV}$$

$$CAPM\_portfolio\_tilt_{ijt} \equiv \sigma_{it}^2(\lambda_{ijt} - \lambda_{ijtV})$$

where λ_{ijtV} is the corresponding value-weight portfolio of the names currently held by the manager.

We identify the "best idea"of a manager as the stock with the highest tilt in his portfolio. Each of our four tilt measures proxies for the manager's relative conviction about his holdings. High tilt ranks indicate strong conviction.

Recent research has emphasized the importance of trades in conveying management opinion on the value of a stock.[3] These results are intuitive: Inefficiencies in the pricing of stocks are unlikely to persist for extended periods. Mutual fund portfolios, on the other hand, exhibit inertia: Most managers cannot fully adjust their portfolios as a reaction to new information on the value of an asset, due to the price impact and the tax implications of their actions. Recent trades, by being incremental changes to managers' exposures, thus reflect "fresh" information on their valuation of a particular asset. We take account of this insight by reporting separate results for best ideas that have been recently bought by managers. Whenever we do so, we refer to them as best "fresh" ideas.

1.4 Data and Sample

Our stock return data comes from CRSP (Center of Research for Security Prices) and covers assets traded on the NYSE, AMEX and NASDAQ. We use the new mutual fund holdings data from Thompson Reuters. Our sample consists of US domestic equity funds that report their holdings in the period from January 1991 to December 2005. The holdings data are gathered from quarterly filings of every U.S. registered mutual fund with the Securities Exchange Commission. The mandatory nature of these filings implies that we can observe the holdings of the vast majority of funds that are in existence during that period. For a portfolio to be eligible for consideration, it must have total net assets exceeding $5 million and at least 5 recorded holdings.[4] A

[3] Chen, Narasimhan, Jegadeesh and Wermers (2000) show that the stock holdings of mutual funds in general do not outperform the rest of the market. In contrast, purchases of fund managers outperform their sales by roughly 2% over the year following the trade. The authors interpret this result as managers possessing superior information and acting on short-lived investment opportunities in the market.

[4] This minimum requirement on the amount of net assets and the number of holdings is a standard in the literature and imposed to filter out the most

crucial assumption of our analysis is that fund managers try to maximize the information ratio of their portfolios. Therefore we exclude portfolios that are unlikely to be managed with this aim in mind, such as index or tax-managed funds. Since we do not have pricing data on stocks traded outside the United States, we also exclude international funds from the sample. We identify best ideas as of the *true* holding date of the fund manager's portfolio since we are primarily interested in whether managers have stock-picking ability, not whether outsiders can piggyback on the information content in managers' holdings data.[5]

Table A.1 provides summary statistics on our sample of mutual fund portfolios over the 15 year period under consideration. It points at the impressive growth of the industry, partly due to the growth in the market itself but also due to the increased demand for equity mutual fund investment. While the number of funds in our sample roughly doubles from the end of 1990 to the end of 2005, assets under management increase from $211.3 billion to more than $2.6 trillion in the same time span. Column 4 indicates that active mutual funds as a whole have grown to be dominant investors in U.S. equity markets. The stocks that managers cover tend to be on average between the sixth and seventh market capitalization decile. This bias towards large capitalization stocks is gradually decreasing over time. During the sample period, the mean number of assets in a fund has increased by roughly half. In summary, our analysis covers a substantial segment of the professional money management industry that in turn scans a substantial part of the U.S stock market for investment ideas.

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obvious errors present in the holdings data as well as incubated funds.

[5]In research not reported here, we have also documented that historically one was able to generate profitable best ideas trading strategies using holdings information as of the date the positions are made public. See Figure A.5 for indirect evidence on this question.

1.5 Empirical Results

a The Distribution of Best Ideas

In theory the number of best ideas that exist in the industry at any point in time could be as many as the number of managers or as few as one (if each manager had the same best idea). Of course this latter case is quite unlikely since mutual fund holdings make up a substantial proportion of the market. Therefore massive overweighting of a stock by mutual funds would be difficult to reconcile with financial market equilibrium. The black bars in Figure A.1 indicate that best ideas generally do not overlap across managers. Over the entire sample period, more than 70% of best ideas do not overlap across managers. Any of these stocks are a best idea of only one manager at the time. Less than 19% of best ideas are considered by two managers, and only 8% of best ideas overlap over three managers at a time. On very rare occasions, it does occur that a stock is the best idea of ten or more funds. Clearly, managers' best ideas are not entirely independent. However, the best idea portfolios we identify do not consist of just a few names that are hot on Wall Street. Rather, it represents the opinions of hundreds of managers each of whom independently found at least one stock about which they appeared to have real conviction.

Figure A.2 graphs the median of top tilts (best ideas) over time. Panel 1 depicts the typical top market and portfolio tilts, while Panel 2 contains the same data for the CAPM-market and CAPM-portfolio tilts. As a group, fund managers exhibit a slightly decreasing tendency over time to tilt away from the market and portfolio benchmarks respectively. Panel 2 shows that the distribution of CAPM-tilts reflects trends in idiosyncratic volatility over time.[6] This is a desirable feature of our measures: a 2% tilt

[6] Campbell, Lettau, Makiel and Xu (2001) document a positive trend in idiosyncratic volatility during the 1962 to 1997 period. See Brandt, Brav, Graham and Kumar (forthcoming) for post-1997 evidence on this time-series variation.

away from the benchmark in 2000 is a stronger sign of conviction than a 2% tilt in 1997, since idiosyncratic risk has risen in between.

Note that at any point in time, a portion of these tilts are very small as they are due to small deviations from benchmarks by essentially passive indexers. As a consequence, most of our analysis will focus on the top 25% of tilts at any point in time. However, we show that our conclusions do not depend on this restriction as our findings are still evident when we consider even the smallest top tilt as indicative of active management.

b The Features and Performance of Best Ideas

We measure the performance of best ideas using two approaches. Our primary approach is to measure the out-of-sample performance of a portfolio of all active managers' best ideas. Each best idea in the portfolio is equal-weighted (if more than one manager considers a stock a best idea we overweight accordingly). Results are qualitatively similar if we equal-weight unique names in the portfolio, if we weight by market capitalization, or if we weight by the amount of dollars invested in the best idea. The portfolio is rebalanced on the first day of every quarter to reflect new information on the stock holdings of fund managers and its performance is tracked until the end of the quarter. Each best ideas portfolio differs according to which of the four tilt measures we use to identify best ideas and whether we require the fund manager to be increasing the position. Our secondary approach is to examine "best-minus-rest" portfolios instead, where for every manager, we are long his or her best idea and short the remaining stocks in the manager's portfolio (with the weights for the rest of the portfolio being proportional to the manager's weights). Thus for each manager we have a style-neutral best idea bet, which we then aggregate over the entire cross-section of managers.[7] Again,

[7]Note that our best-minus-rest approach has at least one attractive benefit: By comparing the manager's best idea to other stocks in the manager's portfolio, the best-minus-rest measure tends to cancel out most style and sec-

we then track the monthly performance of these four portfolios (one for each tilt measure) over the following three months and rebalance thereafter.

We apply three different measures of performance to this test portfolio - that is three different methods to detect managers' abilities to make use of inefficiencies in stock markets. We choose these models, to reflect industry standards in fund evaluation and to make our results comparable to the findings of previous work in the literature. We first examine the simple average excess return of the test portfolio. This is equivalent to using a model of market equilibrium in which all stocks have equal expected return. While financial economists view this model as simplistic, it is still the case that raw returns are an important benchmark against which money managers may be judged by many investors. Second, we use Carhart's four-factor enhancement of the Fama-French model, in which an additional factor is added to take account of correlation with a momentum bet, i.e. a winners-minus-losers portfolio. Third, we report performance results measured by a six-factor specification, which adds two more regressors to the Carhart model. The fifth factor is a standard value-weighted long-short portfolio, long in stocks with high idiosyncratic risk and short in stocks with low idiosyncratic risk. A recent paper by Ang, Hodrick, Xing and Zhang (2006) indicates that stocks with high idiosyncratic risk perform poorly, and given the nature of our tilt measures, not accounting for the performance of such stocks would skew our results. The sixth factor captures the documented short term reversion in the typical stock's performance. A short-term reversal factor is included here for similar reasons as the momentum factor, namely to control for mechanical and thus easily replicable investment strategies that should not be attributed to managers acting on private information. All standard factor return data is gathered from Kenneth

tor effects that might otherwise bias our performance inference. However, we emphasize the first approach for the simple reason that some managers may have the ability to pick more than one good stock.

French's website.[8] We construct the idiosyncratic volatility factor following Ang et al. (2006).

Table A.2 reports the results of analyzing the best ideas of active fund managers. Panel A studies the best ideas portfolios using each tilt measure while Panel B analyzes the best fresh ideas for each tilt measure. We first study the covariance properties of these portfolios. We find that the best ideas of managers covary with small, high-beta, volatile, growth stocks that have recently performed well. Thus, despite considerable evidence that value outperforms growth, as well as weaker but still interesting evidence that low beta as well as less volatile stocks have positive alphas, it does not appear that fund managers systematically find their highest-conviction ideas among these sorts of stocks.

The fact that we find that managers' best ideas are small stocks that load positively on the momentum factor, UMD, is interesting. The first result would be expected even if managers ultimately had no stock-picking ability as the managers themselves would expect to be able to pick smaller stocks better, recognizing that the market for large-cap stocks would be relatively more efficient.

As for the covariance with momentum, when a stock performs well, it tends to load positively on UMD and negatively on SR. Thus, in part what we are finding is a failure to rebalance on the part of managers. Stocks that have a substantial tilt tend to be those that have performed well over the past year, thus, achieving their high position at least in part because of past growth in their stock price. Typical coefficients on the UMD factor are in the range between 0.15 and 0.3. While loadings of this size on hedge portfolios lead to remarkable statistical significance (often with t-statistics above 5), it does not appear that mere price increases are the primary cause of stocks being significantly overweighted in portfolios, since a momentum tilt in the neighborhood of .2 does not imply past performance so high as to massively increase the portfolio weight of the stock. After all, for a stock that is

[8]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

2% of a portfolio to organically become 3.5% of the portfolio, its price has to rise 75% relative to the return on the rest of the stocks in the portfolio. This is a rare occurrence, and generally, as the data are showing, is not the norm among the best idea stocks we are observing.

In Table A.2, we adjust returns using three models of market equilibrium. Across the entire sample, our most straightforward best ideas portfolio has an average return of 126 basis points per month in excess of the risk-free rate. This return has an associated four-factor alpha of 29 b.p. with a t-statistic of 2.24. The six-factor alpha is stronger at 39 basis points resulting in a higher t-statistic of 3.08. When we measure tilt relative to the manager's holdings, the point estimates as well as the t-statistics increase by twenty to thirty percent, suggesting that our benchmark may not be perfect. Finally, once we follow theory and interact our market tilt measure with an estimate of idiosyncratic variance, estimates of alpha increase to 112 basis points (t-statistic of 4.75) and 115 basis points (t-statistic of 5.31) for the market and portfolio tilt measures respectively.

So far our analysis identifies each manager's best individual idea based purely on a snapshot of the manager's holdings. Of course, one would expect that managers are not able to immediately reoptimize their positions. So as a consequence, we focus on those best ideas that are fresh, where the manager is not actively selling the position.[9] This allows us to ignore large positions that managers are slowly scaling down. In every case, the point estimates as well as the significance of risk-adjusted returns on the best ideas portfolios increase substantially. Clearly, best fresh ideas outperform their benchmarks to a statistically and economically significant extent. The portfolio of best fresh ideas yields risk-adjusted returns in the range of 46 to 127 basis points per month.

One concern is that the factor model may not perfectly price

[9] An idea is considered "fresh" if and only if the percentage of the fund allocated to that stock is larger than in the previous quarter, after accounting the appreciation of the position during the quarter.

characteristic-sorted portfolios. The small-growth portfolio and the large-growth portfolio have three-factor alphas of -34 bps/ month (t-stat -3.16) and +21 bps/month (t-stat of 3.20) in Fama and French (1993). As Daniel and Kent (1997) (DGTW) point out, this fact can distort performance evaluation. For example, the passive strategy of buying the S&P 500 growth and selling the Russell 2000 growth results in a 44 bps/month Carhart alpha (Cremers, Petajisto and Zitzewitz (2009)). As a consequence, we also adjust the returns on the best ideas strategy using characteristic-sorted benchmark portfolios as in DGTW. Specifically we assign each best idea to a passive portfolio according to its size, book-to-market, and momentum rank and subtract the passive portfolio's return from the best idea's return. The Characteristic Selectivity (CS) measure for the best ideas portfolio is just the weighted differenced return, $CS_t = r_{p,t} - r_{DGTW,t}$. Tables A.3 and A.4 show the mean of the benchmarked return, CS_t, as well as the mean of the benchmark return, $r_{DGTW,t}$. We also report in those tables the intercept and loadings estimates from corresponding four and six factor regressions. We find that most of the abnormal performance in the four and six-factor regressions comes from stock selection within a characteristic benchmark, not from holding that benchmark passively or tactically [what DGTW denote as Average Style and Characteristic Timing].

Our analysis has focused on the top 25% best ideas across the universe of active managers in order to make sure we were not examining passive funds, sometimes labeled "closet indexers". Table A.5 documents that our findings concerning the performance of best ideas generally hold as we vary this threshold from the top 100% to top 50% to top 5% of active tilts. Even if we consider the entire sample of best fresh ideas in the industry (Panel A in Table A.6) we find that they outperform by 20 to 65 basis points per month, all statistically significant. In particular note the very strong performance of best ideas representing the top 5% of tilts in Panel C of Table A.6. For the top 5% of CAPM-portfolio tilts,

the six-factor alpha is 1.88% per month, or 22.56% per year.
The analysis in Table A.7 indicates that missing controls are probably not responsible for the alphas we measure by examining the performance of a best-minus-rest strategy. Unless best ideas of managers systematically have a different risk or characteristic profile than the rest of the stocks in their portfolios, this strategy controls for any unknown style effects that the manager may possibly be following. Throughout table A.7, the six factor alphas are statistically significant at the 1% level of significance. Managers' best ideas, whether fresh or not, significantly outperform the rest of managers' portfolios.
Table A.8 repeats the analysis of Table A.7 replacing the best idea in the long side of the bet with the manager's top three ideas (Panel A) or top 5 ideas (Panel B). These top positions are weighted within fund by the size of the manager's position in the stock and then equally-weighted across managers. We find that generalizing what managers feel are their top picks continues to show economically and statistically significant performance. Consistent with the idea that managers' tilts reflect their views concerning stocks' prospect, the alpha of the trading strategy is smaller as we include the lower ranked stocks. Consistent with diversification benefits, the standard error of the estimate is usually lower as more stocks are included on the long side.
We examine more carefully how views concerning alpha that are implicit in managers' portfolio weights line up with subsequent performance. Recall that the six-factor alpha for the best idea portfolio of Table A.2 based on $portfolio\_tilt$ was 47 basis points. We repeat the calculation replacing every manager's best idea with their second-best idea. We then repeat again for the third-best idea, and so on down to the tenth ranked idea. We perform the same analysis starting with the lowest tilt measure and moving up a manager's rank.[10] Therefore we calculate the performance of strategies that bet on manager's worst idea, then on

[10]For this analysis, we require that a manager has at least 20 names in his or her portfolio.

manager's second-worst idea and so on. Figure A.5 plots how the six-factor alpha evolves when one moves down the list of best ideas. Figure A.3 strikingly shows that the point estimates monotonically decline as we move down managers' rankings.
Figures A.4 and A.5 plot the cumulative abnormal returns (CAR) of the best ideas portfolios, against the portfolio of all stocks held by mutual fund managers in event time. The CAR's have been adjusted for risk using the six factor model employed above. The graphs show that the superior performance of best ideas is not transitory in nature. The buy-and-hold CAR of the stocks in our best ideas portfolio is increasing even up to 12 months after first appearing in the portfolio. Buying the best ideas portfolios of Table A.2 that exploit variance-weighted tilts and holding these bets for the next twelve months would have returned slightly over 12% per annum, after adjusting for standard factor risk.

c Where are best ideas most effective?

In this subsection, we examine two potential contributing factors to managers' alpha-generating ability. In Table A.9, each month we sort all stocks in the best ideas portfolio based on a standard measure of liquidity, the average daily relative bid-ask spread over the preceding quarter. We find that in every case, the less liquid stocks are generating the majority of the alpha of the best ideas portfolios. For example, Table A.9 shows that for our simplest tilt measure, the less-liquid best ideas outperform by 41 basis points with a t-statistic of 2.64 while the more liquid best ideas actually underperform by 18 basis points. This cross-sectional variation in abnormal return within the best ideas portfolio is not due to our sort on liquidity. In results not shown, we have also controlled for the Pastor and Stambaugh (2003) and Sadka (2006) liquidity factors, and the estimates of alpha remain economically and statistically significant.
In a rational expectations setting, information should be more valuable to the manager the less his or her peers act on it at the same time. Information is a strategic substitute. In order to

shed light on this point, we calculate a stock-specific measure of conviction in the industry. Each quarter, we sort each manager's portfolio by one of the four tilt measures and assign a percentage rank to it (1% for lowest and 100% percent for highest tilt rank). We then cumulate this rank over all managers to arrive at a stock specific popularity measure. Table A.10 provides the risk-adjusted performance of portfolios of above- and below-median popularity stocks. We find that the majority of the abnormal return comes from the best ideas that are the least popular. These results suggest that managers generate alpha in best ideas that other managers do not seem to have. To summarize the results of our analysis so far, a manager's stock pick outperforms if that pick is best, fresh, and first.

d How do best ideas bets perform as a function of fund characteristics

In this subsection, we repeat the analysis of Table A.5 Panel A where we look at the entire universe of active managers. However, we now decompose the result based on fund type. We examine three fund characteristics that might be plausibly related to the performance of a fund's best ideas. First we ask how concentrated the fund is using a normalized Herfindahl index measure of the positions in a fund. Then we ask how focused the manager is based on the number of positions in the portfolio. Then we ask how big the fund is based on assets under management. Tables A.11, A.12, and A.13 show that the best ideas of small or concentrated funds outperform the best ideas of their large, unconcentrated counterparts, though only the latter is statistically significant. However, it is not the case that the performance of the best ideas strategy in earlier Tables is completely due to the best ideas of concentrated funds, as the best ideas of unconcentrated funds still outperform. We find no cross-sectional variation in the performance of best ideas as a function of fund focus.

e Why are the rest of the ideas in the portfolio?

In this subsection, we examine the performance of the non-best ideas stocks more carefully. In particular, we sort the rest of the portfolio into quintiles based on the stock's past correlation with the manager's best idea, as defined in Table A.2. We then measure the performance of a trading strategy that goes long the top quintile (the most correlated stocks) and short the bottom quintile (the least correlated stocks). We find a spread in returns ranging from 12 to 48 basis points per month depending on the definition of best idea. Five of the eight estimates are statistically significant and the point estimates increase as we move to our more preferred measures of best ideas. These results suggest that managers are willing to accept a lower (abnormal) return for stocks that are less correlated with the stock on which they have strong views.

f Discussion and Implications

Modern Portfolio Theory makes clear normative statements about optimal investing by managers on behalf of their clients. Suppose an endowment fund with mean-variance preferences has three possible investments: **M** (the global market portfolio), and X and Y (the two ideas for trades that a skilled manager possesses). Our point is going to be that if a manager has 50 good ideas we may want to invest only in his one, two or five best ideas; in order to show that, we are going to simplify the problem by saying the manager has two good ideas and show that under reasonable conditions we will want only his first-best and not the other one. Let the riskless rate be zero and the expected returns on the assets be: $E\left[R_M\right] = 7\%$, $E\left[R_X\right] = 2\%$, and $E\left[R_Y\right] = 1\%$. Further suppose all three assets are uncorrelated and all have equal volatility.

Assume the manager charges no fees. To fix ideas, imagine that the bets are purchases of catastrophe bonds: X, a bond that pays

3% in the 99% likely case that Florida hurricane losses fall below some cutoff and -100% otherwise, and Y, a similar bond that pays 2% on the 99% chance of below-threshold Japanese windstorm losses and -100% otherwise.

Unconstrained optimization delivers the result 70% in M, 20% in X, and 10% in Y; this is the portfolio that maximizes Sharpe Ratio. The problem is separable: if we optimize the active manager's portfolio, we find that 2/3 X and 1/3 Y is optimal. At Stage 2, we can then optimize between the market and the manager to get 70% and 30%, bringing us back to 70%, 20%, and 10% in M, X , and Y, respectively. Everything is as expected, and the manager has not hurt his investor by maximizing the Sharpe Ratio in his two-asset sub-portfolio.

But, suppose the endowment decides in advance that it will not allocate more than 10% to the manager. Now in many cases, the best we can do in terms of Sharpe Ratio in the absence of short-selling is if the manager puts 100% in the better bet X and zero in Y. In fact, if the manager can sell short, Sharpe Ratio may often be further increased if he shorts Y to fund greater investment in X. Once we put in place the extremely realistic constraint that an endowment fund will cap the allocation to any given manager, then the manager is hurting the endowment's expected utility if he selects the Sharpe-Ratio-maximizing (SRM) portfolio of his ideas rather than concentrating on his best idea(s).

Figure A.6 shows the Sharpe Ratios obtained at different allocations to the ideas X and Y. Each line on the graph shows the results for a different constraint on the total fraction of assets that are managed (i.e. invested in either X or Y). At 30% of the investor's portfolio allocated to the active manager, we get the global optimum as this is the unconstrained choice (i.e., the highest Sharpe Ratio occurs at 20%, which is 2/3 of 30%). When we constrain the managed assets to either 10% or 20% of the portfolio, the maximum Sharpe Ratio is reduced. Less obviously, when managed assets are constrained, the fraction of managed assets that should be held in the best idea X grows from 2/3 in the unconstrained case to 4/5 if managed holdings are capped at 20% of the portfolio (since the maximum Sharpe Ratio is obtained at a 16% investment in the best idea). And in the case where the fixed allocation to the active manager is only 10%, the optimal investment in the best idea becomes 11/10, implying a short position of -1/10 in the second-best idea.

In summary, Figure A.6 demonstrates that constraining the allocation to a manager should simultaneously incentivize the client to push the fund manager to allocate more to best ideas. Otherwise, if managers act myopically by maximizing only their subportfolio's Sharpe Ratio, the overall Sharpe Ratio may be reduced. In the example above, the magnitude of the reduction in Sharpe Ratio is modest. In order for the true impact of the effect to be appreciated, one needs to consider the more realistic situation where the investor allocates to multiple managers, which we do next.

Suppose that the assumptions underlying the CAPM hold, except that each manager has identified a single unit-beta investment opportunity X that has positive CAPM alpha. We assume that there are N managers, each of whom has one best idea so that each manager's portfolio consists of a combination of the best idea and the market portfolio. Note that the best idea could be thought of as an immutable basket of the manager's good ideas. For simplicity, we assume that each manager's idea has the same expected return, volatility, and beta and that the unsystematic components of the manager's best ideas are uncorrelated. In Figure A.7, we display the Sharpe Ratios for such portfolios based on the following set of assumptions. Suppose that each investment X has 4% annual alpha and that the market premium is 6%; let the market's annual volatility be 15% and X's be 40% (with the assumption of unit beta, every X must have a correlation of 0.375 with M, where M again represents the market portfolio). We continue to assume that the risk-free rate is zero.

The optimal risky portfolio for an investor to hold will be a mix of the Xs and M, with each X having equal weight. The weights that are optimal are the weights that maximize the resulting portfolio's Sharpe Ratio. If each individual manager maximizes his Sharpe ratio, the result will be that each manager will have 89% in the market and 11% in his best idea. And if the investor has access to only a single manager, this will be the optimal choice for the investor as well. But as Figure A.7 shows, the conclusion changes dramatically as the number of managers grows. For example, if the investor is allocating among 5 equally-skilled managers, the resulting portfolio will be optimized if each manager allocates approximately 47% to his best idea. If the investor has access to fifty equally-skilled managers, the optimum is found when managers put 468% in their best idea (and -368% in the market).

The top line in Figure A.7 shows the Sharpe Ratio that would result if managers followed this optimal policy. The lowest line shows the Sharpe Ratio the investor will obtain if each manager instead mean-variance optimizes his own portfolio. The middle line gives the resulting Sharpe Ratios if managers choose the portfolio that is best for the investor but with the constraint that they cannot sell the market short.

Difference in Sharpe Ratios are substantial. For fifty managers, manager-level optimization leads to a Sharpe Ratio of 0.4 while the optimum optimorum is 0.8, and the best case scenario with short-selling constraints is 0.6. Moreover, optimal weights in the managers' best ideas are dramatically larger than what results from myopically maximizing manager-level Sharpe Ratio.

In general, it seems likely that borrowing, lending, shorting, and maximum-investment constraints will create a situation where the investor's optimum requires the manager to choose a weight in X far greater than the SRM weight. This would appear to be the case in typical real-world situations. A manager has a small number of good investment ideas. Modern Portfolio Theory says that any portfolio of stocks that maximizes CAPM information ratio is equally good for investors. Nevertheless, if the manager offers a portfolio with small weights in the good ideas and a very large weight in the market [or a near-market portfolio of zero- (or near-zero-) alpha stocks], the results for investors will be entirely unsatisfactory. The small allocation that investors make to any given manager, combined with the small weight such a manager places in the good ideas, mean that the manager adds very little value.

Suppose managers have optimized their Sharpe Ratios and the investor wishes to obtain the constrained optimum. In a world where shorting the market was costless and common, an investor could take 100 dollars of capital and, instead of giving two dollars to each manager, could short the market to the tune of 900 dollars, giving 18 to each manager. Then, if each manager maximized Sharpe Ratio and put 11% into their best idea, the investor would have about two dollars in each best idea and would approximately match the allocation the investor would have had if he had given two dollars to each manager and each manager had put 100% of this capital in their best idea. In reality, it would be shocking to see an endowment fund pursue such an extreme market-shorting strategy.

Modern Portfolio Theory claims that all X-M combinations are equally good. A natural choice for managers would be the SRM portfolio (11/89 in our example). But we see that the more realistic constrained case suggests that managers can serve their clients better by putting a much greater weight in **X** than the SRM weight –e.g. 100% instead of 11%. And yet as we see in Figure A.2, overweights of best ideas by actual managers are smaller than 11%. Indeed overweights of that magnitude are rare. Of course the 11% figure came from our simple example; perhaps managers view their best ideas as having far less than 4% alpha. But this seems unlikely, since we find actual outperformance of this order of magnitude despite our very poor proxy for best ideas. Of course other conditions may differ from our simple example, but it appears probable that what we are observing is a decision by managers to diversify as much or more than the SRM portfolio despite the argument above that their clients would be best served by them diversifying far less than SRM. We identify four reasons why managers may overdiversify.

1. **Regulatory/legal.** A number of regulations make it impossible or at least risky for investment funds to be highly concentrated. Specific regulations bar overconcentration; additionally vague standards such as the "Prudent man" rule make it more attractive for funds to be better diversified from a regulatory perspective. Managers may well feel that a concentrated portfolio that performs poorly is likely to lead to investor litigation against the manager.
   Anecdotally, discussions with institutional fund-pickers reveal their preference for individual funds with low idiosyncratic risk. Some attribute the effect to a lack of understanding of portfolio theory by the selectors. Others argue that the selector's superior (whether inside or outside the organization) will tend to zero in on the worst performing funds, regardless of portfolio performance. Whatever the cause, we have little doubt that most managers feel pressure to be diversified.

2. **Price impact, liquidity and asset-gathering**. Berk and Green (2004) outline a model in which managers attempt to maximize profits by maximizing assets under management. In their model, as in ours, managers mix their positive-alpha ideas with a weighting in the market portfolio. The motivation in their model for the market weight is that investing in an individual stock will affect the stock's price, each purchase pushing it toward fair value. Thus there is a maximum number of dollars of alpha that the manager can extract from a given idea. In the Berk and Green (2004) model managers collect fees as a fixed percentage of assets under management, and investors react to performance, so that in equilibrium each manager will raise assets until the fees are equal to the alpha that can be extracted from his good ideas. This leaves the investors with zero after-fee alpha.

Clearly in the world of Berk and Green, (and in the real world of mutual funds), a manager with one great idea would be foolish to invest his entire fund in that idea, for this would make it impossible for him to capture a very high fraction of the idea's alpha in his fees. In other words, while investors benefit from concentration as noted above, managers under most commonly-used fee structures are better off with a more diversified portfolio. The distribution of bargaining power between managers and investors may therefore be a key determinant of diversification levels in funds.

3. **Manager risk aversion.** While the investor is diversified beyond the manager's portfolio, the manager himself is not. The portfolio's performance is likely to be the central determinant of the manager's wealth, and as such we should expect him to be risk averse over fund performance. A heavy bet on one or a small number of positions can, in the presence of bad luck, cause the manager to lose his business or his job. If manager talent were fully observable this would not be the case – for a skilled manager the poor performance would be correctly attributed to luck, and no penalty would be exacted. But when ability is being estimated by investors based on performance, risk-averse managers will have incentive to overdiversify.

4. **Investor irrationality**. There is ample reason to believe that many investors – even sophisticated institutional investors – do not fully appreciate portfolio theory and therefore tend to judge individual investments on their expected Sharpe Ratio rather than on what they are expected to contribute to the Sharpe Ratio of their portfolio.[11] For example, Morningstar's well-known star rating system is

[11] This behavior is consistent with the general notion of "narrow framing" proposed by Kahneman and Lovallo (1993), Rabin and Thaler (2001), and Barberis, Huang and Thaler (2006).

based on a risk-return trade-off that is highly correlated with Sharpe Ratio. It is very difficult for a highly concentrated fund to get a top rating even if average returns are very high, as the star methodology heavily penalizes idiosyncratic risk. Since 90% of all flows to mutual funds are to four- and five-star funds, concentrated funds would appear to be at a significant disadvantage in fund-raising. Other evidence of this bias includes the prominence of fund-level Sharpe Ratios in the marketing materials of funds, as well as maximum drawdown and other idiosyncratic measures.

Both theory and evidence suggest that investors would benefit from managers holding more concentrated portfolios.[12] Our belief is that we fail to see managers focusing on their best ideas for a number of reasons. Most of these relate to benefits to the manager of holding a diversified portfolio. Indeed Table A.14 provides evidence consistent with this interpretation. But if those were the only causes we would be hearing an outcry from investors about overdiversification by managers, while in fact such cries are rare. Thus we speculate that investor irrationality (or at least bounded rationality) in the form of manager-level analytics and heuristics that are not truly appropriate in a portfolio context, play a major role in causing overdiversification.

1.6 Conclusions

How efficient are stock prices? This is perhaps the central question in the study of investing. Many have interpreted the fact that skilled professionals fail to beat the market by a significant amount as very strong evidence for the efficiency of the stock market. In fact, Rubinstein (2001) describes that evidence as a "nuclear bomb against the puny rifles [of those who believed markets are inefficient]."

[12] See recent work by VanNieuwerburgh and Veldkamp (2008).

This research asks a related simple question. What if each mutual fund manager had only to pick a few stocks, their best ideas? Could they outperform under those circumstances? We document strong evidence that they could, as the best ideas of active managers generate up to an order of magnitude more alpha than their portfolio as whole, depending on the performance benchmark.

We argue that this presents powerful evidence that the typical mutual fund managers can, indeed, consistently pick outperforming stocks. The poor overall performance of mutual fund managers in the past is not due to a lack of stock-picking ability, but rather to institutional factors that encourage them to over-diversify, i.e. pick more stocks than their best alpha-generating ideas. We point out that these factors may include not only the desire to have a very large fund and therefore collect more fees [as detailed in Berk and Green (2004)] but also the desire by both managers *and* investors to minimize a fund's idiosyncratic volatility: though, of course, managers are risk averse, investors appear to judge funds irrationally by measures such as Sharpe Ratio or the Morningstar rating. Both of these measures penalize idiosyncratic volatility, which is not truly appropriate in a portfolio context.

2 "Consult a Specialist" Rational Under-Diversification in Money Management

2.1 Introduction

> *"Wide diversification is only required when investors do not understand what they are doing."* Warren Buffet.

Given the enormous size of the literature on the performance of money managers it is surprising that only a small number of papers have examined the direct impact of management specialization on the performance of mutual funds. In most other fields of everyday life, the idea that specialists perform better than generalists is well accepted. In economics, the link between specialization and productivity of labor, has been understood well before Adam Smith's *Wealth of Nations.* The limited application of this idea to the realm of portfolio management is due to the fact that efficient markets do not allow for gains to specialization. Under such circumstances, the concentration of a portfolio of assets into a subset of the investable universe can, in fact, only be costly. The best that investors can do is to diversify completely over every securitized income stream in the economy.

In a world of asymmetric information and cognitive limitations of investors this conclusion does no longer hold. There will exist a trade-off between the gains to specialization and benefits of diversification. This chapter is centered on this trade-off in the money management industry. I study the relation between the observed degree of concentration in mutual fund portfolios and its effect on their performance. In doing so I build on the recent theoretical work of Nieuverburgh and Veldkamp (2008), who develop a rational expectations model to explain the apparently irrational underdiversification of private and professional investors in the face of asymmetric information about future asset payoffs. In their model underdiversification with respect to the mean-variance optimal portfolio is a rational response to limited information processing capacity of investors. Asymmetric information combined with this constraint creates a trade-off between the benefits of diversification and the gains to specialization. In equilibrium, more concentrated portfolios yield higher returns than diversified portfolios as concentrated investors make more informed asset choices. Optimal portfolios are combinations of an alpha carrying portion of a few assets and a small, highly diversified, non-alpha carrying portion to reduce volatility.

Besides a learning-based argument, there exist further reasons why higher observed portfolio concentration might be associated with better performance. Fund managers face a number of self-imposed style and regulatory constraints that limit their ability to concentrate their portfolios into a small number of assets[1]. In addition mutual funds face investor flows on a daily basis making portfolio liquidity a major concern for managers. The liquidity risk associated with holding sizeable portions of a portfolio in large stakes in listed companies prevents funds, particularly large ones, from concentrating their portfolio into a limited number of stocks[2]. Since all these constraints naturally lead managers

[1]For instance, the Investment Company Act of 1940 stipulates that ownership of more than 5% of the stock outstanding of a company causes the investor and investee company to be considered legally affiliated, which subjects a mutual fund's actions to much tighter regulatory scrutiny. Funds are also limited in the size of the portfolio weight they can assign to any single security. Section 851 of the Internal Revenue Code specifies that funds with portfolio weights in excess of 5% in any single security do not qualify for the status of a pass-through vehicle. For more information on the topic see Bushee and Raedy (2005).

[2]Yan (2005) shows that fund managers are able to offset some the risk associated with the volatility of their investors' flows by holding cash balances. He can also empirically detect a connection between funding liquidity and the liquidity of stock holdings in mutual fund portfolios: funds investing in small caps and funds that face larger volatility in investor flows hold larger stakes of their portfolios in cash. In a related study, Alexander et al. (2007) show that stocks that funds buy for liquidity motives underperform stocks that they trade for valuation motives. Managers clearly trade off performance against the liquidity of their portfolios.

to increase the diversification of their portfolios, the decision to concentrate is likely to signal the manager's conviction about the expected return on his portfolio. Of course, this behaviour can also be a consequence of mere overconfidence on behalf of the manager. Testing for differences in the performance of concentrated and diversified managers will therefore also provide some evidence on the presence of behavioural biases in this group of investors.

Counter to these arguments, concentrated portfolios could be associated with worse performance due to the shape of fund managers' incentive contracts. Chevalier and Ellison (1997) empirically estimate the shape of the relation between relative performance of mutual funds and their flows. They find that the shape of this relationship is convex: fund mangers in the highest performance ranks attract the majority of flows while underperforming funds do not face substantial outflows. Since mutual fund mangers are typically paid proportional to the amount of assets they manage, the convexity found in the flow-performance relationship, directly translates into a convexity in the performance contract of the typical fund manager. Unskilled managers might therefore be inclined to artificially increase the volatility of their portfolio by taking large positions in a limited number of stocks.

Using portfolio level data, I show that fund managers, who concentrate portfolios into on a small number of stocks, consistently beat their benchmarks. In contrast, highly diversified managers construct portfolios that significantly underperform on a risk adjusted basis. Moreover, I find that gains to specialization are not limited to small funds, that are likely to face smaller liquidity cost when holding concentrated portfolios. Performance differences between concentrated and diversified portfolios are present in all but the group of largest fund portfolios. The performance gap between concentrated and diversified portfolios can partly be explained by their differing tilt towards priced risk factors such as small-caps and value stocks. I also show that performance differences are most pronounced in stocks with higher information uncertainty. Concentrated managers outperform diversified ones most pronouncedly when investing in stocks with short listing histories, high bid-ask spreads, low analyst coverage and high analyst dispersion.

I am building on a growing literature addressing the influence of concentration and specialization on the performance of professional money managers. Kacperczyk et al. (2006) construct an industry concentration index for U.S. mutual funds. They assign each fund holding to one of ten broadly defined industry groups. The industry concentration index is then based on aggregating the differences between the weights of the industries in the mutual fund portfolio and their weights in the aggregate market portfolio. They find find that U.S. mutual funds exhibit strong differences in the degree of industry concentration. Portfolios including the 5% most industry-concentrated funds generate an abnormal return of 3.31% per annum before expenses, after adjusting for several well-known risk factors. They interpret their result as skilled managers holding more industry concentrated portfolios to exploit industry specific information.

Cremers and Petajisto (2007) use the difference between weights of stocks in managed portfolios and their weights in the benchmark index to construct a measure of management activity. They find that the most active and concentrated funds perform the best over time. Baks et al. (2006) provide similar results in that concentration goes hand in hand with better performance. Sapp and Yan (2008) provide evidence against these previous findings. They show that funds that only hold a small number of assets do not generate higher risk adjusted returns. Such focused funds do, however, charge higher management fees. They report that net of fees, funds with a small number of holdings underperform by 1.44% annually.

The rest of the chapter is structured as follows. In Section 2.2 I describe the construction of my sample. Section 2.3 explains how I measure portfolio concentration, while section 2.4 outlines the performance attribution models I use for comparing concentrated and diversified portfolios. Section 2.5 outlines the results of my analysis and Section 2.6 concludes.

2.2 Data and Sample Selection

My sample consists of U.S. actively managed domestic equity funds with ivestment styles of Aggressive Growth, Growth&Income, Large Growth and Sector Funds. I gather data on their equity holdings from the Spectrum Database maintained by Thompson Reuters. The data originate from regular mandatory filings of every U.S. registered open-end mutual fund with the Securities Exchange Commission. They contain the stock positions of fund portfolios on a quarterly basis from 1980 to 2005[3]. I shrink the sample cross -sectionally by selecting portfolios, whose composition is likely to convey information on the investment ability fund managers. For this reason, I exclude index funds, tax-managed funds, and variable annuities from our sample. Moreover, I select funds with more than $5 million under management and more than 5 reported holdings. I then enrich the quarterly mutual fund holdings information with monthly stock price and characteristics data from the Chicago Center for Security Prices (hereafter CRSP).

Table A.15 provides summary statistics on my sample from the close of 1990[4] to June 2005. Columns 1 and 2 depict how the number of actively managed fund portfolios and their total net assets evolved over time. Both measures give an indication of

[3]Even though the mandatory filing frequency was semi-annual during certain subperiods of the sample, most holdings data are available on a quarterly basis as Thompson Reuters fill in missing data points *ex post* through other sources such as shareholder reports and voluntary disclosures.

[4]Thompson Reuters report holdings from 1980 onwards. I choose the starting point of my analysis later as before 1990 only an insufficient proportion of assets reported by mutual funds can be reliably matched with CRSP data through the historic CUSIP of each security. From 1990 onwards I am able to merge approximately 97% of capital invested in U.S. domestic equity funds to CRSP data.

the enormous growth the industry underwent during the sample period. While 736 funds managed \$211.3 billion at the end of 1990, more than \$2.6 trillion were managed in 1563 funds at the close of 2005. During the same period, U.S equity market capitalization grew from \$3 trillion to almost \$18 trillion.

This implies that the average ownership stake of corporate equity held in actively managed mutual funds more than doubled from 6.7% in 1990 to 14.6% by the end of 2005. Columns 6 to 10 in Table A.15 provide information on the number of stocks held in the portfolios of active fund managers over the years. The mean number of stocks in fund portfolios steadily rose from 68 in 1990 to 110 in 2005. The distribution is consistently positively skewed with a small group of funds holding highly diversified portfolios containing up to 3000 stocks. Still, in 2005, 50% of funds held less than 67 securities in their portfolios.

A number of developments in the mutual fund industry and equity markets in general have caused the increase in the number of reported assets per fund. First, the average fund size in our sample increased from \$287 million in 1990 to \$1.6 billion by the end of 2005. Mutual funds face limits on the amount of capital they can allocate to any single position. The maximum ownership stake mutual funds will take in any single company is not only self-imposed due to liquidity risk considerations but also legal in nature. Thus the increased number of stocks per fund is partly due to mutual fund manager's efforts to manage liquidity risk and adhere to regulation in the light of the rapidly increasing pool of capital under their management.

Second, as documented by Campbell, Lettau, Malkiel and Xu (2001), the idiosyncratic volatility of U.S. equities has increased substantially over the past two decades. This implies that fund managers today hold a larger number of assets in order to achieve a given degree of diversification than they did 15 years ago.

Lastly, the increased cost competition of index funds in the large cap segment of mutual funds has driven actively managed mutual funds to increasingly invest into stocks that are not part of major equity indices, mostly small-cap issues. This tendency is fostered by the common belief that large caps are more efficiently priced and thus less attractive for active fund managers that have to prevail in an increasingly competitive market for investor funds. Column 5 in Table A.15 reports the average market capitalization decile held by the mutual funds in my sample[5]. Clearly, over the sample period active fund managers display an increasing tendency to invest into the smaller capitalization segment of the U.S. stock market. As liquidity and volatility risk inversely relate to market capitalization, funds today are likely to hold a larger number of (smaller) stocks to maintain a given level of portfolio and liquidity risk than 15 years ago.

2.3 Measuring Concentration

The notion of portfolio concentration is not clearly defined. Most intuitively one could think of it as the inverse of the number of stocks held in a portfolio. Measuring concentration in this way, however, ignores the fact that concentration depends on the distribution of portfolio weights within a portfolio. Most managers are likely to tilt their portfolio towards a limited number of their favorite picks in an attempt to maximize the expected return of their holdings. The remaining capital is often used to purchase a larger number of small positions to round off their portfolios. Such positions are often used to ensure diversification and the liquidity of the fund.

Figure A.8 illustrates the distribution of portfolio weights in funds in the sample. The fraction of portfolio capital is plotted against the fraction of stocks contained in a portfolio. Plotting this graph for a particular portfolio will show how strongly it is tilted towards a small number of large positions. A portfolio that allocates equal weights to each holding would be characterized by the

[5]The decile ranks refer to the cross-sectional distribution of market capitalization of stocks traded on NYSE, NASDAQ and Amex at the end of each year.

45 degree line in this plot. Stronger convexity implies stronger concentration of a portfolio's capital into a limited number of names. The bold line depicts the median portfolio in my sample. Fund managers clearly hold a large fraction of their capital in a small fraction of names in their portfolio: In my sample the median manager holds 20% of his capital in 9% of the number of stocks in his portfolio. Almost half of the typical fund's capital is held in a quarter of the names in the portfolio. The thinner solid lines in Figure A.8 trace out the inter-quartile range around the median, while the broken lines are the 5th and 95th cross-sectional percentiles. This shows that the tendency of funds to concentrate their investment into a limited number of stocks vastly varies in the cross-section. Using the number of stocks in a portfolio to proxy for its effective concentration is therefore too simplistic. An effective proxy for portfolio concentration needs to account for the distribution of weights assigned to its members. In what follows, concentration is measured by the normalized Herfindahl index of a portfolio[6]

$$H_{i,t} = \frac{\sum_{j=1}^{N_{i,t}} \omega_{i,j,t}^2 - \frac{1}{N_{i,t}}}{1 - \frac{1}{N_{i,t}}} \tag{2.1}$$

which I calculate for each fund in my sample on every date it reports its holdings. Here i indexes the portfolio, t the time period and j a stock held in portfolio i. The portfolio weight $\omega_{i,j,t}$ is calculated by dividing the value of the position by the total value of assets in the portfolio i at time t. The number of stocks held in portfolio i at time t is denoted by $N_{i,t}$. The normalized Herfindahl index quantifies the extend to which a fund's portfolio deviates from being equally weighted. It is independent of the number of stocks the fund is holding. Thus, a portfolio that contains 100 assets with 99% of its capital equally invested in 10 stocks will be characterized by a similar degree of concentration

[6]For instance Baks et al. (2006) use this statistic to measure the concentration of portfolios. The industry concentration index developed by Kacperczyk et al. (2006) is in spirit related to this statistic.

as a fund that holds an equally weighted portfolio of 10 stocks.

2.4 Performance Measurement

I am interested in testing whether managers, who concentrate their portfolios into a limited number of assets take more informed investment decisions than highly diversified managers. At each quarter-end between Q4/1990 and Q4/2005 I sort portfolios into quintiles of concentration according to their Herfindahl Index. I then calculate the monthly average buy-and-hold performance of portfolios within each concentration group over the quarter that follows.[7]

I first examine the mean-variance performance of the average portfolio in each concentration quintile, by calculating the Sharpe Ratios of each quintile portfolio over the sample period. Second, I provide performance results after controlling for differences in style and liquidity characteristics between concentrated and diversified portfolios. This serves two purposes: first, I would like to study differences in style tilts and liquidity preferences between concentrated and diversified managers. Second, to reveal the extent to which the differential mean-variance performance of fund managers with varying degrees of concentration arises through genuine differences in stock selection rather than differential ex-

[7]These returns calculated directly from fund holdings differ from observed gross-returns on mutual fund portfolios. Kacperczyk, Sialm and Zheng (2008) label this difference the "return gap". It arises for a number of reasons: transaction costs paid by funds to their brokers and the loss of performance due to cash drag tend to decrease reported portfolio returns relative to returns calculated from holdings data. Value-creating trading activity of managers between reporting periods will positively affect observed portfolio returns relative to returns calculated from holdings data. The goal of this analysis is to find out whether active fund managers' holdings signal stock picking ability and in how far it is related to the concentration of their portfolios. This question is distinct from asking whether managers are able and willing to deliver these returns to their fund investors. The holdings-based portfolio returns I am using provide me with portfolio performance, uncontaminated by transaction cost, cash drag and other actions of managers.

posure to cross-sectionally priced risked factors.
In the tables that follow α_4 refers to the risk-adjusted return with respect to a four-factor Carhart (1997) model

$$\begin{aligned} r_t^c - r_{rf,t} = \alpha^c + \beta^c_{MKT} MKT_t + \beta^c_{SMB} SMB_t \\ + \beta^c_{HML} HML_t + \beta^c_{UMD} UMD_t + \varepsilon_t \end{aligned} \tag{2.2}$$

where r_t^c is the equally-weighted return of stocks held in funds in concentration quintile c in month t. The one-month Treasury bill rate is used to proxy for the risk-free rate of return, $r_{rf,t}$. The regressors include the returns on mimicking portfolios for market risk MKT_t, the small firm effect SMB_t, the value premium HML_t[8] and stock return momentum UMD_t[9]. This performance attribution model, also known as the Carhart four-factor specification, is widely used in the literature on mutual fund performance attribution and included here to make my study comparable to previous research. Additionally, I report the risk-adjusted return with respect to a seven-factor model, α_7, that adds three more regressors to the above specification.

$$\begin{aligned} r_t^c - r_{rf,t} = \alpha^c + \beta^c_{MKT} MKT_t + \beta^c_{SMB} SMB_t + \beta^c_{HML} HML_t \\ + \beta^c_{UMD} UMD_t + \beta^c_{SR} SR_t + \beta^c_{IDI} IDI_t + \beta^c_{LIQ} LIQ_t + \varepsilon_t \end{aligned} \tag{2.3}$$

Here, SR_t captures the tendency of stock returns to revert in the short run. For similar reasons as the momentum factor it is included to capture performance due to mechanic investment strategies of fund managers. The data series for the first five factors are downloaded from Kenneth French's website[10]. The model includes an additional factor, IDI_t , to control for the systematic underperformance of stocks with high idiosyncratic volatility. I

[8]The first three factors in the model are also known as Fama-French factors. For the construction of their mimicking portfolios see Fama and French (1993).

[9]This factor captures momentum in stock returns as documented in Jegadeesh and Titman (1993). The exact construction of the factor is described on Kenneth French's website

[10]$http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html$

construct the factor-mimicking portfolio as outlined in Ang, Hodrick, Xing and Zhang (1997), who first documented this anomaly in the cross-section of international stock returns. In particular, I form a value weighted zero-cost portfolio long in stocks with high idiosyncratic volatility and short in stocks with low idiosyncratic volatility. The stock-specific idiosyncratic volatility estimates with respect to a standard CAPM are calculated from daily stock return data. Finally, I control for differences in portfolio liquidity amongst concentrated and diversified managers. Mutual funds are open-ended investment vehicles facing investor redemptions on a daily basis. Thus, portfolio liquidity is a major objective of their managers. Pastor and Stambaugh (2003) show that liquidity is a priced risk factor in the cross-section of the U.S. stock market. Stocks with low sensitivities to innovations in aggregate market liquidity carry a price premium over stocks that provide little insurance against aggregate liquidity shocks. I therefore include a liquidity factor, LIQ_t[11], developed by the authors to control for differences in the sensitivity of fund portfolios to changes in aggregate market liquidity.

Lastly, I evaluate the performance of funds by adjusting the returns on their holdings directly for size, book-to-market, and momentum characteristics as suggested by Daniel, Grinblatt, Titman and Wermers (1997). Instead of controlling for size, book-to-market and momentum features of fund portfolios via a factor regression this method directly matches each stock to a portfolio of stocks with similar size, book-to-market and momentum features. The method is commonly employed in performance evaluation studies that use holdings data. I include it here not only to make my results comparable to the previous literature on the topic. Daniel et al. (1997) also show that their method has more statistical power in detecting abnormal performance than standard factor models. I thus add two more performance statistics to my analysis. First, the average characteristics-adjusted return

[11]For details on the construction of this factor portfolio see Pastor and Stambaugh (2003)

as suggested in Daniel et al. (1997), α_{DGTW}. Second, I report the characteristics-adjusted return after controlling for short run reversion, idiosyncratic volatility and liquidity using the factor regression approach outlined above.

2.5 Results

a Differential Performance of Concentrated and Diversified Portfolios

The first two columns in Table A.16 contain the average excess-return and Sharpe Ratio of stocks held in each concentration quintile from the end of 1990 to the end of 2005. The stock picks of the 20% most concentrated funds in my sample generated an average monthly return of 98 basis points in excess of the risk-free rate, while the average return in the most diversified quintile lies at 83 basis points. This translates into a annual performance difference of approximately 1.8%. The better performance of very concentrated portfolios does not vanish when adjusting for volatility risk. Concentrated fund portfolios generate higher Sharpe Ratios than highly diversified portfolios. Nevertheless, performance does not seem to be linearly increasing in concentration. Only the quintile of most concentrated funds can really distinguish itself in mean-variance performance from the rest of the sample.

The factor regressions described in the previous section unveil differences in investment preferences between managers of diversified and managers of concentrated portfolios. Diversified managers on average hold stocks with higher beta risk than the typical concentrated manager. All concentration portfolios load positively on the small-firm risk factor. This is not surprising as the concentration portfolios are equally weighted and therefore by construction load positively on the size factor. Concentrated managers as a group, however, expose their portfolios significantly less to stocks with smaller market capitalizations than diversified managers. Similarly, the average portfolio in my sample tilts towards value stocks that carry a return premium but concentrated portfolios do so to a lesser extent than diversified ones.

The loadings on momentum and short run reversion reveal that diversified managers are contrarian, which is consistent with their preference for value stocks. Concentrated managers on the other hand tend to follow momentum strategies. As expected, the loadings on the short run reversal factor have opposite signs to momentum exposure: Concentrated investors are unfavorably exposed to return reversal, while diversified managers benefit from this empirical regularity in the cross-section of U.S. stock returns.

Concentrated and diversified managers also differ in their preference for idiosyncratic volatility. Diversified managers as a group hold stocks with idiosyncratic volatility below the median of the CRSP universe. Concentrated portfolio managers have a slight tendency to hold stocks with above-median idiosyncratic volatility. Given that such stocks command a price premium, the performance of concentrated portfolios is reduced.

As expected, highly concentrated managers limit their portfolios' exposure to market wide liquidity fluctuation. Diversified portfolios show less tilt towards liquid stocks. Given that liquidity is priced in the cross-section of stocks, concentrated managers pay a premium for holding more liquid portfolios.

In sum, the average performance of diversified managers' portfolios can be explained by their exposure to well known and priced risk factors. Diversified portfolios tilt towards small and illiquid value stocks. Once I adjust for these investment style differentials, concentrated mangers clearly demonstrate more skill in stock selection than diversified managers. Stocks held by the 20% most concentrated managers earn a statistically significant excess return of 1.6% to 1.7% per annum, depending on the method of risk-adjustment. The risk-adjusted performance of picks by the most diversified quintile of managers ranges from 0% to -2.3% per annum. The difference between both groups ranges from 1.4% to

4% per annum and is statistically significant for all four models of risk adjustment that I use.

b Concentration, Fund Size and Performance

Chen, Hong, Huang and Kubik (2004) show that mutual fund performance is decreasing in the dollar amount of assets under management. The authors argue that this is mainly due to high liquidity cost as well as organizational diseconomies of scale of large funds. The degree of portfolio concentration is naturally decreasing in the size of the fund's asset base. This relation does not only arise through regulatory disincentives for fund managers to take on large stakes in the equity of listed firms. The fact that mutual funds are open-ended investment vehicles, facing changes to their asset base on a daily basis creates substantial risk of forced liquidations on behalf of the fund manager. Coval and Stafford (2007) show that cash flows in and out of U.S. mutual funds significantly affect the performance of the assets they hold. The ownership of substantial equity stakes in firms increases the cost of transactions in such situations. Performance leakage through funding shocks as well as generally increased transaction costs in large equity stakes induce managers of growing funds to increase their diversification. Managers trade off realized and expected liquidity cost of holding a concentrated portfolio of their top picks against lower expected performance by diversifying their portfolios into stocks they display less conviction about.

In order to study the interaction between size and concentration in determining portfolio performance, I measure the performance of concentrated vs diversified portfolios after conditioning on the size of assets under management. Each quarter I form 25 portfolios, by first sorting the sample of funds into quintiles of fund size. Within each of these five groups I then sort portfolios into five groups of concentration and measure their out-of-sample performance. I report the risk-adjusted returns (α_4,α_7,α_{DGTW},α_3) of the 25 portfolios that result from the double sorts in table

A.17. In bold, I provide the risk-adjusted spread returns between the 20% most concentrated and 20% most diversified portfolios within each quintile of fund size.
The effect of portfolio concentration on performance is independent of the size of the fund. The results in table A.17 show that concentrated portfolios outperform diversified ones in virtually all size groups. The most concentrated portfolios in the group of medium-sized funds generate a risk adjusted return between 21 and 26 basis points per month, which indicates that also some medium-to-large mutual fund managers concentrate their portfolios sufficiently to beat their benchmarks as well as their diversified peers. This shows that even though fund size and concentration are related their effects on performance are distinct.

c Uncertainty of Information

The results presented so far show that concentrated funds generate their performance to a large extend through genuine stock picking. Highly diversified managers on the other hand tend to tilt their portfolios towards risk factors that are priced in the cross-section of stocks.
These results support recent theoretical research by Nieuverburgh and Veldkamp (2008), who develop a rational expectations model in which investors simultaneously take investment and information acquisition choices. They explicitly show that the interaction between both decisions generates gains to specialization: Investors with constrained information processing capacities choose between getting well informed about few stocks or badly informed about many. Concentration arises as the more an investor holds of a particular asset the more valuable it is to acquire more information on it. In turn, as investors learn more about an asset, the more valuable it is to invest into it. In equilibrium more concentrated portfolios have higher expected returns than diversified ones.
One feature of the model is that managers will focus their efforts on learning about assets for which information is scarce.

Information is a strategic complement as investors try to learn about assets that others do not. Thus, performance differentials between concentrated and diversified managers are likely to be more apparent when investing into assets for which information is scarce and uncertain. Zhang (2004) shows that such uncertainty delays the flow of information into stock prices creating opportunities for skilled investors. He defines information uncertainty as the ambiguity regarding the implications of information on the value of a firm. Zhang is able to show that pricing anomalies such as the post-earnings announcement drift are significantly more pronounced in stocks for which information is scarce and uncertain. It is crucial to note that information risk does not appear to be cross-sectionally priced: Investors are not rewarded for taking on information risk per se. On the contrary, blind investment into assets with high information uncertainty is shown to be a *losing* investment strategy[12]. Thus, while any mutual fund manager will find it harder to generate risk-adjusted returns from stocks with high uncertainty of information, benefits to managing a concentrated portfolio should be more apparent in investments characterized by high information uncertainty.

In order to test this hypothesis, I employ four proxies for information uncertainty commonly used in the literature. First, I use the time span a company has been listed on a U.S. stock exchange. Stock market listing increases the transparency of companies as they are subject to stricter reporting standards than unlisted firms. Older companies with longer histories of stock market listing are likely to have more information available to the market than young firms. Zhang (2004) also shows that the age of stock market listing is positively correlated with the maturity of the industry it operates in.

Second, the bid-ask spread of stocks is commonly used to measure asymmetries in information and valuation between buying and selling parties. Controlling for the market capitalization and

[12] For examples see Ackert and Athanassakos (1997), Ang and Ciccone (2001), Diether, Malloy and Scherbina (2002)

turnover of a stock, a history of high average bid-ask spreads indicates investor uncertainty about the valuation of an asset. We thus calculate the average bid-ask spread for each stock in the CRSP database from daily data over the past three month and use it as our second proxy for uncertainty of information.

Third, sell-side equity research is a major source of information in U.S. stock markets. Analysts collect and process company specific information and sell it to investors. Brown, Wei and Wermers (2008) find that the typical mutual fund manager follows analysts recommendations closely. I thus use the number of analysts following a firm during the most recent 12 month period as a third proxy for information certainty.

Finally, the dispersion of analysts' earnings-per-share forecasts (EPS) is commonly used to measure the uncertainty of asset-specific information. I use earnings per share in contrast to other forecasts as it is the most widely reported statistic by equity analysts. High dispersion of EPS-forecasts not only represents substantial noise in a major investment signal to investors. It also indicates that a group of informed individuals arrives at significantly different conclusions about the earnings prospect of a firm. I measure analyst opinion dispersion for a stock by the scaled standard deviation of EPS estimates throughout the preceding 12 month. I use data from I/B/E/S to calculate both, the degree of analyst coverage and dispersion in their opinion.

Each of these four measures of information uncertainty is used to split the sample of stocks held by the entire fund industry into two groups. I then evaluate the performance of concentrated and diversified managers in each of the two stock segments. The tables that follow report the risk-adjusted performance by quintiles of concentration and by information-uncertainty-segment. Besides the reasons mentioned above, I benchmark managers' returns as my proxies for uncertainty of information are likely to be correlated to a number of stock characteristics, in particular size, liquidity and idiosyncratic risk. The adjustment for firm size differentials is of particular importance here, as my measures of uncertainty are highly correlated with the market capitalization of companies: Large caps are generally seasoned companies that are covered by many analysts, who are likely to display stronger agreement in their EPS forecasts. Also bid-ask spreads are negatively related to market capitalization. Both factor models control for systematic differences in the pricing of stocks with different market capitalizations indirectly through the size risk factor (SMB). The characteristics-adjustment method *explicitly* controls for systematic return differentials in stocks with different market capitalizations.

Table A.18 summarizes the results of splitting the sample by firm age. The high loadings on SMB in the panel of young stocks confirm that firm age and size are positively correlated. Moreover, mutual funds' investments in young firms are visibly more tilted towards growth stocks with strong momentum than their investments in old firms. As expected, I find that young firms have significantly higher systematic and idiosyncratic risk exposures than seasoned companies. After controlling for various investment styles all four risk-adjusted returns indicate that mutual fund managers are generally more successful in picking seasoned companies than young firms. Within both age groups, concentrated portfolios perform better than diversified ones. Comparing the performance spreads across firm age groups, I find the performance advantage of concentrated managers is significantly larger for investments into young companies. Even though concentrated managers do not clearly generate higher returns by investing into younger rather than older firms, diversified managers underperform more pronouncedly, when investing in young firms rather than seasoned companies.

In table A.19 I report the performance results when the bid-ask spread is used as a proxy for information uncertainty. It shows that fund holdings with high average bid-ask spreads are generally small glamour stocks. Concentrated mutual funds earn significantly larger risk-adjusted returns on high bid-ask spread stocks. It is evident that the majority of their risk-adjusted performance is generated in stocks with above median bid-ask spreads. Diversified managers on the other hand fail to generate risk adjusted returns in both segments of information uncertainly. Again this supports the hypothesis that concentrated managers have an informational edge above diversified ones, which is particularly apparent in stocks about which information is uncertain and asymmetrically distributed among market participants.

I discover similar results when using analyst coverage and forecast dispersion to proxy for information uncertainty. As for the case of firm age, the results in Table A.20 indicate that overall portfolio managers perform better when investing in stocks that are covered by a large number of analysts. The differences in performance between concentrated and diversified managers, however, are more pronounced in stocks for which coverage is low.

Table A.21 covers the performance results when splitting the investment universe of managers by dispersion in EPS estimates. First I can clearly confirm previous results on the cross-sectional pricing implication of analyst dispersion. Mutual fund holdings with high analyst dispersion clearly underperform holdings for which EPS forecasts signal high analyst agreement. Even the quintile of most concentrated managers does not seem to generate positive alpha in stocks with high dispersion. Nevertheless, the results support my previous conclusions that concentrated managers' performance is less affected in this sector than the performance of their diversified colleagues. The risk-adjusted performance spread between concentrated and diversified managers is significantly larger for stocks with high analyst disagreement. It does remain to be explained, however, why fund managers, particularly diversified ones, choose to invest into this segment of stocks at all.

2.6 Conclusion

This chapter outlined differences in investment behaviour and performance between managers of concentrated and diversified portfolios. In particular I am interested in whether the portfolios of concentrated managers that focus their research efforts on a limited number of stocks, signal better investment decisions than those of managers with highly diversified portfolios. I find that stocks held by mutual fund mangers with highly concentrated portfolios outperform the picks of managers with diversified portfolios. The risk adjusted spread return between picks of the 20% most concentrated and diversified managers ranges from 1.4% and 4% per year, depending on the type of risk adjustment employed. This performance differences can on the one hand be partly explained by diversified managers' stronger tilt towards cross-sectionally priced risk factors, such as firm size and value. Concentrated mangers on the other hand tend to pay a premium for holding more liquid portfolios than diversified managers. The performance differences are most pronounced in assets for which information is scarce and uncertain. Diversified managers most clearly underperform concentrated managers as well as their benchmarks in stocks with short listing histories, high bid-ask spreads, low analyst coverage and high dispersion of analyst opinion. As such, these results support the predictions of recent theoretical work by Nieuverburgh and Veldkamp (2008), who develop a model explaining the apparently irrational under-diversification of private and professional investors. Practically speaking these results suggests that investors are better off diversifying their equity portfolios over a number of specialized managers rather than holding one highly diversified fund. Whether or not mutual fund investors can actually capture the informational advantages of concentrated managers is still an open question and will be the topic of future research.

3 Information-Based Trading in the American Mutual Fund Industry

3.1 Introduction

At the end of 2005, American mutual funds had $8.9 trillion of investors money under management[1]. Every year mutual fund investors pay billions of dollars to fund managers for taking over the task of investing their savings in a skilful manner. This task comprises the identification of promising investment opportunities and the determination of the timing as well as the optimal size of the transactions in these assets. The ability of active mutual fund managers to live up to investors' expectations has been questioned by practitioners and academics alike. The motives of industry insiders such as John Bogle[2] to underline the advantages of passive index benchmarking over active investing seem fairly clear. The doubt of academics about the value of active mutual fund management has been fueled by the dominance of the efficient markets paradigm during the 1970's and 1980's. Thus, most traditional management performance studies have concluded that active managers neither possess stock selection nor market timing abilities[3]. Even more strikingly, Carhart (1997) claims to find an inverse relationship between the degree of active management and performance net of fees. The harder managers try, the worse they perform.

This rather pessimistic view on the value of active mutual fund management has since improved with the findings of more recent research. The newer literature can roughly be divided into two groups. The first branch focuses on the development of accurate performance measures. It includes the application of Bayesian techniques that allow to systematically enrich the information set of the researcher beyond fund portfolio returns to make sharper

[1] Factbook 2006, Investment Company Institute. Available at http://www.icifactbook.org

[2] John Bogle is the Founder of Vanguard Funds

[3] Treynor and Mazury (1966), Jensen (1968), Lintner and John (1969)

inferences on the distribution of skill in the industry[4]. Other studies employ flexible parametric models, accounting for non-linearities in trading strategies of mutual fund managers[5]. The results from these efforts unequivocally point to the existence of substantial differences and persistence in portfolio management skill within the American mutual fund industry.

Instead of using observed portfolio returns to measure the skill of mutual fund managers, the second branch of the newer literature on mutual fund performance directly examines asset holdings of mutual funds. Such disaggregated data gives a more detailed and direct view on mutual fund mangers' actions. Researchers have used these data to specify benchmarks against which fund managers should be evaluated[6] and to judge stock-picking and market-timing abilities of managers in a more direct way[7]. More recently Cremers and Petajisto (2006) find a clear positive relationship between the net performance of portfolios and the degree of their managers' trading activity.

In this chapter, I focus on the information content of observed mutual fund portfolio rebalances by U.S. mutual fund managers. In particular, I am interested in whether recent trading decisions of historically successful managers predict future stock returns. This question is interesting for a number of reasons. First, it provides additional evidence on the existence and persistence of abnormal investment performance among U.S. fund managers. As argued by Chen et al. (2000), "asset trades are likely to represent stronger management opinion about value than the passive decision to hold an asset in the portfolio" (ibid, p.12). The argument is fostered by the fact that trading results in transaction cost and tax liabilities. Concentrating on the performance of incremental changes to the portfolio rather than fund performance overall is therefore likely to give a clearer picture of the viability

[4]Baks, Metrick and Wachter (2001), Pastor and Stambaugh (2002), Jones and Shanken (2002), Huij and Verbeek (2007)

[5]See Maymansky, Spiegel and Zhang (2006)

[6]Daniel and Kent (1997)

[7]Grinblatt and Titman (1989), Chen et al. (2000), Wermers (2000)

of valuation-driven decisions on part of the fund manager.
Second, the analysis provides input to the ongoing discussion about mutual fund portfolio transparency. Currently, every U.S.-registered mutual fund is obliged to periodically report its entire portfolio to the Securities Exchange Commission, which in turn makes this information publicly available. Given that particularly large mutual funds build positions in stocks over extended periods of time, this might allow outsiders to front-run funds' trading and harm their performance. Thus, while the S.E.C. transparency legislation aims at protecting fund investors, it might indirectly harm them by reducing the performance of their investments.
Third, as mutual fund holdings become public through the fund filing process the results to this analysis indicate whether U.S. stock markets have been efficiently incorporating this information into prices.
My results point to the existence of substantial differences in the abilities of active mutual fund managers to predict future stock returns and to trade accordingly. The quality of managers' trading decisions is measured by the risk adjusted out-of-sample performance of the assets they have been trading most recently. Managers that have been evaluated to be skilled *ex ante* take significantly better *ex post* purchase and sales decisions than managers that have been initially identified as unskilled. Skilled managers are not only able to identify stocks that beat their benchmark out of sample. They also show statistically and economically significant abilities in trading these assets in appropriate amounts. This stands in stark contrast to the set of unskilled managers, who systematically commit errors in the selection and trading of assets.
Methodologically this analysis is most closely related to Baker, Litov, Wachter and Wurgler (2004). The authors study information-based trading in the mutual fund industry from evidence on transactions prior to corporate earnings announcements. They find that the average fund manager possesses statistically signifi-

cant skill in predicting stock returns related to earnings surprises. This chapter is structured as follows: Section 3.2 discusses the data and methodology employed in the analysis. The results of the analysis are presented in Section 3.3 and tested for their robustness in Section 3.4. Section 3.5 describes and back-tests trading strategies based on the results of the preceding analysis and Section 3.6 concludes.

3.2 Methodology and Data

I am interested in the *ex post* differences in the extend of information-based trading between managers that can be classified as skilled and unskilled *ex ante*. The measure of skill, alpha (α_f), is defined as the performance of a managed portfolio adjusted for commonly known risk factors. Further in the text, the set of skilled managers (S) will be defined as managing portfolios with positive alpha and the set of unskilled managers (U) as managing portfolios with negative alpha. Before each date of portfolio disclosure, I estimate this performance measure for the entire cross-section of U.S. mutual funds using the following 4-factor Carhart model

$$r_{f,t} = \alpha_f + \beta_f^M r_{M,t} + \beta_f^{SMB} r_{SMB,t} + \beta_f^{HML} r_{HML,t} + \beta_f^{MOM} r_{MOM,t} + \varepsilon_{f,t} \tag{3.1}$$

where $r_{f,t}$ is the historic gross return on the fund portfolio in month t and $r_{M,t}$ the return on the CRSP value-weighted market portfolio in month t. All returns are expressed in excess of the risk-free interest rate. The gross returns on the fund portfolios computed from from data of the CRSP Survivorship-Bias-Free Mutual Fund Database, hereafter SBFMFD, and are calculated by adding the monthly increment of the expense ratio to the net returns provided in the database. The regressors $r_{SMB,t}$ and $r_{HML,t}$ are returns on zero-cost portfolios capturing the small-firm and value-effects. The momentum factor $r_{MOM,t}$, conceptually following Jegadeesh and Titman (1993), is the return on a zero-cost portfolio long in winning stock and short in losing stock during the 6 month prior to its formation. Not being a risk factor *per se*, it is included in this specification to control for mechanical momentum strategies pursued by mutual funds, which cannot be attributed to distinctive stock selection or market timing skills. The data on all four explanatory variables in model (3.1) were downloaded from Kenneth French's website[8].

The sample under consideration is drawn from the population of all actively managed domestic equity funds, classified as aggressive growth, growth & income as well as large growth listed in SBFMFD. The period considered ranges from July 1981 to March 2005. Index trackers were eliminated from the sample. The resulting sample of actively managed US-fund offerings is chosen to correspond with the risk adjustment model described above. It includes funds that can invest in a large class of U.S. equities, whose risk is likely to be priced by the four factors in model (3.1). Applying the model to funds with more narrow investment objectives could lead to a misinterpretation of the respective fund managers' skills, relative to each other. The sample is therefore selected to minimize performance inference errors due to benchmark misspecification[9]. Equation (3.1) is estimated for each share class in the cross-section using a rolling 48-month window beginning in Q3/1983 and ending with Q1/2005. Hence, the evaluation period runs from the end of quarter 2 of 1985 to the end of quarter 1 of 2005.

The central part of the chapter studies differences in the extent of informative trading between skilled and unskilled managers. In order to do so, two more data sources are used. First, Thompson Financial offers data on mutual fund portfolio holdings, better known as the CDA/ Spectrum database. Second, CRSP data on U.S. equity returns of companies listed on the NYSE, NASDAQ

[8]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[9]Coles, Daniel and Nardari (2006) run Monte Carlo studies to show that benchmark misspecification leads to strong biases in performance ranks, while model misspecification impacts overall performance rankings to a lesser extent.

and the AMEX is matched to the equity holdings data. The holdings data is used to gather a snap-shot of each fund's portfolio at the end of every quarter during the sample period. It is compiled from mandatory filings of all fund companies registered with the SEC[10]. The change in the composition of a fund's portfolio allows to infer the security transactions made by its manager during each quarter, but obviously not their exact timing.
At each quarter end, the trades of every fund are classified into four different groups by comparing the current portfolio with the one of the preceding quarter. I then classify each trade into one of four groups. Additions to existing positions (A), reductions of existing positions (R), new positions (N) and deletions (D). For both, the group of skilled and the group of unskilled managers, equally-weighted "trade portfolios" are formed that are long in A, R, N, and D over the quarter following the publication of the fund portfolios. The trade portfolios are rebalanced each quarter to reflect the changes in the composition of S and U as well as the trades made by these groups during the preceding quarter. This results in eight monthly time series of trade portfolio returns spanning the 20 year period from July 1985 to June 2005. The maximum turnover of these portfolios is 400% p.a., by construction.
Figure A.9 shows the evolution of the number of stocks in these eight portfolios, for both, the set of skilled and unskilled managers over the period under consideration. Several points should be noted. First, the number of quarterly additions to fund portfolios are closely matched by the number of reductions, while the number of new acquisitions is matched by the number of deletions. This effect is particularly visible for the set of skilled individuals and suggests that managers try to keep the number of assets in their portfolio constant over time. Moreover, A's are generally replaced by R's, while N's seem to be replaced by

[10]Even though the mandatory filing frequency to the SEC was semi-annually during certain periods, most holdings data are available quarterly as Thompson Financial fill in missing data points through other sources such as shareholder reports and voluntary disclosures.

D's. Second, while no particular trend in the number of acquisitions and deletions is detectable, additions and reductions seem to have increased over time. These results should not be interpreted as being due to the trading behaviour of managers but rather caused by the construction of the portfolios. An asset is qualified as $N(D)$ if its *average* holding over all managers in a particular skill group at the preceding (current) quarter end is zero while its average position over all managers at the current (preceding) quarter is positive. As more and more managers trade the same assets over time, the likelihood of an asset belonging to N or D decreases relative to the likelihood of this asset belonging to A or R. This explains why A and R increase in number over time, while the number of N and D is approximately constant.

In addition to the above mentioned equally weighted portfolios, further portfolios are constructed using two different weighting methods. The first method is designed to capture the average size of the trade in assets included in A, R, N and D. Each stock in these portfolios is therefore weighted by the average active change in the portfolio weights of managers invested in this stock. The attribute "active" indicates that the portfolio weight change is deflated by the return of the stock during the trading quarter.

The second weighting scheme uses the absolute value of the alpha estimate of the manager making a particular asset transaction. With alpha being a measure of portfolio management skill, it is reasonable to assume that managers with higher (lower) past risk adjusted performance should on average make better (worse) asset choices. Both alternative weighting schemes aim to answer two distinct questions, by comparing the performance of the equally weighted portfolio to the respective weighted portfolio. Comparing the equally weighted portfolios of A, R, N, and D with their trade-size-weighted counterpart shows whether skilled (unskilled) managers do not only make well (badly) informed choices on *what* but also on *how much* they buy or sell. Comparing the equally weighted portfolios to their alpha-weighted

counterparts shows whether better (worse) managers within skill groups take better (worse) asset choice decisions.
Figure A.10 summarizes how the trade portfolios are constructed for skilled and unskilled managers. It is crucial to understand that the portfolios are formed on past and present information at any point in time. One issue that might be of concern is the fact that funds must have a minimum return history of 48 months to be included in the analysis. It is not entirely clear how the exclusion of funds that are younger than four years biases the performance of the forward looking portfolios. Huij and Verbeek (2007) show that young funds persistently outperform older funds on a risk adjusted basis. The exclusions of young funds is therefore likely to deflate the size and possibly the out-of-sample performance of the skilled set of managers[11].

3.3 Results

a Average and Mean Variance Performance of Trade Portfolios

Table A.22 summarizes the stochastic features of the trading portfolios constructed over the entire sample period from July 1985 to June 2005. It allows for a basic comparison between the stock selection abilities across skill groups of managers. The left panel of Table A.22 refers to the portfolios formed on trades observed by skilled managers, while the right panel refers to trades made by unskilled managers. The vertical subsections refer to the weighting method employed when forming the portfolios.
The summary statistics on the eight equally-weighted portfolios suggest several differences across skilled and unskilled managers

[11] An *ad hoc* solution to this problem would be to reduce the size of the estimation window. This, however, would sacrifice precision of the performance measure (alpha). An elegant solution would be the use of Bayesian estimators that allow relatively precise inference using short return histories. See Huij and Verbeek (2007) or Pastor and Stambaugh (2002) for examples of these techniques.

to trade a stock based on its prospects over the next quarter. First, the trading decisions of skilled managers seem to be consistent with information-based trading. The Sharpe Ratio of new additions is larger than the Sharpe Ratio of deletions. The average return on the new acquisitions of good managers exceeds the average return of their deletions by 83 basis points per month. The Sharpe Ratio of skilled managers' additions is larger than that of their reductions. The difference in monthly returns between additions and reductions is 9 basis points for skilled managers. Second, the same can be said, although to a much weaker extend, for the set of unskilled managers, when judging performance by the Sharpe ratios of the trade portfolios. At 35 basis points, the difference between the returns on new acquisitions and deletions is less than half for unskilled managers compared to skilled managers. The return difference between additions and reductions of unskilled managers is negative.

Comparing the performance of the four different portfolios *across* the two sets of managers gives further support for differences in the trading success of skilled and unskilled managers. While additions and new acquisitions of skilled managers perform better than additions and acquisitions of unskilled ones, the result is reversed in the case of deletions. The deletions portfolio of U outperforms the one of S in terms of average returns and its Sharpe Ratio. The purchase portfolios of skilled individuals (A_S, N_S) furthermore exhibit less excess kurtosis and are more positively skewed than the purchase portfolios of U, which are two desirable properties of managed portfolios. This suggests that skilled managers take systematically better purchase decisions than unskilled ones, but also have better abilities to identify assets that should be deleted from their portfolios.

At a first glance, the data suggest that the two different sets of managers (S, U) possess unequal skills in selecting *what* to include in or delete from their portfolios. A natural questions that arises is whether skilled managers also possess better judgement in choosing *how much* they purchase or sell of each security. Comparing the results on the equally-weighted portfolios with the results on trade-size-weighted portfolios in Table A.22 gives a basic answer to this question. While skilled managers clearly exhibit abilities in selecting how much to sell (D_S, R_S) and newly acquire (N_S) of each asset, this cannot be said for their additions to existing positions (A_S). The Sharpe Ratio of the trade-size-weighted additions portfolio is slightly lower than the Sharpe Ratio of the equally-weighted additions portfolio. Unskilled managers, on the other hand, exhibit remarkable abilities to take wrong decisions with respect to the quantities they trade of each security. Both of unskilled managers' purchase portfolios (N_U, A_U) are characterised by lower Sharpe Ratios once weighted with the trade-size measure. More strikingly, they seem to systematically reduce assets that perform well during the following quarter to a larger extend than ones that perform badly. This can be inferred from the fact that the portfolio of trade-size-weighted reductions of unskilled managers belongs to the top performing portfolios studied in Table A.22.

The last vertical section in Table A.22 indicates that there is not much information to be gathered from the absolute size of the performance measure. The relative weights of assets in these portfolios are determined by the absolute value of the alphas of managers trading them. Better individuals within the set of skilled managers do not take unambiguously better trading decisions than the rest of this subset. The worst individuals within the set of unskilled managers do not seem to trade significantly worse than slight underperformers. The likely reason for this result is that the hypothesis tested here puts too much confidence into the estimated performance measure α_f. A large number of the estimated alphas in regression equation 3.1, are not statistically significant. While this does not impede the measure's usefulness in splitting the sample of managers into a group of skilled and unskilled individuals, the estimation error in the alphas is too large for making finer skill-differentiations between managers. Again, the use of estimation techniques that allow

sharper inferences on the parameter values in equation 3.1, could be a fruitful step ahead on this matter.
In addition, as Huij and Verbeek (2007) show in Monte-Carlo simulations, cross-sectional-alpha rankings of mutual funds based on factor regressions suffer from sampling errors. This is particularly true for the extreme tails of the estimated cross-sectional skill distribution. Put differently, extremely high (low) alpha estimates are more likely to be due to good (bad) luck, as compared to true skill, than alpha estimates closer to the centre of the distribution. This implies that the performance weighted portfolios in Table A.22 are tilted towards the trading behaviour of managers who have been lucky over the previous evaluation period rather than skillful. Huij and Verbeek (2007) show that these problems can be solved by applying a Bayesian alpha estimator that systematically shrinks sampling error sensitive candidates towards the center of the posterior alpha distribution.

b Factor-Risk Adjusted Performance of Trade Portfolios

Until now, the analysis was focused on apparent differences in skill from the perspective of an investor whose only source of risk arises from the variance of returns. Also, it is not yet clear, whether the performance differences apparent in Table A.22 are statistically significant once well known risk factors are controlled for. It is crucial to understand whether skilled managers achieve significantly higher out-of-sample trading performance through truly superior stock selection and weighting abilities or simply by exposing their portfolios more aggressively to risk factors, that are known to be rewarded in financial markets. In order to shed light on these issues Table A.23 provides the results of regressions taking the following general form.

$$r_{i-j,t} = \alpha_{i-j} + \beta_{i-j}^{M} r_{M,t} + \beta_{i-j}^{SMB} r_{SMB,t} + \beta_{i-j}^{HML} r_{HML,t} + \beta_{i-j}^{MOM} r_{MOM,t} + \varepsilon_{i-j,t} \quad (3.2)$$

The factor structure of specification (3.2) is identical to the one in specification (3.1). The dependent variable is the return spread between portfolio i and j. Thus, the coefficients on each of the four factors in specification (3.2) allow to determine the sources of the performance differential between portfolios i and j. The point estimate of the intercept α_{i-j} indicates whether the differential performance of i and j is due to reasons outside the scope of the four risk factors, such as differences in the stock selection skill of individuals who manage the portfolios.

Table A.23 provides the results of regression equation (3.2) when applied to the spreads of $N-D$ and $A-R$ of skilled and unskilled managers, respectively. The left panel refers to the spreads calculated from equally-weighted portfolios, while the right panel refers to spreads that are calculated from portfolios weighted by the size of trades. The statistics provided in Table A.23 therefore allow inferences on the out-of-sample quality of managers' purchase decisions as compared to their *own* sales decisions.

The first point to notice is the strong positive loading of all portfolios on the momentum factor, suggesting that skilled as well as unskilled managers heavily rely on momentum strategies in their trading decisions.

An alternative explanation for the high loadings on the momentum factor refers to the construction of the portfolios. The formation of the portfolios is based on trading decisions taken during the preceding quarter. If mutual funds exert significant contemporaneous price pressures through their trading, the positive loadings on the momentum factor arise by construction: Stocks that have been purchased (sold) last quarter experienced positive (negative) price pressure during that period. The momentum factor, on the other hand, is mimicked by a portfolio that buys winners and sells losing stocks of the past six months. The portfolio spreads between stocks that have been purchased and sold last quarter are therefore positively correlated to the momentum portfolio. Also, the fact that the momentum loadings are unambiguously higher for the trade-size-weighted portfolios, supports

the price pressure explanation.
The size and significance of loadings on the remaining factors suggests that skilled managers are more consistent in following trading strategies that exploit the small-firm and high-book-to-market effects than unskilled managers. The returns on the $N-D$ spreads load highly on the size factor for both manager groups, but to a greater and more significant extend for skilled managers. The $A-R$ spreads load positively on the book-to-market factor, but again more so for the set of skilled managers. The only perverse result in this respect is the negative loading of the equally weighted $A_S - R_S$ spread on the size factor for skilled managers. It is however, the only one of the above mentioned results that vanishes once the trade-size weighting is applied.
The most striking results in Table A.22 are the significance and sign of the risk adjusted spread returns (α). For the group of skilled managers, the risk adjusted performance of the equally weighted $N_S - D_S$ spread is 42 basis points per month. This performance difference almost doubles to 80 basis points when the size of transactions are taken into account. Both alphas are greater than zero at a 5% level of significance. This is not true for the spread between additions and reductions of existing positions by skilled managers. They are statistically indistinguishable from zero, once risk factors are controlled for. Unskilled managers on the other hand seem to exhibit statistically and economically significant adverse trading skill. The $A_U - R_U$ spread portfolio of unskilled managers yields a statistically significant monthly loss of 12 basis points. This loss rises to 70 basis points per month and increases in statistical significance when the size of the individual transactions is considered. This result is statistically the most reliable in Table A.23. It leads to the somewhat cynical conclusion that an outside investor is well advised to follow the opposite trading strategies of unskilled managers than to copy the trades of skilled managers. The implementability and profitability of such trading strategies is explored in section, 3.5.
To complete this section the performance difference of the new

acquisitions, additions, reductions and deletions across the sets of skilled and unskilled managers is presented in Table A.24. In spirit similar to the above discussion, spreads are constructed for this purpose. Here however, spreads refer to differences between S and U. For instance, the first column of Table A.24, headed by $N_S - N_U$, depicts the results of regressing the spread between new acquisitions of skilled and unskilled managers on the risk factors in specification (3.2). The risk adjusted difference in performance between skilled and unskilled managers fosters the impression that there exist significant differences in trading abilities. This is particularly true for the purchase activity of managers. New acquisitions of S outperform the ones of U by 49 basis points per month on a risk adjusted basis. Once the size of the position-changes are accounted for this statistic rises to 74 basis points. Additions to the portfolio of S outperform additions of U by 18 basis points. Similarly, if the size of trades is taken into account this performance spread rises to 40 basis points. All of the estimates are significantly larger than zero at 5%. The same trading skill difference cannot be found on the sale side of the portfolios. All spreads are generally negative and decrease with weighting, which one would expect *a priori*. However, none of them is statistically significant at any conventional level.

3.4 Robustness

In order to check the stability of the results over the 20 years under consideration, all regressions reported in the previous section are estimated separately for two non-overlapping 10-year periods. The first sample covers the time span from July 1985 to June 1995, while the second one covers the period from July 1995 to June 2005. Table A.25 reports the results of this robustness check. The bold statistics refer to estimates from the second period. The t-statistics in parentheses below the coefficients are calculated using the Newey-West procedure. They are robust to

the presence of heteroskedasticity and first-order autocorrelation in the error structure of specification (3.2).
A first point to notice is the significantly better fit of the spread regressions in the second sub-sample. Disregarding the fact that relatively low R^2 are expected a priori, when spreads between portfolios are regressed on risk factors, it is likely that the fit of the regressions increases as portfolios contain more assets during the second sub-period. The coefficients on the size and book-to-market factors are very unstable over time for all portfolios in Table A.25, often even reversing their sign. No time trend in the size or the significance of the factor loadings is apparent. In contrast, the size as well as significance of the momentum factor increases systematically over time for all portfolios. This provides further support for the price pressure explanation of the positive loading on this factor, as the relative trade share of mutual funds in American stock markets has increased over time. Certainly it is also possible that managers trade stronger on momentum, as this empirical fact in stock returns has been better understood during the later period.
Referring to the intercept estimates, some of the statements made in the previous section have to be qualified: The superior performances of skilled managers' new acquisitions above their own deletions ($N_S - D_S$) is more apparent during the first period. During the second period, the momentum factor accounts for most of the superior performance of new acquisitions over deletions. Taking account of the size of the positions (right panel of Table A.25) increases the risk adjusted spread in the directions one would expect during both periods. It clearly supports the conclusions drawn previously, namely that skilled managers weight their sales and purchases skillfully and unskilled managers possess adverse weighting abilities. The adverse trading performance of unskilled managers, whereby their reductions outperform their additions, is much more apparent in terms of size and significance during the second time period. The average risk adjusted loss of this spread portfolio ($A_U - R_U$) amounts to a significant 16 basis

points per month. The figure increases to 94 basis points per month once the size of trades is taken into account.

An equivalent robustness check is performed on the spreads of N, A, D and R across manager groups. It is summarized in Table A.26 in the Appendix. The performance difference of new acquisitions between groups ($N_S - N_U$) is much more pronounced in the second sample period. On a risk adjusted basis, equally-weighted acquisitions of skilled managers outperform the ones of unskilled managers by 75 basis points per month on average. The figure increases to 112 basis points when assets are weighted by the size of trades. Both figures are greater than zero at a 5% level of significance. The difference between the additions of skilled and unskilled managers ($A_S - A_U$) is approximately constant over both periods. Equally weighted additions of skilled managers outperform the ones of unskilled managers by 15 to 19 basis points per month. Trade-size-weighted additions of skilled managers outperform the ones of unskilled managers by a monthly 37 to 39 basis points.

One striking result in Table A.26 is the alpha estimate on the weighted $D_S - D_U$ spread during the second sample period. It implies that weighted deletions of good managers underperform the ones of unskilled managers by 174 basis points per month. This would in turn imply an extraordinary ability of skilled managers as compared to unskilled ones to identify and appropriately sell stock with the worst prospects. The result, however, is likely to be driven by several negative outliers towards the end of the sample. Re-running the same regression, but using a quantile-regression that down-weights the influence of outliers on the coefficient estimates, reduces the risk adjusted performance differential to 91 basis points and its t-statistic to -1.41 from -1.64. Even though no definitive statement can be made on this matter the evidence suggests that good managers have relatively skillfully deleted assets from their portfolios during the previous ten years, when compared to their unskilled colleagues.

To summarize, most of the results presented in the previous section are robust between the two non-overlapping time periods or even more pronounced in the second sample period. The results of the robustness check do not alter the conclusion that skilled managers possess significantly better abilities than unskilled ones in identifying under-(over-)priced assets and in trading them in appropriated amounts. The next section briefly discusses how this knowledge of differential trading performance can be used to construct profitable trading strategies.

3.5 Trading Strategies

The trade portfolios discussed in the previous sections are constructed solely by using current and past information on the performance of fund managers and their transactions. The analysis shows that, conditional on observing this information, it is possible to predict short run performance-differentials of assets traded by skilled and unskilled managers. A natural question following from this observation is whether an outside investor can economically profit from the public availability of this information. Put differently: Is it possible to free-ride on the skill and research efforts of mutual fund managers simply by observing their actions over the recent past and by copying a subset of their trades? This issue is not only of importance from the standpoint of an investor in search of profitable investment opportunities but also from the view point of the mutual fund industry. It is, however, not clear what the position of the industry should be on this issue. As shown above, the mandatory disclosure of portfolio positions provides outsiders with valuable information originally gathered at the expense of the fund or better said, the investors of the fund. Disseminating this information essentially for free via the public disclosure of portfolio positions is *a priori* not in the interest of funds and their investors. This is particularly true if portfolio positions are altered over long time periods to minimize impacts on the price of the traded securities. Outside investors' ability to "front-run" mutual funds would diminish the performance of the

latter[12].
On the contrary, it would be in the interest of certain funds to disclose frequently if their trades can be completed within a span of three month. The price impact of outside investors copying the behaviour of the managers would increase the performance of their picks. Rather than hiding their actions such funds would be inclined to disclose as soon as they have completed their trades. Not surprisingly many fund companies therefore voluntarily disclose their positions to the public, even at higher frequencies than quarters[13]. For this reason it would be interesting to examine the relation between the portfolio disclosure policies of funds and their trading activity.
To clarify the possibility to economically profit from the knowledge of the skill distribution in the fund industry in combination with information on fund portfolios, two simple factor-neutral trading strategies are analysed. Both of them build on insights from the previous empirical analysis. The general hedging method used in constructing these portfolios is commonly employed in the hedge-fund industry and the asset pricing literature to construct portable alpha strategies.
Both trading portfolios are constructed following the methodology of Franzoni and Marin (2005). From July 1985 to March 2005, each quarter end a portfolio of assets is identified that is thought to be under-priced. The exposures to market, size and book-to-market factors of the portfolio are then estimated by using the preceding 48-month window of portfolio returns. Subsequently, a trading strategy is pursued over the next quarter that is long in one unit of the under-priced portfolio and short in the three risk-factor-mimicking portfolios in the amounts specified by the previously estimated exposures on the factors. Any leftover is invested in the risk-free rate. The strategy is then pursued until the next quarter end, when a new under-priced portfolio is available due the updated information on the skill distribution of

[12]For a more detailed discussion of these issues see Wermers (2001).
[13]An example is Pearl Funds, who discloses its portfolio positions monthly on the internet at www.pearlfunds.com.

Table 3.1: **Summary Statistics on the Monthly Performance of Trading Strategies**

	$S(A_S)$	$S(R_U)$	CRSP-VW
Mean	1.1	1.03	1.03
Volatility	3.5	3.07	4.49
Skewness	2.58	0.8	-0.99
Excess Kurtosis	18.25	4.77	3.1
Minimum	-8.17	-10.45	-22.53
Maximum	29.56	15	12.85
Sharpe Ratio	0.21	0.21	0.14

managers and their trades. The process is thereafter repeated in the same fashion for all quarters until March 2005. The resulting returns of this strategy are approximately neutral to the factor portfolios considered, in particular neutral with respect to the market portfolio.

Two particular portfolios of under-priced assets are considered. First, the above strategy is applied to the trade-size-weighted addition of skilled managers (A_S). Second, the trade-size-weighted reductions portfolio of unskilled managers (R_U) is used to construct the trading strategy. Both portfolios are considered to be under-priced, based on the results previously presented. Table 3.1 shows summary statistics of the monthly returns from both strategies.

Pursuing these strategies has historically been superior to a buy and hold strategy of the CRSP value weighted market portfolio in several aspects. Both trading portfolios exhibit higher Sharpe Ratios than the market portfolios since their return distributions second-order stochastically dominate the market portfolio. The strategy based on additions of skilled managers ($S(A_S)$) has historically been dominating, as it is highly positively skewed. The large estimate of its kurtosis is solely an outcome of this positive skew. Also, in terms of historical shortfall risk, the first strategy dominates the latter two portfolios. Even though the strategy based on the reduction portfolio of the unskilled managers ($S(R_U)$) is dominated by the strategy based on the additions of skilled managers, it in turn stochastically dominates the market portfolio up to the third order. Betting on systematic trading errors of unskilled managers has been an attractive investment strategy over the past 20 years. Figure A.11 depicts QQ-plots of the return distributions of both strategies against the distributions of the CRSP value-weighted market index. Both strategies clearly exhibit a thinner lower tail and a fatter upper tail than the market portfolio.

Some points concerning the implementability of these trading strategies have to be kept in mind. First, the figures quoted in Table 3.1 do not account for any transaction cost involved in pursuing these strategies. Both portfolios, A_S and R_U, contain a very large number of assets at any point in time as depicted in Figure A.9. Second, the portfolios have to be turned over up to 4 times per year, which could possibly erode much of the superior performance of the strategies. Third, the portfolios are reconstructed at the beginning of every quarter, implying that they have to be turned over completely within a very short period of time. This might not be feasible at all or only at a substantial loss in performance. Finally, the SEC allows mutual fund managers to report their holdings up to 60 days late. Even though the majority of managers do not make use of this option, late reporting could obviously be destructive to the success of the trading strategies.

3.6 Conclusion

The central issue of this study is the out-of-sample trading performance of mutual fund managers. The evidence presented in this chapter points to the existence of systematic differences in the ability of mutual fund managers to identify and trade on inefficiencies in U.S. equity markets. Skilled managers are successful in predicting the abnormal performance of assets. Unskilled managers on the other hand commit systematic errors when trading. They tend to purchase future losers and sell future winners. Moreover, the relationship between the degree of miss-pricing in the stocks traded and the intensity of trading them is positive for skilled and negative for unskilled managers. Skilled managers tend to tilt their purchases (sales) more intensely towards stocks that are relatively more under- (over-)priced. In contrast, unskilled individuals systematically underweight stocks in their trades that exhibit the strongest miss-pricing *ex post*. These differences in trading performance have generally been constant over time or even increased in recent periods. Their economic and statistical significance allows to construct portable alpha strategies that are by far superior to a buy-and-hold strategy of the aggregate U.S. stock market. The apparent profitability of these trading strategies should be of concern to the mutual fund industry but also to outside investors observing the trading behaviour of funds via their quarterly portfolio disclosures.

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A Appendix

Table A.1: **Sample Summary Statistics**

The table reports year-end summary statistics from January 1990 to December 2005 for all mutual fund portfolios detailed on Thompson Financial that contain at least five stocks, are not index or tax-managed funds, have total net assets exceeding five million dollars, and have disclosed fund holdings within the past six months. Column 2 reports the total number of these funds. Column 3 reports the average fund size while Column 4 reports the total value of stocks held in those portfolios (both columns in billions of dollars). Column 4 reports the average market capitalization decile of the stocks held by the funds in the sample. Column 5 reports the average number of stocks in a fund.

Year	Number of Funds	Average Fund Size	Total Assets	Average Market-Cap Decile	Mean Number of Assets
1990	736	0.29	211.3	6.9	68.1
1991	844	0.36	300.4	6.8	74.1
1992	935	0.45	423.7	6.7	87.2
1993	1471	0.46	671.8	6.4	91.1
1994	1588	0.36	570.4	6.1	92.4
1995	1645	0.55	899.9	5.9	96.2
1996	2078	0.56	1172.5	6.3	96.8
1997	2210	0.68	1513.0	6.3	94.6
1998	2389	0.79	1877.6	6.1	98.5
1999	2324	1.01	2337.4	6.2	96.9
2000	2223	1.06	2350.1	5.8	105.8
2001	2061	0.93	1920.3	5.7	107.6
2002	1890	0.83	1565.6	5.8	104.2
2003	1848	1.11	2059.4	5.7	107.4
2004	1666	1.38	2301.4	6.0	106.6
2005	1563	1.68	2619.7	5.8	110.0

Table A.2: **Performance of Best Ideas**
We report coefficients from monthly regressions of

$$r_{p,t} - r_{f,t} =$$
$$= a_6 + bRMRF_t + sSMB_t + hHML_t + mMOM_t + iIDI_t + rSTREV_t + \varepsilon_{p,t}$$

where $r_{p,t}$ is the equal-weight excess return on the portfolio of the stocks that represent the best idea of each active manager. The best idea is determined within each fund as the stock with the maximum value of one of four possible tilt measures:

1) $market\_tilt_{ijt} = \tau_{ijt}(\lambda_{ijt} - \lambda_{iMt})$,
2) $portfolio\_tilt_{ijt} = \tau_{ijt}(\lambda_{ijt} - \lambda_{ijtV})$,
3) $CAPM\_tilt_{ijt} = \tau_{ijt}\sigma^2_{it}(\lambda_{ijt} - \lambda_{iMt})$,
and 4) $CAPM\_portfolio\_tilt_{ijt} = \tau_{ijt}\sigma^2_{it}(\lambda_{ijt} - \lambda_{ijtV})$

where λ_{ijt} is manager j's portfolio weight in stock i, λ_{iMt} is the weight of stock i in the market portfolio, λ_{ijtV} is the value weight of stock i in manager j's portfolio, σ^2_{it} is the most-recent estimate of a stock's CAPM-idiosyncratic variance, and τ_{ijt} is a dummy variable which is 1 whenever manager j's recent trade in i was a buy and 0 otherwise. We set τ_{ijt}=1 throughout the analysis of Panel A, meaning that all best ideas are considered. The explanatory variables in the regression are all from Ken French's website except for IDI which we construct following Ang, Hodrick, and Xi (2004). We also report intercept estimates, α_4, when IDI and $STREV$ are excluded from the regression. We restrict the analysis to those managers whose maximum tilt is in the top 25% of all maximum tilts at the time. t-statistics are can be found below the parameter estimates. The sample period for the dependent variables is January 1991 - December 2005.

Table A.2: **Performance of Best Ideas**

	Mean	$\widehat{\alpha_4}$	$\widehat{\alpha_6}$	$\widehat{b}$	$\widehat{s}$	$\widehat{h}$	$\widehat{m}$	$\widehat{i}$	$\widehat{r}$
				Panel A: Best Ideas					
r_1	0.0126	0.0029	0.0039	1.02	0.09	0.00	0.22	0.07	-0.07
		2.24	3.08	26.40	1.79	-0.03	8.28	2.53	-2.30
r_2	0.0142	0.0038	0.0047	1.03	0.23	0.09	0.18	0.05	-0.06
		3.13	3.77	27.33	4.91	1.99	7.10	1.97	-1.98
r_3	0.0170	0.0059	0.0112	1.15	0.09	-0.32	0.29	0.52	-0.03
		2.06	4.75	16.16	1.00	-3.63	5.95	10.14	-0.53
r_4	0.0188	0.0070	0.0115	1.20	0.29	-0.30	0.27	0.44	-0.04
		2.75	5.31	18.26	3.57	-3.73	5.92	9.22	-0.77
				Panel B: Best Fresh Ideas					
r_1	0.0135	0.0037	0.0046	1.06	0.13	-0.01	0.19	0.04	-0.10
		2.53	3.14	24.01	2.31	-0.14	6.31	1.33	-2.68
r_2	0.0151	0.0049	0.0057	1.06	0.26	0.07	0.15	0.04	-0.08
		3.53	4.03	24.80	4.82	1.24	5.04	1.18	-2.36
r_3	0.0179	0.0070	0.0127	1.19	0.06	-0.37	0.26	0.55	-0.05
		2.21	4.74	14.69	0.60	-3.68	4.61	9.40	-0.83
r_4	0.0193	0.0077	0.0127	1.26	0.26	-0.34	0.21	0.48	-0.06
		2.65	5.04	16.58	2.70	-3.57	4.07	8.62	-1.00

Table A.3: **Performance of Best Ideas: Characteristic Selectivity**
We report coefficients from monthly regressions of

$$r_{p,t} - r_{f,t} =$$
$$= a_6 + bRMRF_t + sSMB_t + hHML_t + mMOM_t + iIDI_t + rSTREV_t + \varepsilon_{p,t}$$

where $r_{p,t} - r_{DGTW,t}$ is the equal-weight and DGTW characteristic-benchmark-matched excess return on the portfolio of the stocks that represent the best idea of each active manager. The best idea is determined within each fund as the stock with the maximum value of one of four possible tilt measures:

1) $market\_tilt_{ijt} = \tau_{ijt}(\lambda_{ijt} - \lambda_{iMt})$,
2) $portfolio\_tilt_{ijt} = \tau_{ijt}(\lambda_{ijt} - \lambda_{ijtV})$,
3) $CAPM\_tilt_{ijt} = \tau_{ijt}\sigma^2_{it}(\lambda_{ijt} - \lambda_{iMt})$,
and 4) $CAPM\_portfolio\_tilt_{ijt} = \tau_{ijt}\sigma^2_{it}(\lambda_{ijt} - \lambda_{ijtV})$

where λ_{ijt} is manager j's portfolio weight in stock i, λ_{iMt} is the weight of stock i in the market portfolio, λ_{ijtV} is the value weight of stock i in manager j's portfolio, σ^2_{it} is the most-recent estimate of a stock's CAPM-idiosyncratic variance, and τ_{ijt} is a dummy variable which is 1 whenever manager j's recent trade in i was a buy and 0 otherwise. We set τ_{ijt}=1 throughout the analysis of Panel A, meaning that all best ideas are considered. The explanatory variables in the regression are all from Ken French's website except for IDI which we construct following Ang, Hodrick, and Xi (2004). We also report intercept estimates, α_4, when IDI and $STREV$ are excluded from the regression. We restrict the analysis to those managers whose maximum tilt is in the top 25% of all maximum tilts at the time. t-statistics are can be found below the parameter estimates. The sample period for the dependent variables is January 1991 - December 2005.

Table A.3: **Performance of Best Ideas: Characteristic Selectivity**

	Mean	$\widehat{\alpha_4}$	$\widehat{\alpha_6}$	$\widehat{b}$	$\widehat{s}$	$\widehat{h}$	$\widehat{m}$	$\widehat{i}$	$\widehat{r}$
Panel A: Best Ideas									
r_1	0.0041	0.0024	0.0035	0.03	-0.08	-0.02	0.19	0.07	-0.09
		1.91	2.86	0.81	-1.81	-0.53	7.50	2.53	-3.11
r_2	0.0049	0.0033	0.0044	0.03	-0.07	-0.01	0.18	0.05	-0.10
		2.53	3.36	0.66	-1.38	-0.23	6.73	1.90	-3.28
r_3	0.0095	0.0072	0.0106	0.17	-0.20	-0.21	0.24	0.32	-0.08
		2.72	4.29	2.26	-2.11	-2.21	4.77	5.85	-1.39
r_4	0.0107	0.0083	0.0111	0.20	-0.11	-0.25	0.22	0.25	-0.08
		3.37	4.64	2.81	-1.20	-2.76	4.39	4.76	-1.30
Panel B: Best Fresh Ideas									
r_1	0.0054	0.0036	0.0047	0.05	-0.07	-0.05	0.19	0.06	-0.12
		2.27	2.98	1.12	-1.21	-0.84	5.92	1.62	-2.97
r_2	0.0062	0.0045	0.0057	0.07	-0.09	-0.03	0.17	0.05	-0.14
		2.86	3.64	1.42	-1.44	-0.50	5.08	1.47	-3.58
r_3	0.0120	0.0092	0.0130	0.24	-0.19	-0.17	0.20	0.31	-0.15
		3.06	4.48	2.72	-1.74	-1.56	3.38	4.91	-2.05
r_4	0.0120	0.0094	0.0126	0.29	-0.12	-0.23	0.16	0.27	-0.14
		3.32	4.63	3.58	-1.21	-2.23	2.90	4.47	-2.08

Table A.4: **Performance of Best Ideas: Characteristic Timing / Average Style**

We report coefficients from monthly regressions of

$$r_{DGTW,t} - r_{f,t} =$$
$$= a_6 + bRMRF_t + sSMB_t + hHML_t + mMOM_t + iIDI_t + rSTREV_t + \varepsilon_{p,t}$$

where $r_{DGTW,t} - r_{f,t}$ is the DGTW characteristic-benchmark-matched return for the equal-weight portfolio of the stocks that represent the best idea of each active manager. The best idea is determined within each fund as the stock with the maximum value of one of four possible tilt measures:

1) $market\_tilt_{ijt} = \tau_{ijt}(\lambda_{ijt} - \lambda_{iMt})$,
2) $portfolio\_tilt_{ijt} = \tau_{ijt}(\lambda_{ijt} - \lambda_{ijtV})$,
3) $CAPM\_tilt_{ijt} = \tau_{ijt}\sigma^2_{it}(\lambda_{ijt} - \lambda_{iMt})$,
and 4) $CAPM\_portfolio\_tilt_{ijt} = \tau_{ijt}\sigma^2_{it}(\lambda_{ijt} - \lambda_{ijtV})$

where λ_{ijt} is manager j's portfolio weight in stock i, λ_{iMt} is the weight of stock i in the market portfolio, λ_{ijtV} is the value weight of stock i in manager j's portfolio, σ^2_{it} is the most-recent estimate of a stock's CAPM-idiosyncratic variance, and τ_{ijt} is a dummy variable which is 1 whenever manager j's recent trade in i was a buy and 0 otherwise. We set τ_{ijt}=1 throughout the analysis of Panel A, meaning that all best ideas are considered. The explanatory variables in the regression are all from Ken French's website except for IDI which we construct following Ang, Hodrick, and Xi (2004). We also report intercept estimates, α_4, when IDI and $STREV$ are excluded from the regression. We restrict the analysis to those managers whose maximum tilt is in the top 25% of all maximum tilts at the time. t-statistics are can be found below the parameter estimates. The sample period for the dependent variables is January 1991 - December 2005.

Table A.4: **Performance of Best Ideas: Characteristic Timing / Average Style**

	Mean	$\widehat{\alpha_4}$	$\widehat{\alpha_6}$	$\widehat{b}$	$\widehat{s}$	$\widehat{h}$	$\widehat{m}$	$\widehat{i}$	$\widehat{r}$
				Panel A: Best Ideas					
r_1	0.0091	0.0011	0.0010	1.05	0.10	-0.06	0.07	-0.01	-0.01
		2.05	1.85	63.08	5.00	-2.95	6.01	-1.00	-0.61
r_2	0.0097	0.0011	0.0010	1.05	0.27	0.03	0.04	-0.02	-0.02
		1.78	1.66	55.07	11.54	1.36	2.77	-1.15	-1.26
r_3	0.0098	0.0006	0.0020	1.09	0.39	-0.03	0.02	0.12	-0.04
		0.60	2.06	36.84	10.62	-0.76	1.13	5.67	-1.86
r_4	0.0100	0.0004	0.0016	1.08	0.51	-0.01	0.03	0.11	-0.04
		0.41	1.83	40.39	15.25	-0.27	1.76	5.46	-1.90
				Panel B: Best Fresh Ideas					
r_1	0.0092	0.0013	0.0011	1.05	0.11	-0.04	0.04	-0.02	-0.01
		2.09	1.80	54.50	4.70	-1.58	3.25	-1.65	-0.87
r_2	0.0099	0.0016	0.0016	1.04	0.27	0.05	0.00	-0.02	-0.03
		2.31	2.20	48.89	10.07	1.73	-0.13	-1.49	-1.91
r_3	0.0096	0.0004	0.0018	1.09	0.41	-0.03	0.02	0.12	-0.05
		0.41	1.81	36.49	11.02	-0.78	0.88	5.40	-1.87
r_4	0.0100	0.0005	0.0017	1.09	0.52	-0.02	0.02	0.10	-0.04
		0.51	1.78	38.90	14.79	-0.46	1.14	4.84	-1.80

Table A.5: **Performance of Best Ideas at Different Threshold Levels**
We report coefficients from monthly regressions of

$$r_{p,t} - r_{f,t} =$$
$$= a_6 + bRMRF_t + sSMB_t + hHML_t + mMOM_t + iIDI_t + rSTREV_t + \varepsilon_{p,t}$$

where $r_{p,t}$ is the equal-weight excess return on the portfolio of the stocks that represent the best idea of each active manager. The best idea is determined within each fund as the stock with the maximum value of one of four possible tilt measures:

1) $market\_tilt_{ijt} = \tau_{ijt}(\lambda_{ijt} - \lambda_{iMt})$,
2) $portfolio\_tilt_{ijt} = \tau_{ijt}(\lambda_{ijt} - \lambda_{ijtV})$,
3) $CAPM\_tilt_{ijt} = \tau_{ijt}\sigma^2_{it}(\lambda_{ijt} - \lambda_{iMt})$,
and 4) $CAPM\_portfolio\_tilt_{ijt} = \tau_{ijt}\sigma^2_{it}(\lambda_{ijt} - \lambda_{ijtV})$

where λ_{ijt} is manager j's portfolio weight in stock i, λ_{iMt} is the weight of stock i in the market portfolio, λ_{ijtV} is the value weight of stock i in manager j's portfolio, σ^2_{it} is the most-recent estimate of a stock's CAPM-idiosyncratic variance, and τ_{ijt} is a dummy variable which is set to 1 throughout this table's analysis. The explanatory variables in the regression are all from Ken French's website except for IDI which we construct following Ang, Hodrick, and Xi (2004). We also report intercept estimates, α_4, when IDI and $STREV$ are excluded from the regression. t-statistics are can be found below the parameter estimates. The sample period for the dependent variables is January 1991 - December 2005.

Table A.5: **Performance of Best Ideas at Different Threshold Levels**

	Mean	$\widehat{\alpha_4}$	$\widehat{\alpha_6}$	$\widehat{b}$	$\widehat{s}$	$\widehat{h}$	$\widehat{m}$	$\widehat{i}$	$\widehat{r}$
				Panel A: Top 100% of Tilts					
r_1	0.0110	0.0008	0.0012	1.08	0.14	0.01	0.22	0.01	-0.06
		0.93	1.34	41.47	4.20	0.29	12.33	0.33	-2.67
r_2	0.0121	0.0011	0.0013	1.09	0.30	0.15	0.17	-0.01	-0.06
		1.14	1.37	37.54	8.19	4.22	8.71	-0.41	-2.55
r_3	0.0133	0.0026	0.0061	1.22	0.14	-0.14	0.13	0.32	-0.07
		1.34	3.76	24.93	2.25	-2.22	4.01	9.04	-1.82
r_4	0.0138	0.0025	0.0049	1.24	0.32	-0.06	0.11	0.23	-0.03
		1.56	3.40	28.76	5.91	-1.18	3.58	7.28	-0.94
				Panel B: Top 50% of Tilts					
r_1	0.0122	0.0023	0.0029	1.06	0.12	-0.01	0.21	0.03	-0.06
		2.29	2.84	34.71	3.12	-0.34	9.95	1.15	-2.57
r_2	0.0134	0.0026	0.0033	1.06	0.24	0.12	0.19	0.03	-0.06
		2.46	2.99	32.08	5.77	2.95	8.47	1.23	-2.31
r_3	0.0149	0.0036	0.0084	1.21	0.14	-0.26	0.24	0.45	-0.07
		1.47	4.23	19.98	1.87	-3.48	5.74	10.37	-1.45
r_4	0.0164	0.0046	0.0083	1.24	0.34	-0.20	0.20	0.36	-0.04
		2.17	4.65	22.91	4.96	-2.99	5.29	9.21	-0.96
				Panel C: Top 5% of Tilts					
r_1	0.0139	0.0039	0.0055	0.98	0.18	0.00	0.24	0.10	-0.12
		1.80	2.52	14.94	2.21	-0.05	5.38	2.04	-2.30
r_2	0.0155	0.0048	0.0066	1.02	0.30	-0.01	0.23	0.09	-0.16
		2.39	3.27	16.70	3.89	-0.11	5.40	2.13	-3.20
r_3	0.0207	0.0094	0.0151	1.12	0.15	-0.53	0.41	0.54	-0.09
		2.33	4.07	10.02	1.10	-3.78	5.35	6.61	-1.02
r_4	0.0238	0.0118	0.0170	1.22	0.31	-0.57	0.40	0.47	-0.12
		3.20	4.92	11.61	2.37	-4.38	5.53	6.14	-1.42

Table A.6: **Performance of Best Fresh Ideas at Different Threshold Levels**
We report coefficients from monthly regressions of

$$r_{p,t} - r_{f,t} =$$
$$= a_6 + bRMRF_t + sSMB_t + hHML_t + mMOM_t + iIDI_t + rSTREV_t + \varepsilon_{p,t}$$

where $r_{p,t}$ is the equal-weight excess return on the portfolio of the stocks that represent the best idea of each active manager. The best idea is determined within each fund as the stock with the maximum value of one of four possible tilt measures:

1) $market\_tilt_{ijt} = \tau_{ijt}(\lambda_{ijt} - \lambda_{iMt})$,
2) $portfolio\_tilt_{ijt} = \tau_{ijt}(\lambda_{ijt} - \lambda_{ijtV})$,
3) $CAPM\_tilt_{ijt} = \tau_{ijt}\sigma^2_{it}(\lambda_{ijt} - \lambda_{iMt})$,
and 4) $CAPM\_portfolio\_tilt_{ijt} = \tau_{ijt}\sigma^2_{it}(\lambda_{ijt} - \lambda_{ijtV})$

where λ_{ijt} is manager j's portfolio weight in stock i, λ_{iMt} is the weight of stock i in the market portfolio, λ_{ijtV} is the value weight of stock i in manager j's portfolio, σ^2_{it} is the most-recent estimate of a stock's CAPM-idiosyncratic variance, and τ_{ijt} is a dummy variable which is 1 whenever manager j's recent trade in i was a buy and 0 otherwise. The explanatory variables in the regression are all from Ken French's website except for IDI which we construct following Ang, Hodrick, and Xi (2004). We also report intercept estimates, α_4, when IDI and $STREV$ are excluded from the regression. t-statistics are can be found below the parameter estimates. The sample period for the dependent variables is January 1991 - December 2005.

Table A.6: **Performance of Best Fresh Ideas at Different Threshold Levels**

	Mean	$\widehat{\alpha_4}$	$\widehat{\alpha_6}$	$\widehat{b}$	$\widehat{s}$	$\widehat{h}$	$\widehat{m}$	$\widehat{i}$	$\widehat{r}$
				Panel A: Top 100% of Tilts					
r_1	0.0115	0.0016	0.0020	1.09	0.15	0.01	0.17	0.00	-0.08
		1.61	1.97	35.71	4.04	0.17	8.31	-0.21	-3.15
r_2	0.0128	0.0021	0.0024	1.10	0.31	0.12	0.14	-0.01	-0.08
		1.97	2.24	34.21	7.71	3.02	6.27	-0.59	-3.20
r_3	0.0144	0.0042	0.0081	1.24	0.13	-0.22	0.11	0.34	-0.10
		2.05	4.70	23.86	1.98	-3.39	2.96	9.11	-2.45
r_4	0.0145	0.0037	0.0065	1.26	0.31	-0.15	0.08	0.25	-0.05
		2.16	4.19	26.97	5.30	-2.56	2.35	7.49	-1.37
				Panel B: Top 50% of Tilts					
r_1	0.0127	0.0030	0.0035	1.08	0.15	-0.01	0.16	0.00	-0.09
		2.60	3.01	30.91	3.38	-0.32	6.76	0.09	-3.18
r_2	0.0142	0.0038	0.0045	1.08	0.25	0.08	0.15	0.02	-0.09
		3.21	3.74	29.70	5.44	1.88	6.16	0.67	-3.16
r_3	0.0158	0.0050	0.0102	1.24	0.12	-0.35	0.20	0.48	-0.11
		1.88	4.67	18.66	1.44	-4.28	4.41	9.91	-1.97
r_4	0.0172	0.0056	0.0098	1.27	0.31	-0.27	0.16	0.39	-0.06
		2.45	4.95	21.35	4.22	-3.63	3.93	8.99	-1.23
				Panel C: Top 5% of Tilts					
r_1	0.0164	0.0060	0.0081	1.01	0.27	-0.06	0.23	0.09	-0.23
		2.44	3.31	13.67	2.90	-0.67	4.61	1.61	-3.84
r_2	0.0168	0.0062	0.0079	1.04	0.32	0.02	0.18	0.09	-0.16
		2.51	3.17	13.80	3.44	0.23	3.41	1.61	-2.60
r_3	0.0254	0.0139	0.0203	1.21	0.10	-0.58	0.39	0.59	-0.11
		3.02	4.70	9.29	0.64	-3.57	4.35	6.24	-1.01
r_4	0.0256	0.0132	0.0188	1.32	0.26	-0.56	0.36	0.51	-0.13
		3.04	4.58	10.58	1.71	-3.61	4.27	5.67	-1.26

Table A.7: **Performance of Best-Minus-Rest Portfolios**
We report coefficients from monthly regressions of

$$spread_{p,t} = \\ = a_6 + bRMRF_t + sSMB_t + hHML_t + mMOM_t + iIDI_t + rSTREV_t + \varepsilon_{p,t}$$

where $spread_{p,t}$ is the return on an equal-weight long-short portfolio, long a dollar in each manager's best idea and short a dollar in each manager's investment-weight portfolio of the rest of their ideas. The best idea is determined within each fund as the stock with the maximum value of one of four possible tilt measures:

1) $market\_tilt_{ijt} = \tau_{ijt}(\lambda_{ijt} - \lambda_{iMt})$,
2) $portfolio\_tilt_{ijt} = \tau_{ijt}(\lambda_{ijt} - \lambda_{ijtV})$,
3) $CAPM\_tilt_{ijt} = \tau_{ijt}\sigma^2_{it}(\lambda_{ijt} - \lambda_{iMt})$,
and 4) $CAPM\_portfolio\_tilt_{ijt} = \tau_{ijt}\sigma^2_{it}(\lambda_{ijt} - \lambda_{ijtV})$

where λ_{ijt} is manager j's portfolio weight in stock i, λ_{iMt} is the weight of stock i in the market portfolio, λ_{ijtV} is the value weight of stock i in manager j's portfolio, σ^2_{it} is the most-recent estimate of a stock's CAPM-idiosyncratic variance, and τ_{ijt} is a dummy variable which is 1 whenever manager j's recent trade in i was a buy and 0 otherwise. We set τ_{ijt}=1 throughout the analysis of Panel A. The explanatory variables in the regression are all from Ken French's website except for IDI which we construct following Ang, Hodrick, and Xi (2004). We also report intercept estimates, α_4, when IDI and $STREV$ are excluded from the regression. We restrict the analysis to those managers whose maximum tilt is in the top 25% of all maximum tilts at the time. t-statistics are can be found below the parameter estimates. The sample period for the dependent variables is January 1991 - December 2005.

Table A.7: **Performance of Best-Minus-Rest Portfolios**

	Mean	$\widehat{\alpha_4}$	$\widehat{\alpha_6}$	$\widehat{b}$	$\widehat{s}$	$\widehat{h}$	$\widehat{m}$	$\widehat{i}$	$\widehat{r}$
				Panel A: Best Ideas					
$spread_1$	0.0046	0.0015	0.0027	0.03	0.10	0.01	0.26	0.06	-0.10
		1.32	2.39	0.84	2.47	0.30	11.22	2.62	-3.70
$spread_2$	0.0069	0.0029	0.0039	0.03	0.31	0.18	0.20	0.05	-0.09
		2.42	3.26	0.87	6.86	4.08	8.30	2.07	-3.00
$spread_3$	0.0085	0.0053	0.0103	0.11	-0.01	-0.20	0.24	0.48	-0.07
		1.93	4.51	1.52	-0.13	-2.28	5.08	9.57	-1.21
$spread_4$	0.0107	0.0063	0.0103	0.16	0.29	-0.12	0.21	0.38	-0.07
		2.62	4.89	2.44	3.58	-1.56	4.80	8.10	-1.35
				Panel B: Best Fresh Ideas					
$spread_1$	0.0057	0.0026	0.0036	0.04	0.15	0.02	0.22	0.05	-0.09
		1.89	2.55	0.99	2.80	0.46	7.67	1.53	-2.71
$spread_2$	0.0080	0.0041	0.0050	0.05	0.34	0.18	0.17	0.04	-0.10
		2.95	3.56	1.10	6.46	3.32	5.76	1.27	-2.77
$spread_3$	0.0092	0.0064	0.0118	0.13	-0.05	-0.21	0.18	0.51	-0.08
		2.03	4.36	1.60	-0.50	-2.08	3.17	8.63	-1.27
$spread_4$	0.0113	0.0072	0.0117	0.20	0.25	-0.13	0.14	0.42	-0.08
		2.53	4.58	2.53	2.54	-1.32	2.68	7.48	-1.28

Table A.8: **Performance of Best-Minus-Rest Portfolios: Top Three / Top Five**
We report coefficients from monthly regressions of

$$r_{p,t} - r_{f,t} =$$
$$= a_6 + bRMRF_t + sSMB_t + hHML_t + mMOM_t + iIDI_t + rSTREV_t + \varepsilon_{p,t}$$

where $spread_{p,t}$ is the return on an equal-weight long-short portfolio, long a dollar in each manager's best ideas and short a dollar in each manager's investment-weight portfolio of the rest of their ideas. The best ideas are determined within each fund as the top three (Panel A) or top five (Panel B) stocks with the maximum value of one of four possible tilt measures:

1) $market\_tilt_{ijt} = \tau_{ijt}(\lambda_{ijt} - \lambda_{iMt})$,
2) $portfolio\_tilt_{ijt} = \tau_{ijt}(\lambda_{ijt} - \lambda_{ijtV})$,
3) $CAPM\_tilt_{ijt} = \tau_{ijt}\sigma^2_{it}(\lambda_{ijt} - \lambda_{iMt})$,
and 4) $CAPM\_portfolio\_tilt_{ijt} = \tau_{ijt}\sigma^2_{it}(\lambda_{ijt} - \lambda_{ijtV})$

where λ_{ijt} is manager j's portfolio weight in stock i, λ_{iMt} is the weight of stock i in the market portfolio, λ_{ijtV} is the value weight of stock i in manager j's portfolio, σ^2_{it} is the most-recent estimate of a stock's CAPM-idiosyncratic variance, and τ_{ijt} is a dummy variable which is set to 1 throughout the analysis. The explanatory variables in the regression are all from Ken French's website except for IDI which we construct following Ang, Hodrick, and Xi (2004). We also report intercept estimates, α_4, when IDI and $STREV$ are excluded from the regression. We restrict the analysis to those managers whose maximum tilt is in the top 25% of all maximum tilts at the time. t-statistics are can be found below the parameter estimates. The sample period for the dependent variables is January 1991 - December 2005.

Table A.8: **Performance of Best-Minus-Rest Portfolios: Top Three / Top Five**

	Mean	$\widehat{\alpha_4}$	$\widehat{\alpha_6}$	$\widehat{b}$	$\widehat{s}$	$\widehat{h}$	$\widehat{m}$	$\widehat{i}$	$\widehat{r}$
				Panel A: Best Three Ideas					
$spread_1$	0.0037	0.0008	0.0016	0.02	0.15	0.07	0.21	0.04	-0.08
		0.99	1.98	0.73	4.92	2.40	12.34	2.09	-3.97
$spread_2$	0.0058	0.0017	0.0023	0.05	0.36	0.24	0.15	0.02	-0.06
		1.73	2.26	1.54	9.47	6.20	7.05	1.04	-2.55
$spread_3$	0.0067	0.0036	0.0074	0.09	0.12	-0.10	0.17	0.39	-0.01
		1.74	4.47	1.75	1.91	-1.55	5.08	10.71	-0.20
$spread_4$	0.0093	0.0054	0.0083	0.12	0.36	-0.02	0.12	0.30	0.01
		2.97	5.18	2.40	5.97	-0.31	3.75	8.44	0.18
				Panel B: Best Five Ideas					
$spread_1$	0.0033	0.0005	0.0010	0.03	0.16	0.11	0.17	0.02	-0.06
		0.75	1.51	1.23	6.27	4.29	11.78	1.42	-3.41
$spread_2$	0.0050	0.0012	0.0016	0.05	0.38	0.28	0.11	0.02	-0.05
		1.28	1.70	1.61	10.38	7.65	5.39	0.77	-2.14
$spread_3$	0.0055	0.0023	0.0057	0.10	0.15	-0.07	0.15	0.35	-0.01
		1.35	4.29	2.35	3.07	-1.38	5.48	11.78	-0.16
$spread_4$	0.0079	0.0044	0.0069	0.11	0.39	0.01	0.08	0.25	0.00
		2.85	5.13	2.60	7.63	0.23	3.01	8.64	0.00

Table A.9: **Performance of Best Ideas by Liquidity**
We estimate coefficients from monthly regressions of

$$r_{p,t} - r_{f,t} =$$
$$= a_6 + bRMRF_t + sSMB_t + hHML_t + mMOM_t + iIDI_t + rSTREV_t + \varepsilon_{p,t}$$

where $r_{p,t}$ is the equal-weight excess return on the portfolio of the stocks that represent the best idea of each active manager. The best idea is determined within each fund as the stock with the maximum value of one of four possible tilt measures:

1) $market\_tilt_{ijt} = \tau_{ijt}(\lambda_{ijt} - \lambda_{iMt})$,
2) $portfolio\_tilt_{ijt} = \tau_{ijt}(\lambda_{ijt} - \lambda_{ijtV})$,
3) $CAPM\_tilt_{ijt} = \tau_{ijt}\sigma^2_{it}(\lambda_{ijt} - \lambda_{iMt})$,
and 4) $CAPM\_portfolio\_tilt_{ijt} = \tau_{ijt}\sigma^2_{it}(\lambda_{ijt} - \lambda_{ijtV})$

where λ_{ijt} is manager j's portfolio weight in stock i, λ_{iMt} is the weight of stock i in the market portfolio, λ_{ijtV} is the value weight of stock i in manager j's portfolio, σ^2_{it} is the most-recent estimate of a stock's CAPM-idiosyncratic variance, and τ_{ijt} is a dummy variable which is 1 whenever manager j's recent trade in i was a buy and 0 otherwise. We set τ_{ijt}=1 throughout this table. The explanatory variables in the regression are all from Ken French's website except for IDI which we construct following Ang, Hodrick, and Xi (2004). We also report intercept estimates, α_4, when IDI and $STREV$ are excluded from the regression. We report decompositions of these coefficients based on whether the best idea stock is above, $r_{p,high,t}$, or below, $r_{p,low,t}$, the portfolio's median bid-ask spread. t-statistics are below the parameter estimates. Sample period for the dependent variables is January 1991 - December 2005.

Table A.9: **Performance of Best Ideas by Liquidity**

	Mean	$\widehat{\alpha_4}$	$\widehat{\alpha_6}$	$\widehat{b}$	$\widehat{s}$	$\widehat{h}$	$\widehat{m}$	$\widehat{i}$	$\widehat{r}$
			Low and High Bid-Ask Spread Splits						
$r_{1.low}$	0.0139	0.0019	0.0041	1.18	0.15	-0.15	0.36	0.16	-0.11
		1.16	2.64	25.22	2.60	-2.61	11.18	4.84	-2.89
$r_{1.high}$	0.0081	-0.0004	-0.0018	0.97	0.13	0.17	0.08	-0.15	0.00
		-0.36	-1.86	33.35	3.55	4.79	4.02	-6.90	-0.09
$r_{2.low}$	0.0143	0.0015	0.0034	1.22	0.34	-0.06	0.31	0.13	-0.12
		0.94	2.17	25.55	5.62	-0.99	9.33	3.69	-3.15
$r_{2.high}$	0.0094	0.0001	-0.0013	0.97	0.25	0.33	0.04	-0.15	0.00
		0.15	-1.41	35.32	7.38	9.60	2.31	-7.40	-0.13
$r_{3.low}$	0.0146	0.0037	0.0092	1.29	0.11	-0.42	0.19	0.54	-0.04
		1.22	3.69	17.17	1.23	-4.55	3.77	9.97	-0.61
$r_{3.high}$	0.0118	0.0013	0.0030	1.15	0.14	0.14	0.09	0.10	-0.12
		0.86	1.95	24.85	2.47	2.41	2.82	3.13	-3.12
$r_{4.low}$	0.0157	0.0042	0.0089	1.33	0.31	-0.42	0.17	0.46	-0.04
		1.65	4.13	20.27	3.85	-5.12	3.72	9.63	-0.78
$r_{4.high}$	0.0117	0.0007	0.0009	1.15	0.30	0.28	0.05	0.00	-0.03
		0.58	0.71	30.36	6.44	5.90	1.94	0.14	-0.92

Table A.10: **Performance of Best Ideas by Popularity**
We estimate coefficients from monthly regressions of

$$r_{p,t} - r_{f,t} =$$
$$= a_6 + bRMRF_t + sSMB_t + hHML_t + mMOM_t + iIDI_t + rSTREV_t + \varepsilon_{p,t}$$

where $r_{p,t}$ is the equal-weight excess return on the portfolio of the stocks that represent the best idea of each active manager. The best idea is determined within each fund as the stock with the maximum value of one of four possible tilt measures:

1) $market\_tilt_{ijt} = \tau_{ijt}(\lambda_{ijt} - \lambda_{iMt})$,
2) $portfolio\_tilt_{ijt} = \tau_{ijt}(\lambda_{ijt} - \lambda_{ijtV})$,
3) $CAPM\_tilt_{ijt} = \tau_{ijt}\sigma^2_{it}(\lambda_{ijt} - \lambda_{iMt})$,
and 4) $CAPM\_portfolio\_tilt_{ijt} = \tau_{ijt}\sigma^2_{it}(\lambda_{ijt} - \lambda_{ijtV})$

where λ_{ijt} is manager j's portfolio weight in stock i, λ_{iMt} is the weight of stock i in the market portfolio, λ_{ijtV} is the value weight of stock i in manager j's portfolio, σ^2_{it} is the most-recent estimate of a stock's CAPM-idiosyncratic variance, and τ_{ijt} is a dummy variable which is 1 whenever manager j's recent trade in i was a buy and 0 otherwise. We set τ_{ijt}=1 throughout this table. The explanatory variables in the regression are all from Ken French's website except for IDI which we construct following Ang, Hodrick, and Xi (2004). We also report intercept estimates, α_4, when IDI and $STREV$ are excluded from the regression. We report decompositions of these estimates based on whether the best idea stock is above, $r_{p,high,t}$, or below, $r_{p,low,t}$, the portfolio's median popularity. Popularity is defined as follows: Within each portfolio we rank each stock by the tilt measure in question and assign a percentage rank to it. To arrive at the tilt–stock-specific popularity measure we cumulate this statistic over the cross-section of managers. t-statistics are below the parameter estimates. Sample period for the dependent variables is January 1991 - December 2005.

Table A.10: **Performance of Best Ideas by Popularity**

	Mean	$\widehat{\alpha_4}$	$\widehat{\alpha_6}$	$\widehat{b}$	$\widehat{s}$	$\widehat{h}$	$\widehat{m}$	$\widehat{i}$	$\widehat{r}$
				Low and High Popularity Splits					
$r_{1.low}$	0.0145	0.0017	0.0027	1.08	0.37	0.21	0.30	0.05	-0.08
		1.32	2.00	26.73	7.36	4.12	10.84	1.70	-2.50
$r_{1.high}$	0.0077	-0.0001	-0.0002	1.08	-0.08	-0.19	0.14	-0.03	-0.03
		-0.10	-0.21	32.09	-2.02	-4.43	6.11	-1.27	-1.20
$r_{2.low}$	0.0139	0.0022	0.0023	1.06	0.50	0.25	0.15	-0.01	-0.06
		2.06	2.19	32.68	12.37	6.21	6.75	-0.60	-2.33
$r_{2.high}$	0.0099	-0.0004	-0.0001	1.13	0.09	0.02	0.20	0.00	-0.06
		-0.35	-0.08	32.45	2.06	0.46	8.34	-0.16	-2.25
$r_{3.low}$	0.0164	0.0038	0.0080	1.21	0.42	-0.16	0.24	0.39	-0.06
		1.70	4.19	21.04	5.82	-2.28	6.19	9.41	-1.24
$r_{3.high}$	0.0106	0.0016	0.0045	1.24	-0.15	-0.11	0.04	0.25	-0.09
		0.72	2.21	20.03	-1.91	-1.42	0.94	5.69	-1.72
$r_{4.low}$	0.0172	0.0049	0.0068	1.21	0.63	-0.02	0.12	0.21	0.02
		3.13	4.73	27.92	11.53	-0.36	4.06	6.69	0.64
$r_{4.high}$	0.0108	0.0006	0.0036	1.26	0.00	-0.11	0.10	0.25	-0.09
		0.31	1.88	22.15	0.00	-1.60	2.50	6.05	-1.93

Table A.11: **Best Ideas by Concentration of Portfolio**
We estimate coefficients from monthly regressions of

$$r_{p,t} - r_{f,t} =$$
$$= a_6 + bRMRF_t + sSMB_t + hHML_t + mMOM_t + iIDI_t + rSTREV_t + \varepsilon_{p,t}$$

where $r_{p,t}$ is the equal-weight excess return on the portfolio of the stocks that represent the best idea of each active manager. The best idea is determined within each fund as the stock with the maximum value of one of four possible tilt measures:

1) $market\_tilt_{ijt} = \tau_{ijt}(\lambda_{ijt} - \lambda_{iMt})$,
2) $portfolio\_tilt_{ijt} = \tau_{ijt}(\lambda_{ijt} - \lambda_{ijtV})$,
3) $CAPM\_tilt_{ijt} = \tau_{ijt}\sigma^2_{it}(\lambda_{ijt} - \lambda_{iMt})$,
and 4) $CAPM\_portfolio\_tilt_{ijt} = \tau_{ijt}\sigma^2_{it}(\lambda_{ijt} - \lambda_{ijtV})$

where λ_{ijt} is manager j's portfolio weight in stock i, λ_{iMt} is the weight of stock i in the market portfolio, λ_{ijtV} is the value weight of stock i in manager j's portfolio, σ^2_{it} is the most-recent estimate of a stock's CAPM-idiosyncratic variance, and τ_{ijt} is a dummy variable which is 1 whenever manager j's recent trade in i was a buy and 0 otherwise. We set τ_{ijt}=1 throughout the analysis of Panel A, meaning that all best ideas are considered. The explanatory variables in the regression are all from Ken French's website except for IDI which we construct following Ang, Hodrick, and Xi (2004). We also report intercept estimates, α_4, when IDI and $STREV$ are excluded from the regression. We restrict the analysis to those managers whose maximum tilt is in the top 25% of all maximum tilts at the time. We report decompositions of these estimates based on how concentrated are the holdings of the fund manager. We measure concentration as the normalized Herfindahl index of the fund, sorting managers into tritles (Panel A: low, Panel B: medium, Panel C: high, Panel D: high-minus-low) based on this measure. t-statistics are can be found below the parameter estimates. The sample period for the dependent variables is January 1991 - December 2005.

Table A.11: **Best Ideas by Concentration of Portfolio**

	Mean	$\widehat{\alpha_4}$	$\widehat{\alpha_6}$	$\widehat{b}$	$\widehat{s}$	$\widehat{h}$	$\widehat{m}$	$\widehat{i}$	$\widehat{r}$
				Panel A: Low					
$r_{1.low}$	0.0113	-0.0004	-0.0002	1.12	0.26	0.14	0.25	-0.02	-0.07
		-0.40	-0.18	34.06	6.41	3.36	11.28	-0.64	-2.67
$r_{2.low}$	0.0112	-0.0007	-0.0008	1.13	0.41	0.24	0.17	-0.04	-0.06
		-0.65	-0.69	32.61	9.47	5.67	7.20	-1.53	-2.16
$r_{3.low}$	0.0124	0.0008	0.0046	1.30	0.20	-0.18	0.15	0.35	-0.08
		0.36	2.35	21.92	2.69	-2.40	3.66	8.09	-1.59
$r_{4.low}$	0.0128	0.0009	0.0033	1.33	0.41	-0.09	0.09	0.23	-0.02
		0.53	1.94	26.09	6.39	-1.45	2.48	6.15	-0.40
				Panel B: Medium					
$r_{1.medium}$	0.0105	0.0006	0.0007	1.10	0.14	-0.05	0.20	-0.03	-0.05
		0.72	0.71	39.54	3.98	-1.46	10.56	-1.32	-2.18
$r_{2.medium}$	0.0120	0.0011	0.0011	1.11	0.31	0.12	0.17	-0.04	-0.08
		1.06	1.08	35.15	7.79	3.01	7.71	-1.79	-3.07
$r_{3.medium}$	0.0127	0.0023	0.0057	1.24	0.13	-0.17	0.10	0.30	-0.09
		1.10	3.10	22.25	1.90	-2.41	2.68	7.42	-2.07
$r_{4.medium}$	0.0130	0.0020	0.0043	1.27	0.33	-0.10	0.07	0.21	-0.06
		1.14	2.63	25.30	5.26	-1.57	2.14	5.67	-1.59
				Panel C: High					
$r_{1.high}$	0.0114	0.0022	0.0032	1.02	0.03	-0.06	0.21	0.07	-0.06
		1.85	2.64	28.19	0.56	-1.34	8.51	2.52	-2.00
$r_{2.high}$	0.0125	0.0025	0.0032	1.05	0.16	0.03	0.19	0.05	-0.05
		2.18	2.84	30.47	3.67	0.72	8.14	2.06	-1.88
$r_{3.high}$	0.0156	0.0052	0.0087	1.12	0.06	-0.07	0.18	0.32	-0.05
		2.74	5.37	22.93	1.02	-1.15	5.25	9.16	-1.36
$r_{4.high}$	0.0163	0.0054	0.0081	1.12	0.20	-0.02	0.17	0.26	-0.03
		3.24	5.45	25.02	3.55	-0.32	5.61	7.98	-0.69
				Panel D: High-Low					
$r_{1.high-low}$	0.0001	0.0026	0.0034	-0.09	-0.24	-0.20	-0.04	0.08	0.01
		2.02	2.54	-2.36	-4.75	-3.96	-1.53	2.81	0.38
$r_{2.high-low}$	0.0013	0.0032	0.0040	-0.07	-0.25	-0.21	0.02	0.09	0.01
		2.75	3.46	-2.07	-5.68	-4.85	0.93	3.52	0.27
$r_{3.high-low}$	0.0032	0.0044	0.0040	-0.19	-0.14	0.11	0.03	-0.03	0.02
		2.67	2.36	-3.59	-2.14	1.67	0.74	-0.67	0.55
$r_{4.high-low}$	0.0035	0.0045	0.0049	-0.20	-0.21	0.07	0.09	0.03	-0.01
		3.00	3.14	-4.33	-3.54	1.27	2.71	0.98	-0.23

Table A.12: **Best Ideas by Focus of Portfolio**
We report coefficients from monthly regressions of

$$r_{p,t} - r_{f,t} =$$
$$= a_6 + bRMRF_t + sSMB_t + hHML_t + mMOM_t + iIDI_t + rSTREV_t + \varepsilon_{p,t}$$

where $r_{p,t}$ is the equal-weight excess return on the portfolio of the stocks that represent the best idea of each active manager. The best idea is determined within each fund as the stock with the maximum value of one of four possible tilt measures:

1) $market\_tilt_{ijt} = \tau_{ijt}(\lambda_{ijt} - \lambda_{iMt})$,
2) $portfolio\_tilt_{ijt} = \tau_{ijt}(\lambda_{ijt} - \lambda_{ijtV})$,
3) $CAPM\_tilt_{ijt} = \tau_{ijt}\sigma^2_{it}(\lambda_{ijt} - \lambda_{iMt})$,
and 4) $CAPM\_portfolio\_tilt_{ijt} = \tau_{ijt}\sigma^2_{it}(\lambda_{ijt} - \lambda_{ijtV})$

where λ_{ijt} is manager j's portfolio weight in stock i, λ_{iMt} is the weight of stock i in the market portfolio, λ_{ijtV} is the value weight of stock i in manager j's portfolio, σ^2_{it} is the most-recent estimate of a stock's CAPM-idiosyncratic variance, and τ_{ijt} is a dummy variable which is 1 whenever manager j's recent trade in i was a buy and 0 otherwise. We set τ_{ijt}=1 throughout the analysis of Panel A, meaning that all best ideas are considered. The explanatory variables in the regression are all from Ken French's website except for IDI which we construct following Ang, Hodrick, and Xi (2004). We also report intercept estimates, α_4, when IDI and $STREV$ are excluded from the regression. We restrict the analysis to those managers whose maximum tilt is in the top 25% of all maximum tilts at the time. We report decompositions of these estimates based on how focused are the holdings of the fund manager. We measure focus as the number of assets within the fund, sorting managers into tritles (Panel A: low, Panel B: medium, Panel C: high, Panel D: high-minus-low) based on this measure. t-statistics are can be found below the parameter estimates. The sample period for the dependent variables is January 1991 - December 2005.

Table A.12: **Best Ideas by Focus of Portfolio**

	Mean	$\widehat{\alpha_4}$	$\widehat{\alpha_6}$	$\widehat{b}$	$\widehat{s}$	$\widehat{h}$	$\widehat{m}$	$\widehat{i}$	$\widehat{r}$
				Panel A: Low					
$r_{1.low}$	0.0110	0.0003	0.0012	1.09	0.09	-0.05	0.30	0.05	-0.06
		0.31	1.08	33.43	2.21	-1.33	13.25	2.16	-2.35
$r_{2.low}$	0.0124	0.0008	0.0014	1.13	0.27	0.11	0.23	0.01	-0.10
		0.68	1.24	32.51	6.20	2.49	9.81	0.58	-3.35
$r_{3.low}$	0.0129	0.0014	0.0063	1.26	0.04	-0.25	0.25	0.42	-0.15
		0.56	3.07	20.35	0.55	-3.20	5.94	9.32	-3.02
$r_{4.low}$	0.0138	0.0015	0.0049	1.30	0.27	-0.16	0.22	0.30	-0.10
		0.75	2.85	24.88	4.19	-2.51	6.06	7.83	-2.44
				Panel B: Medium					
$r_{1.medium}$	0.0109	0.0008	0.0009	1.12	0.14	-0.04	0.21	-0.02	-0.05
		0.78	0.86	37.16	3.69	-1.02	10.07	-0.87	-2.18
$r_{2.medium}$	0.0115	0.0006	0.0007	1.12	0.28	0.11	0.17	-0.02	-0.07
		0.58	0.68	34.68	7.00	2.66	7.50	-1.05	-2.55
$r_{3.medium}$	0.0138	0.0034	0.0070	1.23	0.10	-0.18	0.12	0.34	-0.04
		1.67	3.91	22.90	1.50	-2.69	3.21	8.62	-0.99
$r_{4.medium}$	0.0135	0.0026	0.0052	1.25	0.25	-0.10	0.10	0.26	0.00
		1.44	3.16	25.21	4.09	-1.62	2.82	7.35	-0.01
				Panel C: High					
$r_{1.high}$	0.0113	0.0013	0.0016	1.02	0.20	0.12	0.16	-0.01	-0.06
		1.42	1.67	35.71	5.52	3.31	8.19	-0.39	-2.71
$r_{2.high}$	0.0119	0.0014	0.0013	1.04	0.33	0.19	0.13	-0.02	-0.03
		1.40	1.30	34.07	8.80	5.00	6.08	-0.99	-1.20
$r_{3.high}$	0.0137	0.0033	0.0055	1.17	0.26	0.02	0.05	0.21	-0.03
		2.06	3.72	25.97	4.59	0.30	1.69	6.53	-0.74
$r_{4.high}$	0.0147	0.0042	0.0054	1.17	0.41	0.06	0.01	0.13	0.00
		3.04	3.99	28.37	8.06	1.17	0.46	4.29	0.04
				Panel D: High-Low					
$r_{1.high-low}$	0.0003	0.0010	0.0004	-0.07	0.11	0.17	-0.14	-0.06	0.00
		1.03	0.43	-2.39	2.92	4.69	-6.75	-2.77	-0.02
$r_{2.high-low}$	-0.0005	0.0006	-0.0001	-0.09	0.07	0.08	-0.11	-0.04	0.07
		0.63	-0.11	-3.21	1.82	2.30	-5.42	-1.75	2.77
$r_{3.high-low}$	0.0008	0.0019	-0.0008	-0.09	0.21	0.26	-0.20	-0.21	0.13
		1.10	-0.47	-1.92	3.50	4.31	-5.96	-5.79	3.14
$r_{4.high-low}$	0.0010	0.0027	0.0005	-0.13	0.14	0.22	-0.20	-0.17	0.11
		1.78	0.36	-3.02	2.60	4.12	-6.85	-5.35	2.97

Table A.13: **Best Ideas by Size of Portfolio**
We report coefficients from monthly regressions of

$$r_{p,t} - r_{f,t} =$$
$$= a_6 + bRMRF_t + sSMB_t + hHML_t + mMOM_t + iIDI_t + rSTREV_t + \varepsilon_{p,t}$$

where $r_{p,t}$ is the equal-weight excess return on the portfolio of the stocks that represent the best idea of each active manager. The best idea is determined within each fund as the stock with the maximum value of one of four possible tilt measures:

1) $market\_tilt_{ijt} = \tau_{ijt}(\lambda_{ijt} - \lambda_{iMt})$,
2) $portfolio\_tilt_{ijt}= \tau_{ijt}(\lambda_{ijt}-\lambda_{ijtV})$,
3) $CAPM\_tilt_{ijt}= \tau_{ijt}\sigma^2_{it}(\lambda_{ijt}-\lambda_{iMt})$,
and 4) $CAPM\_portfolio\_tilt_{ijt}= \tau_{ijt}\sigma^2_{it}(\lambda_{ijt}-\lambda_{ijtV})$

where λ_{ijt} is manager j's portfolio weight in stock i, λ_{iMt} is the weight of stock i in the market portfolio, λ_{ijtV} is the value weight of stock i in manager j's portfolio, σ^2_{it} is the most-recent estimate of a stock's CAPM-idiosyncratic variance, and τ_{ijt} is a dummy variable which is 1 whenever manager j's recent trade in i was a buy and 0 otherwise. We set τ_{ijt}=1 throughout the analysis of Panel A, meaning that all best ideas are considered. The explanatory variables in the regression are all from Ken French's website except for IDI which we construct following Ang, Hodrick, and Xi (2004). We also report intercept estimates, α_4, when IDI and $STREV$ are excluded from the regression. We restrict the analysis to those managers whose maximum tilt is in the top 25% of all maximum tilts at the time. We report decompositions of these estimates based on how large is the manager's fund. We measure size as Assets under management, sorting managers into tritles (Panel A: low, Panel B: medium, Panel C: high, Panel D: high-minus-low) based on this measure. t-statistics are can be found below the parameter estimates. The sample period for the dependent variables is January 1991 - December 2005.

Table A.13: **Best Ideas by Size of Portfolio**

	Mean	$\widehat{\alpha_4}$	$\widehat{\alpha_6}$	$\widehat{b}$	$\widehat{s}$	$\widehat{h}$	$\widehat{m}$	$\widehat{i}$	$\widehat{r}$
					Panel A: Low				
$r_{1.low}$	0.0122	0.0021	0.0021	1.03	0.26	0.02	0.20	-0.02	-0.05
		1.63	1.63	26.27	5.26	0.49	7.53	-0.72	-1.50
$r_{2.low}$	0.0132	0.0029	0.0029	1.02	0.37	0.11	0.14	-0.03	-0.04
		2.23	2.13	25.22	7.39	2.22	5.00	-0.98	-1.33
$r_{3.low}$	0.0150	0.0035	0.0061	1.26	0.40	-0.06	0.08	0.23	-0.08
		1.64	3.02	20.50	5.27	-0.82	1.80	5.14	-1.66
$r_{4.low}$	0.0156	0.0043	0.0061	1.22	0.51	-0.02	0.05	0.17	-0.05
		2.36	3.46	22.81	7.65	-0.25	1.38	4.33	-1.04
					Panel B: Medium				
$r_{1.medium}$	0.0118	0.0013	0.0017	1.06	0.17	0.01	0.25	0.01	-0.06
		1.11	1.40	28.16	3.59	0.29	9.68	0.21	-2.08
$r_{2.medium}$	0.0123	0.0015	0.0018	1.05	0.31	0.12	0.20	-0.01	-0.07
		1.15	1.36	26.97	6.26	2.39	7.40	-0.27	-2.19
$r_{3.medium}$	0.0142	0.0033	0.0073	1.15	0.13	-0.16	0.21	0.36	-0.08
		1.48	3.66	19.16	1.70	-2.18	5.13	8.21	-1.65
$r_{4.medium}$	0.0147	0.0037	0.0063	1.17	0.32	-0.10	0.15	0.25	-0.05
		1.93	3.58	21.84	4.79	-1.51	4.20	6.39	-1.06
					Panel C: High				
$r_{1.high}$	0.0092	-0.0005	0.0001	1.09	0.06	-0.06	0.22	0.02	-0.07
		-0.59	0.08	41.79	1.76	-1.75	12.43	1.10	-3.34
$r_{2.high}$	0.0116	0.0011	0.0016	1.03	0.21	0.08	0.23	0.02	-0.07
		0.77	1.12	23.34	3.86	1.52	7.56	0.57	-1.88
$r_{3.high}$	0.0114	0.0009	0.0047	1.25	0.00	-0.17	0.15	0.35	-0.08
		0.44	2.73	23.74	0.00	-2.56	4.15	9.19	-1.76
$r_{4.high}$	0.0118	0.0005	0.0031	1.30	0.18	-0.10	0.13	0.25	-0.02
		0.28	1.97	27.20	3.09	-1.70	4.07	7.38	-0.59
					Panel D: High-Low				
$r_{1.high-low}$	-0.0029	-0.0026	-0.0020	0.05	-0.20	-0.08	0.02	0.04	-0.02
		-2.12	-1.64	1.39	-4.27	-1.72	0.71	1.51	-0.73
$r_{2.high-low}$	-0.0015	-0.0018	-0.0012	0.01	-0.16	-0.03	0.09	0.05	-0.02
		-1.47	-0.97	0.14	-3.40	-0.60	3.42	1.70	-0.76
$r_{3.high-low}$	-0.0035	-0.0026	-0.0014	-0.01	-0.40	-0.11	0.07	0.12	0.01
		-1.51	-0.83	-0.23	-6.27	-1.63	2.08	3.24	0.18
$r_{4.high-low}$	-0.0038	-0.0038	-0.0030	0.07	-0.33	-0.08	0.08	0.09	0.02
		-2.36	-1.87	1.48	-5.38	-1.38	2.45	2.43	0.57

Table A.14: **Sorting on correlation with manager's best idea**
We report coefficients from monthly regressions of

$$r_{p,t} - r_{f,t} =$$
$$= a_6 + bRMRF_t + sSMB_t + hHML_t + mMOM_t + iIDI_t + rSTREV_t + \varepsilon_{p,t}$$

where $spread_{p,t}$ is the return on an equal-weight long-short portfolio, long a dollar in the top 20% of the rest of their ideas which are the most correlated with each manager's best ideas and short a dollar in the 20% of the rest of their ideas which are the least correlated with each manager's best ideas. The best idea is determined within each fund as the stock with the maximum value of one of four possible tilt measures:

1) $market\_tilt_{ijt} = \tau_{ijt}(\lambda_{ijt} - \lambda_{iMt})$,
2) $portfolio\_tilt_{ijt} = \tau_{ijt}(\lambda_{ijt} - \lambda_{ijtV})$,
3) $CAPM\_tilt_{ijt} = \tau_{ijt}\sigma^2_{it}(\lambda_{ijt} - \lambda_{iMt})$,
and 4) $CAPM\_portfolio\_tilt_{ijt} = \tau_{ijt}\sigma^2_{it}(\lambda_{ijt} - \lambda_{ijtV})$

where λ_{ijt} is manager j's portfolio weight in stock i, λ_{iMt} is the weight of stock i in the market portfolio, λ_{ijtV} is the value weight of stock i in manager j's portfolio, σ^2_{it} is the most-recent estimate of a stock's CAPM-idiosyncratic variance, and τ_{ijt} is a dummy variable which is 1 whenever manager j's recent trade in i was a buy and 0 otherwise. We set τ_{ijt}=1 throughout the analysis of Panel A, meaning that all best ideas are considered. The explanatory variables in the regression are all from Ken French's website except for IDI which we construct following Ang, Hodrick, and Xi (2004). We also report intercept estimates, α_4, when IDI and $STREV$ are excluded from the regression. We restrict the analysis to those managers whose maximum tilt is in the top 25% of all maximum tilts at the time. t-statistics are can be found below the parameter estimates. The sample period for the dependent variables is January 1991 - December 2005.

Table A.14: **Sorting on correlation with manager's best idea**

	Mean	$\widehat{\alpha_4}$	$\widehat{\alpha_6}$	$\widehat{b}$	$\widehat{s}$	$\widehat{h}$	$\widehat{m}$	$\widehat{i}$	$\widehat{r}$
	Rest Ideas Performance based on Correlation with Best Idea								
	Panel A: Best Ideas								
$spread_1$	0.0006	0.0001	0.0012	0.08	-0.19	-0.24	0.17	0.08	-0.07
		0.05	1.06	2.32	-4.47	-5.91	7.57	3.16	-2.51
$spread_2$	0.0026	0.0013	0.0021	0.14	-0.07	-0.14	0.12	0.05	-0.07
		1.33	2.27	4.85	-2.12	-3.92	6.00	2.58	-2.83
$spread_3$	0.0027	0.0018	0.0041	0.16	-0.17	-0.26	0.10	0.21	-0.04
		1.28	3.21	4.22	-3.43	-5.41	3.79	7.59	-1.22
$spread_4$	0.0033	0.0018	0.0035	0.22	-0.08	-0.22	0.08	0.16	-0.03
		1.43	2.97	6.01	-1.74	-4.89	3.29	6.20	-0.92
	Panel B: Best Fresh Ideas								
$spread_1$	0.0012	0.0005	0.0012	0.12	-0.15	-0.21	0.14	0.04	-0.06
		0.42	0.98	3.27	-3.27	-4.61	5.47	1.35	-2.11
$spread_2$	0.0024	0.0013	0.0020	0.14	-0.05	-0.15	0.09	0.04	-0.07
		1.14	1.77	4.00	-1.13	-3.49	3.87	1.40	-2.58
$spread_3$	0.0010	0.0013	0.0048	0.14	-0.32	-0.39	0.06	0.34	-0.02
		0.69	3.07	2.94	-5.52	-6.65	1.95	10.04	-0.64
$spread_4$	0.0013	0.0015	0.0046	0.14	-0.27	-0.35	0.05	0.32	0.00
		0.83	3.06	3.13	-4.72	-6.20	1.55	9.64	0.01

Table A.15: **Sample Summary Statistics**

Table A.15 provides summary statistics on the sample of mutual funds and their stock holdings at the end of each year, from 1990 to 2005. The sample is drawn from the CDA/Spectrum Database maintained by Thompson Financial. It includes all actively managed mutual funds with investment objective codes of Aggressive Growth, Growth&Income as well as Large Growth. We exclude any fund with less then 10 reported positions or less then $5 Million in assets under management. The first two columns present the total number of funds and the value of their stock holdings, which can be compared to the total market capitalization of the NYSE, NASDAQ and AMEX (3) at the end of each year. Column 4 contains the average fund size in our sample while (4) presents the average decile of market capitalization held in funds. The deciles are defined with respect to the all stocks in the CRSP universe at each particular year end. The last five columns of Table 1 describe the distribution of the number of stocks within the portfolios of mutual funds in our sample.

Table A.15: **Sample Summary Statistics**

						Number of Assets in Portfolio				
Year	(1) Number of Stocks	(2) Assets in $tn.	(3) Market Cap in $tn.	(4) Average Fund Size in $bn.	(5) Mean Size Decile	(6) Mean	(7) Q1	(8) Q2	(9) Q3	(10) Max
1990	736	0.2	3.0	0.3	6.9	68.1	33	49	73	1376
1991	844	0.3	4.1	0.4	6.8	74.1	35.5	52.5	81	1221
1992	935	0.4	4.5	0.5	6.7	87.2	39	58	89	1496
1993	1471	0.7	5.2	0.5	6.4	91.1	41	60	95	2322
1994	1588	0.6	5.1	0.4	6.1	92.4	42	62	96.5	2538
1995	1645	0.9	6.9	0.6	5.9	96.2	43	63	103	3416
1996	2078	1.2	8.5	0.6	6.3	96.8	44	65	103	3449
1997	2210	1.5	11.1	0.7	6.3	94.6	43	66	100	2795
1998	2389	1.9	13.6	0.8	6.1	98.5	41	63	98	3149
1999	2324	2.3	17.6	1.0	6.2	96.9	41	64	98	3384
2000	2223	2.4	16.1	1.1	5.8	105.8	42	65	99	3572
2001	2061	1.9	14.2	0.9	5.7	107.6	42	66	104	3758
2002	1890	1.6	11.3	0.8	5.8	104.2	42	66	102	3734
2003	1848	2.1	14.9	1.1	5.7	107.4	44	70	105	3586
2004	1666	2.3	16.8	1.4	6	106.6	43	67	102	3688
2005	1563	2.6	17.8	1.7	5.8	110	44	67	103	3702

Table A.16: **Performance of fund portfolios with different degrees of concentration**

Table A.16 reports the performance of portfolios of different degrees of concentration. Concentration is measured by the Normalized Herfindahl Index of a portfolio. Each quarter-end we divide the cross-section of mutual fund portfolios into five equally-sized concentration groups. We then calculate the average returns of the portfolios within each group of concentration over each of the following three month. The dependent variable is the monthly average portfolio return in excess of the 1-month T-bill from January 1991 until December 2005. The Sharpe Ratio is calculated as the mean excess return over this period divided by its standard deviation. α_4 and α_7 are the intercepts from factor regressions with the following generalized specification: $R_t - R_{rf,t} = \alpha + \Sigma\beta_f R_{f,t} + \varepsilon_t$, where $f \in \{MKT, SMB, HML, UMD, SR, IDI, LIQ\}$ are mimicking portfolios for a set of risk factors: MKT is the return on the value-weighted portfolio of the U.S. stock market in excess of the 1-month T-bill rate. SMB is a zero cost portfolio long in small capitalization stocks and short in large capitalization stocks. HML is a zero cost portfolio long in stocks with high book to market ratios and short in stocks with low book to market ratios. UMD is a zero cost portfolio capturing momentum in stock returns. SR captures short-term reversal in stock returns. IDI is a zero cost portfolio long in stocks with high idiosyncratic volatility and short in stocks with low idiosyncratic volatility. LIQ is a zero cost portfolio long in stocks that are strongly exposed to innovations in aggregate market liquidity and short in stocks with low exposure to innovations in aggregate market liquidity. α_{DGTW} is the average return of portfolios in different concentration quintiles after adjusting the return of each holding by the return of a stock portfolio matched by size-, book-to-market and momentum characteristics. $\alpha_{DGTW,3}$ is the same return adjusted for SR, IDI and LIQ using a factor regression. T-statistics are in parenthesis.

Table A.16: **Performance of fund portfolios with different degrees of concentration**

Dep. Var.	Mean	Sharpe Ratio	α_4	α_{DGTW}	α_7	$\alpha_{DGTW,3}$	β_{MKT}	β_{SMB}	β_{HML}	β_{UMD}	β_{SR}	β_{IDI}	β_{LIQ}
r_1	0.0083	0.15	-0.0011	0.0001	-0.0019	-0.0002	1.11	0.31	0.18	-0.01	0.04	-0.05	0.01
			(-1.54)	(0.28)	(-2.23)	(-0.12)	(50.25)	(11.48)	(6.44)	(-0.38)	(2.19)	(-3.15)	(0.63)
r_2	0.0083	0.15	-0.0004	0.0005	-0.0009	0.0007	1.11	0.20	0.10	-0.01	0.01	-0.04	0.00
			(-0.71)	(1.38)	(-1.22)	(1.48)	(57.60)	(8.31)	(4.23)	(-0.70)	(0.43)	(-3.18)	(-0.10)
r_3	0.0080	0.15	-0.0001	0.0005	-0.0003	0.0006	1.07	0.14	0.05	0.00	0.02	-0.04	-0.01
			(-0.12)	(1.46)	(-0.43)	(1.61)	(63.83)	(6.91)	(2.34)	(-0.03)	(1.78)	(-3.10)	(-0.78)
r_4	0.0083	0.16	0.0001	0.0007	0.0004	0.0012	1.06	0.11	0.07	0.01	0.02	0.00	-0.03
			(0.21)	(2.03)	(0.56)	(2.99)	(60.73)	(5.30)	(3.04)	(1.14)	(1.07)	(-0.31)	(-1.54)
r_5	0.0098	0.18	0.0013	0.0013	0.0014	0.0013	1.04	0.18	0.10	0.02	-0.01	0.02	-0.05
			(1.55)	(3.00)	(2.00)	(3.77)	(39.52)	(5.44)	(3.02)	(1.35)	(-0.30)	(1.28)	(-1.76)
r_{5-1}	0.0015	0.03	0.0024	0.0012	0.0033	0.0015	-0.07	-0.14	-0.08	0.03	-0.05	0.07	-0.06
			(2.49)	(3.11)	(3.49)	(3.40)	(-2.37)	(-3.79)	(-2.15)	(1.51)	(-1.93)	(3.55)	(-2.07)

Table A.17: **Performance of Concentrated and Diversified Portfolios Conditional on Fund Size**

Table A.17 reports the performance of portfolios of different degrees of concentration, conditional on the fund size. Concentration is measured by the Normalized Herfindahl Index and fund size is the dollar value of funds' portfolio holdings. We report the four different risk adjusted returns of portfolio formed on quintile sorts of performance conditional on fund size. T-statistics are in parenthesis. α_4 and α_7 are the intercepts from factor regressions with the following generalized specification: $r_t - r_{rf,t} = \alpha_F + \Sigma\beta_f r_{f,t} + \varepsilon_t$, where $f \in \{MKT, SMB, HML, UMD, SR, IDI, LIQ\}$ are mimicking portfolios for a set of risk factors: MKT is the return on a value-weighted market portfolio of the U.S. stock market in excess of the 1-month T-bill rate. SMB is a zero cost portfolio long in small capitalization stock and short in large capitalization stocks. HML is a zero cost portfolio long in stocks with high book to market ratios and short in stocks with low book to market ratios. UMD is a zero cost portfolio capturing momentum in stock returns. SR captures short-term reversal in stock returns. IDI is a zero cost portfolio long in stocks with high idiosyncratic volatility and short in stocks with low idiosyncratic volatility. LIQ is a zero cost portfolio long in stocks that are strongly exposed to innovations in market liquidity and short in stocks with low exposure to innovations in market liquidity. α_{DGTW} is the average return of portfolios in different concentration quintiles after adjusting the return of each holding by the return of a stock portfolio matched by size-, book-to-market and momentum characteristics. $\alpha_{DGTW,3}$ is the same return adjusted for SR, IDI and LIQ using a factor regression.

Table A.17: **Performance of Concentrated and Diversified Portfolios Conditional on Fund Size**

	α_4					α_7				
	1(*large*)	2	3	4	5(*small*)	1(*large*)	2	3	4	5(*small*)
1(*div*)	-0.14	-0.15	-0.09	-0.13	-0.05	-0.21	-0.22	-0.16	-0.20	-0.12
2	-0.10	-0.05	-0.07	0.04	-0.03	-0.13	-0.09	-0.11	-0.03	-0.10
3	-0.07	0.02	-0.12	0.01	0.02	-0.11	-0.03	-0.16	-0.04	0.00
4	-0.01	-0.04	0.01	0.08	0.04	0.01	-0.05	-0.01	0.08	-0.01
5(*conc*)	-0.02	0.10	0.21	0.14	0.14	0.01	0.17	0.26	0.14	0.17
5-1	**0.13**	**0.25**	**0.30**	**0.27**	**0.19**	**0.22**	**0.39**	**0.42**	**0.33**	**0.29**
t-stat	**1.41**	**2.30**	**2.45**	**1.89**	**1.51**	**2.54**	**3.62**	**3.42**	**2.32**	**2.28**
	α_{DGTW}					$\alpha_{DGTW,3}$				
	1(*large*)	2	3	4	5(*small*)	1(*large*)	2	3	4	5(*small*)
1(*div*)	0.05	0.08	0.07	0.04	0.06	0.05	0.07	0.05	0.01	0.04
2	0.07	0.09	0.06	0.12	0.09	0.07	0.09	0.05	0.11	0.08
3	0.05	0.09	0.03	0.08	0.08	0.05	0.09	0.03	0.07	0.07
4	0.08	0.10	0.11	0.13	0.07	0.09	0.11	0.11	0.13	0.05
5(*conc*)	0.05	0.24	0.22	0.21	0.12	0.06	0.27	0.26	0.24	0.14
$5-1$	**0.00**	**0.16**	**0.15**	**0.17**	**0.06**	**0.01**	**0.20**	**0.21**	**0.23**	**0.10**
$t-stat$	**-0.06**	**2.40**	**1.93**	**1.90**	**0.72**	**0.09**	**3.20**	**2.73**	**2.63**	**1.31**

Table A.18: **Gains to Concentration by Age of Stock Listing**
Table A.18 reports the performance of portfolios of different degrees of concentration, when investing into companies with short and long histories of stock market listing. Each quarter-end, we subdivide fund managers' portfolios into subgroups of stocks that are older and younger than the median mutual fund holding at the time. We then calculate the average performance of fund managers with different degrees of concentration in each age-group and estimate risk-adjusted returns using the same methodology as in Table A.16.

Table A.18: **Gains to Concentration by Age of Stock Listing**

	α_4	α_{DGTW}	α_7	$\alpha_{DGTW,3}$	β_{MKT}	β_{SMB}	β_{HML}	β_{UMD}	β_{SR}	β_{IDI}	β_{LIQ}
					Young Listings						
r_1	-0.0035	-0.0008	-0.0033	-0.0005	1.00	0.56	0.04	0.09	0.05	0.05	0.00
	(-3.02)	(-0.76)	(-2.79)	(-0.49)	(33.04)	(12.55)	(0.83)	(3.72)	(1.90)	(1.80)	(0.17)
r_2	-0.0029	-0.0006	-0.0021	0.0001	1.20	0.45	0.02	0.09	0.08	-0.01	0.00
	(-2.47)	(-0.51)	(-1.78)	(0.05)	(32.98)	(10.05)	(0.34)	(3.50)	(2.98)	(-0.22)	(-0.04)
r_3	-0.0014	-0.0002	-0.0008	0.0004	1.14	0.38	-0.02	0.08	0.09	0.03	-0.01
	(-1.22)	(-0.20)	(-0.64)	(0.38)	(31.16)	(8.46)	(-0.37)	(3.15)	(3.40)	(1.08)	(-0.26)
r_4	-0.0005	0.0008	0.0007	0.0017	1.11	0.32	0.04	0.10	0.12	-0.01	0.00
	(-0.40)	(0.61)	(0.56)	(1.51)	(29.69)	(7.05)	(0.86)	(4.10)	(4.43)	(-0.26)	(-0.04)
r_5	0.0007	0.0010	0.0021	0.0021	1.09	0.33	0.10	0.07	0.13	-0.03	0.00
	(0.49)	(0.62)	(1.49)	(1.72)	(25.51)	(6.26)	(1.86)	(2.29)	(4.19)	(-0.87)	(-0.15)
r_{5-1}	0.0042	0.0018	0.0054	0.0026	-0.11	-0.23	0.06	-0.03	0.08	-0.08	-0.01
	(2.88)	(1.39)	(3.67)	(2.24)	(-2.40)	(-4.18)	(1.10)	(-0.83)	(2.46)	(-2.29)	(-0.28)
					Old Listings						
r_1	0.0000	0.0005	-0.0011	0.0001	1.09	0.23	0.22	-0.05	-0.09	0.03	0.01
	(-0.05)	(1.07)	(-1.50)	(0.20)	(48.64)	(8.39)	(8.04)	(-3.24)	(-5.84)	(1.72)	(0.59)
r_2	0.0004	0.0007	-0.0005	0.0005	1.09	0.12	0.12	-0.04	-0.08	0.01	0.00
	(0.58)	(2.13)	(-0.82)	(1.61)	(59.81)	(5.29)	(5.51)	(-3.52)	(-6.27)	(0.90)	(-0.29)
r_3	0.0004	0.0005	-0.0004	0.0003	1.06	0.08	0.07	-0.03	-0.07	0.02	0.00
	(0.74)	(1.79)	(-0.88)	(1.17)	(70.83)	(4.17)	(3.78)	(-2.83)	(-6.96)	(1.83)	(-0.45)
r_4	0.0004	0.0006	-0.0002	0.0005	1.05	0.05	0.08	-0.02	-0.05	0.03	-0.02
	(0.79)	(2.18)	(-0.37)	(1.74)	(69.46)	(2.62)	(4.26)	(-1.56)	(-4.21)	(2.33)	(-1.88)
r_5	0.0017	0.0014	0.0015	0.0014	1.02	0.11	0.10	0.01	-0.02	0.01	-0.04
	(2.20)	(3.62)	(1.86)	(3.70)	(42.06)	(3.73)	(3.22)	(0.41)	(-1.27)	(0.31)	(-2.69)
r_{5-1}	0.0018	0.0010	0.0026	0.0014	-0.07	-0.12	-0.13	0.06	0.07	-0.02	-0.05
	(1.90)	(1.94)	(2.82)	(2.90)	(-2.38)	(-3.48)	(-3.64)	(2.95)	(3.57)	(-1.10)	(-2.81)

Table A.19: **Gains to Concentration by Relative Bid-Ask Spread**
Table A.19 reports the performance of portfolios of different degrees of concentration, when investing into stocks with high and low relative bid-ask spreads. We calculate bid-ask spreads of stocks by taking an average over the daily relative bid-ask spread each stock over the preceeding three month. Each quarter-end, we subdivide fund managers' portfolios into subgroups of stocks that have lower and higher bid-ask spreads than the median stock in the entire universe of stocks held by mutual funds at the time. We then calculate the average performance of fund managers with different degrees of concentration in each liquidity-group and estimate risk-adjusted returns using the same methodology as in Table A.16.

Table A.19: **Gains to Concentration by Relative Bid-Ask Spread**

	α_4	α_{DGTW}	α_7	$\alpha_{DGTW,3}$	β_{MKT}	β_{SMB}	β_{HML}	β_{UMD}	β_{SR}	β_{IDI}	β_{LIQ}
Low Bid-Ask Spread											
r_1	-0.0006	-0.0002	-0.0024	-0.0011	1.00	0.21	0.35	-0.02	-0.16	0.03	0.01
	(-0.63)	(-0.25)	(-2.68)	(-2.16)	(37.71)	(6.25)	(10.24)	(-0.90)	(-8.47)	(1.41)	(0.66)
r_2	-0.0008	-0.0002	-0.0023	-0.0009	1.03	0.12	0.27	0.00	-0.15	0.02	0.01
	(-0.81)	(-0.26)	(-2.85)	(-1.98)	(41.37)	(4.01)	(8.68)	(-0.08)	(-8.56)	(0.86)	(0.52)
r_3	-0.0006	-0.0003	-0.0021	-0.0010	1.00	0.10	0.22	0.01	-0.14	0.02	0.00
	(-0.68)	(-0.45)	(-2.85)	(-2.28)	(44.53)	(3.71)	(7.88)	(0.95)	(-8.94)	(1.28)	(0.17)
r_4	-0.0004	-0.0003	-0.0017	-0.0010	0.99	0.10	0.24	0.02	-0.13	0.02	0.00
	(-0.51)	(-0.42)	(-2.34)	(-2.22)	(43.43)	(3.71)	(8.43)	(1.30)	(-7.65)	(1.18)	(0.07)
r_5	0.0006	0.0001	-0.0004	-0.0007	0.96	0.15	0.25	0.03	-0.10	0.00	0.01
	(0.66)	(0.09)	(-0.45)	(-1.36)	(36.80)	(4.78)	(7.82)	(1.81)	(-5.28)	(0.17)	(0.42)
r_{5-1}	0.0012	0.0003	0.0020	0.0004	-0.06	-0.06	-0.09	0.05	0.07	-0.03	0.00
	(1.56)	(0.66)	(2.56)	(0.90)	(-2.69)	(-1.89)	(-3.10)	(3.00)	(3.86)	(-1.41)	(-0.28)
High Bid-Ask Spread											
r_1	-0.0020	0.0009	-0.0015	0.0017	1.28	0.54	-0.10	0.03	0.08	0.04	0.00
	(-1.44)	(0.62)	(-1.04)	(1.54)	(30.01)	(10.35)	(-1.82)	(1.11)	(2.52)	(1.26)	(0.05)
r_2	-0.0004	0.0018	0.0006	0.0030	1.29	0.41	-0.20	0.01	0.11	0.01	-0.01
	(-0.29)	(1.15)	(0.38)	(2.47)	(28.52)	(7.30)	(-3.56)	(0.49)	(3.29)	(0.23)	(-0.54)
r_3	-0.0005	0.0016	0.0006	0.0028	1.26	0.32	-0.24	0.01	0.13	0.02	-0.02
	(-0.32)	(1.02)	(0.43)	(2.30)	(27.53)	(5.69)	(-4.24)	(0.40)	(3.98)	(0.65)	(-0.72)
r_4	-0.0001	0.0021	0.0017	0.0034	1.24	0.23	-0.22	0.03	0.20	0.01	-0.04
	(-0.09)	(1.25)	(1.14)	(2.84)	(27.49)	(4.17)	(-3.86)	(1.08)	(6.11)	(0.35)	(-1.34)
r_5	0.0014	0.0031	0.0037	0.0047	1.20	0.25	-0.16	0.03	0.23	-0.01	-0.07
	(0.77)	(1.72)	(2.13)	(3.68)	(22.53)	(3.88)	(-2.48)	(0.94)	(6.07)	(-0.34)	(-2.08)
r_{5-1}	0.0034	0.0022	0.0052	0.0030	-0.08	-0.29	-0.07	0.00	0.16	-0.06	-0.07
	(2.14)	(2.14)	(3.39)	(3.20)	(-1.66)	(-5.02)	(-1.17)	(0.06)	(4.64)	(-1.54)	(-2.42)

Table A.20: **Gains to Concentration by Analyst Coverage**

Table A.20 reports the performance of portfolios of different degrees of concentration, when investing into companies with high and low analyst coverage. Coverage is measured by the number of analysts providing EPS forecasts in the most recent 12 month. Each quarter-end, we subdivide fund managers' portfolios into subgroups of stocks that have more and less analyst coverage than the median stock in the entire universe of mutual fund holdings at the time. We then calculate the average performance of fund managers with different degrees of concentration in each coverage-group and estimate risk-adjusted returns using the same methodology as in Table A.16.

Table A.20: **Gains to Concentration by Analyst Coverage**

	α_4	α_{DGTW}	α_7	$\alpha_{DGTW,3}$	β_{MKT}	β_{SMB}	β_{HML}	β_{UMD}	β_{SR}	β_{IDI}	β_{LIQ}
					Low Analyst Coverage						
r_1	-0.0016	-0.0013	-0.0025	-0.0024	1.00	0.78	0.16	0.07	-0.03	0.13	0.04
	(-1.48)	(-1.30)	(-2.40)	(-2.75)	(30.95)	(19.66)	(3.99)	(3.03)	(-1.21)	(4.85)	(2.04)
r_2	-0.0011	-0.0009	-0.0017	-0.0017	1.02	0.78	0.15	0.08	-0.04	0.05	0.03
	(-1.03)	(-1.09)	(-1.55)	(-2.05)	(30.67)	(19.14)	(3.58)	(3.48)	(-1.53)	(1.69)	(1.71)
r_3	0.0014	-0.0001	0.0005	-0.0012	0.93	0.70	0.12	0.01	-0.04	0.10	0.03
	(1.03)	(-0.09)	(0.35)	(-1.46)	(22.49)	(13.87)	(2.43)	(0.40)	(-1.46)	(2.89)	(1.08)
r_4	0.0012	0.0004	0.0009	0.0000	0.88	0.66	0.21	0.05	-0.01	0.05	0.02
	(0.86)	(0.48)	(0.63)	(-0.05)	(20.33)	(12.34)	(3.84)	(1.76)	(-0.19)	(1.35)	(0.81)
r_5	0.0021	0.0004	0.0021	-0.0004	0.88	0.63	0.22	0.05	0.03	0.05	0.02
	(1.43)	(0.38)	(1.42)	(-0.34)	(19.31)	(11.31)	(3.81)	(1.57)	(0.91)	(1.27)	(0.75)
r_{5-1}	0.0037	0.0017	0.0046	0.0020	-0.13	-0.15	0.05	-0.02	0.06	-0.08	-0.02
	(2.83)	(1.62)	(3.54)	(1.92)	(-3.11)	(-3.06)	(1.10)	(-0.67)	(2.01)	(-2.48)	(-0.80)
					High Analyst Coverage						
r_1	-0.0008	0.0004	-0.0015	0.0002	1.13	0.25	0.16	-0.02	-0.06	0.03	0.01
	(-1.01)	(0.89)	(-1.91)	(0.51)	(47.09)	(8.64)	(5.37)	(-0.98)	(-3.46)	(1.39)	(0.44)
r_2	-0.0001	0.0007	-0.0006	0.0007	1.12	0.15	0.07	-0.02	-0.05	0.00	-0.01
	(-0.12)	(1.79)	(-0.90)	(1.74)	(55.96)	(5.93)	(2.88)	(-1.20)	(-3.69)	(0.08)	(-0.43)
r_3	0.0001	0.0005	-0.0005	0.0005	1.09	0.09	0.02	0.00	-0.04	0.02	-0.01
	(0.11)	(1.71)	(-0.84)	(1.59)	(63.87)	(4.21)	(0.85)	(0.11)	(-3.60)	(1.48)	(-0.58)
r_4	0.0003	0.0008	0.0001	0.0008	1.09	0.04	0.00	0.01	-0.01	0.01	-0.02
	(0.60)	(2.18)	(0.26)	(2.35)	(63.12)	(2.02)	(0.06)	(0.68)	(-1.05)	(0.75)	(-1.98)
r_5	0.0014	0.0016	0.0016	0.0019	1.09	0.09	-0.01	0.00	0.01	-0.02	-0.04
	(2.26)	(3.32)	(2.60)	(4.17)	(56.73)	(3.65)	(-0.57)	(-0.02)	(0.81)	(-1.43)	(-3.39)
r_{5-1}	0.0022	0.0013	0.0031	0.0017	-0.04	-0.17	-0.17	0.02	0.07	-0.05	-0.05
	(2.89)	(2.24)	(4.33)	(3.32)	(-1.71)	(-6.18)	(-6.31)	(1.04)	(4.45)	(-2.74)	(-3.42)

Table A.21: **Gains to Concentration by Analyst Dispersion**

Table A.21 reports the performance of portfolios of different degrees of concentration, when investing into companies with high and low analyst dispersion. Dispersion is measured by the scaled standard deviation of EPS-forecasts in the most recent 12 month. Each quarter-end, we subdivide fund managers' portfolios into subgroups of stocks that have lower and higher analyst dispersion than the median covered stock in the entire universe of mutual fund holdings at the time. We then calculate the average performance of fund managers with different degrees of concentration in each dispersion-group and estimate risk-adjusted returns using the same methodology as in Table A.16.

Table A.21: **Gains to Concentration by Analyst Dispersion**

	α_4	α_{DGTW}	α_7	$\alpha_{DGTW,3}$	β_{MKT}	β_{SMB}	β_{HML}	β_{UMD}	β_{SR}	β_{IDI}	β_{LIQ}
Low Dispersion											
r_1	0.0011	0.0012	-0.0004	0.0006	1.00	0.27	0.11	-0.02	-0.13	0.05	0.00
	(1.09)	(2.10)	(-0.45)	(1.37)	(40.17)	(7.97)	(3.39)	(-0.86)	(-6.52)	(2.08)	(-0.16)
r_2	0.0015	0.0014	0.0003	0.0011	1.09	0.15	0.02	-0.01	-0.12	0.02	-0.01
	(1.74)	(3.06)	(0.35)	(2.63)	(45.52)	(5.20)	(0.51)	(-0.71)	(-6.71)	(0.99)	(-0.73)
r_3	0.0017	0.0014	0.0005	0.0010	1.06	0.09	-0.04	0.00	-0.10	0.04	-0.01
	(2.24)	(3.36)	(0.75)	(2.96)	(51.40)	(3.38)	(-1.49)	(0.16)	(-6.89)	(2.13)	(-0.90)
r_4	0.0019	0.0016	0.0010	0.0013	1.06	0.04	-0.05	0.01	-0.08	0.03	-0.02
	(2.73)	(3.87)	(1.46)	(3.52)	(52.97)	(1.76)	(-1.84)	(0.98)	(-5.66)	(2.05)	(-1.59)
r_5	0.0031	0.0022	0.0025	0.0020	1.05	0.06	-0.05	0.01	-0.07	0.01	-0.03
	(4.60)	(4.96)	(3.73)	(4.85)	(52.22)	(2.38)	(-2.09)	(0.57)	(-4.57)	(0.49)	(-2.07)
r_{5-1}	0.0021	0.0010	0.0029	0.0014	-0.04	-0.21	-0.17	0.02	0.06	-0.04	-0.02
	(3.24)	(2.21)	(4.65)	(3.14)	(-2.23)	(-8.99)	(-7.14)	(1.85)	(4.55)	(-2.50)	(-1.99)
High Dispersion											
r_1	-0.0057	-0.0022	-0.0046	-0.0015	1.19	0.39	0.26	0.01	0.13	0.03	0.04
	(-3.97)	(-1.64)	(-3.26)	(-1.29)	(27.73)	(7.40)	(4.79)	(0.30)	(4.26)	(0.80)	(1.61)
r_2	-0.0046	-0.0019	-0.0032	-0.0011	1.19	0.28	0.24	-0.01	0.14	-0.01	0.03
	(-3.30)	(-1.36)	(-2.36)	(-0.90)	(28.43)	(5.47)	(4.52)	(-0.20)	(4.76)	(-0.19)	(1.14)
r_3	-0.0042	-0.0022	-0.0029	-0.0014	1.13	0.24	0.17	0.00	0.14	0.02	0.03
	(-3.10)	(-1.67)	(-2.22)	(-1.29)	(28.50)	(4.89)	(3.36)	(-0.04)	(5.00)	(0.49)	(1.13)
r_4	-0.0033	-0.0016	-0.0014	-0.0005	1.11	0.19	0.14	0.01	0.19	0.00	0.01
	(-2.33)	(-1.11)	(-1.08)	(-0.50)	(28.16)	(3.83)	(2.95)	(0.31)	(6.82)	(-0.11)	(0.21)
r_5	-0.0012	-0.0002	0.0005	0.0011	1.10	0.27	0.12	0.00	0.17	-0.02	-0.03
	(-0.78)	(-0.13)	(0.35)	(0.78)	(23.77)	(4.77)	(2.14)	(-0.02)	(5.23)	(-0.53)	(-0.91)
r_{5-1}	0.0044	0.0020	0.0051	0.0026	-0.08	-0.12	-0.13	-0.01	0.04	-0.05	-0.07
	(3.17)	(1.77)	(3.59)	(2.28)	(-1.94)	(-2.20)	(-2.43)	(-0.31)	(1.38)	(-1.36)	(-2.56)

Table A.22: **Summary Statistics on Trade Portfolios**
This table summarizes the out-of sample performance of trades by skilled (S) and unskilled (U) mutual fund managers. Each quarter end the entire cross-section of funds is divided into these two groups using the point estimate of α_f from running a 48-month regression with the following specification

$$r_{f,t} = \alpha_f + \beta_f^M r_{M,t} + \beta_f^{SMB} r_{SMB,t} + \beta_f^{HML} r_{HML,t} + \beta_f^{MOM} r_{MOM,t} + \varepsilon_{f,t}$$

where $r_{f,t}$ is the historic gross-return on fund f in month t and $r_{M,t}$ the return on the CRSP value weighted market portfolio in month t. All returns are expressed in excess of the risk-free interest rate. The gross returns on the fund portfolios computed from from data of the CRSP Survivorship-Bias-Free Mutual Fund Database©, and are calculated by adding the monthly increment of the expense ratio to the net returns provided in the database. The regressors $r_{SMB,t}$ and $r_{HML,t}$ are returns on zero-cost portfolios capturing the small-firm and value-effects. The momentum factor $r_{MOM,t}$ is the return on a zero-cost portfolio long in winning stock and short in losing stock during the 6 month prior to its formation. Mutual fund portfolios with positive point estimates of α_f are classified as skilled (S), while fund portfolios with negative point estimates of α_f are classified as unskilled (U). A, R, N, and D refer to the performance of portfolios of aggregate additions, reductions, new additions and deletions of managers within each skill group (S, U) over the 3 month following the publication of their holdings. Panel 1 presents the results when equally weighting each stock in these portfolios. Panel 2 refers to the results when weighting each stock by the average change in the portfolio weight of managers in a particular skill-group. Panel 3 presents the results when weighting each stock by the averageα_f of managers who traded them in each skill group.

Table A.22: **Summary Statistics on Trade Portfolios**

	Skilled Manager (S)				Unskilled Manager(U)			
	N_S	A_S	D_S	R_S	N_U	A_U	D_U	R_U
Equally Weighted								
Mean	0.0122	0.0091	0.0039	0.0082	0.0102	0.0076	0.0067	0.0078
Std. Dev.	0.0769	0.0537	0.0828	0.0595	0.0729	0.0543	0.0766	0.0584
Skewness	0.17	-0.95	0.92	-0.62	-0.16	-1.08	0.02	-0.83
Kurtosis	5.96	6.42	12.52	5.94	7.05	7.03	6.36	6.37
Sharpe Ratio	0.109	0.098	0.001	0.073	0.087	0.069	0.037	0.068
Trade-Size Weighted								
Mean	0.0152	0.0094	0.0021	0.0078	0.0064	0.0063	0.0036	0.0106
Std. Dev.	0.0847	0.0629	0.0944	0.069	0.0698	0.061	0.1126	0.0674
Skewness	0.05	-0.8	0.48	-0.44	-0.12	-0.99	3.39	-0.09
Kurtosis	7.71	5.29	8.96	6.03	5.97	6.06	39.06	7.12
Sharpe Ratio	0.135	0.089	-0.018	0.058	0.037	0.041	-0.002	0.101
Performance Weighted								
Mean	0.0125	0.0089	0.0008	0.0072	0.0106	0.0079	0.0034	0.0081
Std. Dev.	0.0789	0.0573	0.082	0.0642	0.077	0.0575	0.0778	0.0617
Skewness	-0.17	-0.96	0.12	-0.7	0.03	-0.95	-0.47	-0.71
Kurtosis	4.8	5.88	8.49	5.08	6.81	6.33	5.16	6.02
Sharpe Ratio	0.11	0.089	-0.037	0.053	0.088	0.071	-0.005	0.07

Table A.23: **4-Factor Fama French RegressionsoSpread Portfolios within Skill Groups**
This table summarizes the risk adjusted performance of portfolios several long-short portfolios formed on the basis of observed mutual fund trades of skilled S and unskilled U managers. Each quarter end the entire cross-section of funds is divided into these two skill groups using the point estimate of α_f from running a 48-month regression with the following specification

$$r_{f,t} = \alpha_f + \beta_f^M r_{M,t} + \beta_f^{SMB} r_{SMB,t} + \beta_f^{HML} r_{HML,t} + \beta_f^{MOM} r_{MOM,t} + \varepsilon_{f,t}$$

where $r_{f,t}$ is the historic gross-return on fund f in month t and $r_{M,t}$ the return on the CRSP value weighted market portfolio in month t. All returns are expressed in excess of the risk-free interest rate. The gross returns on the fund portfolios computed from from data of the CRSP Survivorship-Bias-Free Mutual Fund Database©, and are calculated by adding the monthly increment of the expense ratio to the net returns provided in the database. The regressors $r_{SMB,t}$ and $r_{HML,t}$ are returns on zero-cost portfolios capturing the small-firm and value-effects. The momentum factor $r_{MOM,t}$ is the return on a zero-cost portfolio long in winning stock and short in losing stock during the 6 month prior to its formation. Mutual fund portfolios with positive point estimates of α_f are classified as skilled (S), while fund portfolios with negative point estimates of α_f are classified as unskilled (U). $N_i - D_i$ refers to a portfolio long in new additions to fund portfolios and short in deletions from fund portfolios in skill group $i \in (S, U)$ over the 3 month following the publication of the fund portfolios. $A_i - R_i$ refers to to a portfolio long in additions to existing positions of fund portfolios and short in reductions of existing positions of funds in skill group i. The left section of the table presents the results when equally weighting each stock in the long and short side of the portfolio. The right section refers to the results when weighting each stock by the average change in the portfolio weight of managers in a particular skill-group. All the portfolio returns calculated are then risk adjusted by estimating the four factor Carhart model described above over the sample period from Q2/1985 to Q1/2005.

Table A.23: **4-Factor Fama French RegressionsoSpread Portfolios within Skill Groups**

	Equally Weighted				**Trade-Size-Weighted**			
	Skilled Manager		Unskilled Manager		Skilled Manager		Unskilled Manager	
	$N_S - D_S$	$A_S - R_S$	$N_U - D_U$	$A_U - R_U$	$N_S - D_S$	$A_S - R_S$	$N_U - D_U$	$A_U - R_U$
α	0.0042	0.0001	-0.0015	-0.0012	0.0080	-0.0001	-0.0041	-0.0070
	(1.94)	(0.12)	(-0.68)	(-2.01)	(1.65)	(-0.26)	(-0.72)	(-3.49)
β_{MKT}	-0.027	-0.002	-0.007	-0.041	-0.015	-0.011	0.042	-0.036
	(-0.53)	(-0.15)	(-0.12)	(-2.98)	(-0.13)	(-0.26)	(0.14)	(-0.72)
β_{SMB}	0.245	-0.141	0.096	-0.014	0.271	0.012	-0.231	0.118
	(3.79)	(-7.36)	(1.37)	(-0.83)	(1.85)	(0.23)	(-1.35)	(1.94)
β_{HML}	-0.021	0.154	-0.122	0.048	-0.051	0.182	0.132	0.108
	(-0.26)	(6.54)	(-1.42)	(2.28)	(-0.29)	(2.19)	(0.63)	(1.45)
β_{MOM}	0.494	0.039	0.650	0.126	0.626	0.216	0.766	0.306
	(10.80)	(2.91)	(13.5)	(10.39)	(6.06)	(5.97)	(6.34)	(7.12)

Table A.24: **4-Factor Fama French Regressions Spread Portfolios across Skill Groups**

This table summarizes the risk adjusted performance of portfolios several long-short portfolios formed on the basis of observed mutual fund trades of skilled S and unskilled U managers. Each quarter end the entire cross-section of funds is divided into these two skill groups using the point estimate of α_f from running a 48-month regression with the following specification

$$r_{f,t} = \alpha_f + \beta_f^M r_{M,t} + \beta_f^{SMB} r_{SMB,t} + \beta_f^{HML} r_{HML,t} + \beta_f^{MOM} r_{MOM,t} + \varepsilon_{f,t}$$

where $r_{f,t}$ is the historic gross-return on fund f in month t and $r_{M,t}$ the return on the CRSP value weighted market portfolio in month t. All returns are expressed in excess of the risk-free interest rate. The gross returns on the fund portfolios computed from from data of the CRSP Survivorship-Bias-Free Mutual Fund Database©, and are calculated by adding the monthly increment of the expense ratio to the net returns provided in the database. The regressors $r_{SMB,t}$ and $r_{HML,t}$ are returns on zero-cost portfolios capturing the small-firm and value-effects. The momentum factor $r_{MOM,t}$ is the return on a zero-cost portfolio long in winning stock and short in losing stock during the 6 month prior to its formation. Mutual fund portfolios with positive point estimates of α_f are classified as skilled (S), while fund portfolios with negative point estimates of α_f are classified as unskilled (U). $N_S - N_U$ refers to a portfolio long in new additions to fund portfolios of skilled managers and short in new additions to fund portfolios of unskilled managers. $A_S - A_U$ refers to a portfolio long in additions to existing positions in fund portfolios of skilled managers and short in additions to existing positions of fund portfolios of unskilled managers. $D_S - D_U$ refers to a portfolio long in deletions from fund portfolios of skilled managers and short in deletions from fund portfolios of unskilled managers. $R_S - R_U$ refers to a portfolio long in reductions of existing positions in fund portfolios of skilled managers and short in reductions of existing positions of fund portfolios of unskilled managers. The left section of the table presents the results when equally weighting each stock in the long and short side of the portfolio. The right section refers to the results when weighting each stock by the average change in the portfolio weight of managers in a particular skill-group. All portfolio returns are risk adjusted by estimating the four factor Carhart model described above over the entire sample period from Q2/1985 to Q1/2005.

Table A.24: **4-Factor Fama French Regressions Spread Portfolios across Skill Groups**

	Equally Weighted				**Trade-Size-Weighted**			
	$N_S - N_U$	$A_S - A_U$	$D_S - D_U$	$R_S - R_U$	$N_S - N_U$	$A_S - A_U$	$N_S - N_U$	$R_S - R_U$
α	0.0049	0.0018	-0.0007	0.0006	0.0074	0.0040	-0.0046	-0.0024
	(2.65)	(3.95)	(-0.37)	(1.06)	(1.85)	(3.18)	(-0.85)	(-1.41)
β_{MKT}	0.010	0.013	0.031	-0.026	0.131	0.035	0.166	0.011
	(0.12)	(1.20)	(0.64)	(-2.00)	(1.34)	(1.16)	(1.24)	(0.25)
β_{SMB}	-0.026	-0.085	-0.174	0.042	0.161	-0.070	-0.341	0.036
	(0.45)	(-6.26)	(-2.90)	(2.60)	(1.33)	(-1.86)	(-2.08)	(0.70)
β_{HML}	-0.171	0.021	-0.272	-0.085	-0.154	-0.129	0.030	-0.159
	(-2.45)	(1.23)	(-3.68)	(-4.34)	(-1.04)	(-2.79)	(0.15)	(-2.48)
β_{MOM}	-0.298	-0.057	-0.142	0.040	0.116	-0.070	0.256	0.019
	(-7.43)	(-5.93)	(-3.33)	(2.63)	(1.37)	(-2.65)	(2.21)	(0.53)

Table A.25: **4-Factor Fama-French regressions on spread portfolios within Skill Groups**
This table summarizes the risk adjusted performance of portfolios several long-short portfolios formed on the basis of observed mutual fund trades of skilled S and unskilled U managers. Each quarter end the entire cross-section of funds is divided into these two skill groups using the point estimate of α_f from running a 48-month regression with the following specification

$$r_{f,t} = \alpha_f + \beta_f^M r_{M,t} + \beta_f^{SMB} r_{SMB,t} + \beta_f^{HML} r_{HML,t} + \beta_f^{MOM} r_{MOM,t} + \varepsilon_{f,t}$$

where $r_{f,t}$ is the historic gross-return on fund f in month t and $r_{M,t}$ the return on the CRSP value weighted market portfolio in month t. All returns are expressed in excess of the risk-free interest rate. The gross returns on the fund portfolios computed from from data of the CRSP Survivorship-Bias-Free Mutual Fund Database©, and are calculated by adding the monthly increment of the expense ratio to the net returns provided in the database. The regressors $r_{SMB,t}$ and $r_{HML,t}$ are returns on zero-cost portfolios capturing the small-firm and value-effects. The momentum factor $r_{MOM,t}$ is the return on a zero-cost portfolio long in winning stock and short in losing stock during the 6 month prior to its formation. Mutual fund portfolios with positive point estimates of α_f are classified as skilled (S), while fund portfolios with negative point estimates of α_f are classified as unskilled (U). $N_i - D_i$ refers to a portfolio long in new additions to fund portfolios and short in deletions from fund portfolios in skill group $i \in (S, U)$ over the 3 month following the publication of the fund portfolios. $A_i - R_i$ refers to to a portfolio long in additions to existing positions of fund portfolios and short in reductions of existing positions of funds in skill group i. The left section of the table presents the results when equally weighting each stock in the long and short side of the portfolio. The right section refers to the results when weighting each stock by the average change in the portfolio weight of managers in a particular skill-group. All the portfolio returns calculated are then risk adjusted by estimating the four factor Carhart model described above over two non-overlapping 10 year periods. The first sample covers the time span from July 1985 to June 1995, while the second one covers the period from July 1995 to June 2005. The statistics in bold refer to the later period. The t-statistics in parenthesis below the coefficients are calculated using the Newey-West procedure.

Table A.25: **4-Factor Fama-French regressions on spread portfolios within Skill Groups**

	Equally Weighted							
	Skilled Manager				Unskilled Manager			
	$N_S - D_S$		$A_S - R_S$		$N_U - D_U$		$A_U - R_U$	
α	0.0050	**0.0041**	0.0010	**-0.0006**	0.0027	**-0.0043**	-0.0005	**-0.0016**
	(2.59)	**(1.03)**	(1.43)	**(-0.42)**	(1.32)	**(-0.96)**	(-0.67)	**(-2.02)**
β_{MKT}	0.033	**-0.001**	-0.001	**-0.007**	-0.019	**0.132**	-0.033	**-0.023**
	(0.63)	**(-0.01)**	(-0.01)	**(-0.24)**	(-0.36)	**(1.29)**	(-2.16)	**(-1.00)**
β_{SMB}	-0.076	**0.322**	-0.143	**-0.121**	-0.042	**0.105**	-0.105	**0.013**
	(-1.03)	**(3.64)**	(-3.75)	**(-3.70)**	(-0.51)	**(1.03)**	(-1.62)	**(0.64)**
β_{HML}	-0.161	**0.056**	-0.034	**0.224**	-0.398	**0.025**	-0.039	**0.094**
	(-1.99)	**(0.37)**	(-0.99)	**(5.73)**	(-3.65)	**(0.17)**	(-0.81)	**(3.20)**
β_{MOM}	0.146	**0.558**	0.006	**0.040**	0.134	**0.793**	0.015	**0.149**
	(2.00)	**(6.32)**	(0.20)	**(1.01)**	(1.53)	**(9.43)**	(0.71)	**(10.65)**
R^2	0.11	**0.49**	0.2	**0.6**	0.2	**0.57**	0.13	**0.58**
	Trade-Size-Weighted							
	Skilled Manager				Unskilled Manager			
	$N_S - D_S$		$A_S - R_S$		$N_U - D_U$		$A_U - R_U$	
α	0.0080	**0.0096**	0.0014	**-0.0021**	0.0012	**-0.0019**	-0.0035	**-0.0094**
	(1.68)	**(1.11)**	(0.84)	**(-0.65)**	(1.78)	**(-1.51)**	(-1.58)	**(-2.73)**
β_{MKT}	0.078	**0.025**	0.026	**-0.029**	-0.122	**0.244**	-0.040	**0.037**
	(0.69)	**(0.10)**	(0.70)	**(-0.38)**	(-0.62)	**(0.87)**	(-0.80)	**(0.49)**
β_{SMB}	-0.060	**0.314**	-0.074	**0.059**	0.048	**-0.261**	0.121	**0.096**
	(-0.39)	**(1.30)**	(-0.91)	**(0.51)**	(0.19)	**(-0.97)**	(1.03)	**(1.00)**
β_{HML}	-0.199	**0.010**	-0.119	**0.234**	-0.558	**0.477**	-0.055	**0.184**
	(-0.91)	**(0.03)**	(-1.47)	**(1.88)**	(-1.67)	**(1.47)**	(-0.47)	**(1.62)**
β_{MOM}	0.068	**0.743**	0.085	**0.229**	0.362	**0.921**	0.004	**0.393**
	(0.50)	**(3.79)**	(1.49)	**(2.46)**	(1.08)	**(2.13)**	(0.04)	**(4.36)**
R^2	0.02	**0.23**	0.07	**0.23**	0.05	**0.26**	0.02	**0.35**

Table A.26: **4-Factor Fama-French Regressions on Spread Portfolios across Skill Groups**

This table summarizes the risk adjusted performance of portfolios several long-short portfolios formed on the basis of observed mutual fund trades of skilled S and unskilled U managers. Each quarter end the entire cross-section of funds is divided into these two skill groups using the point estimate of α_f from running a 48-month regression with the following specification

$$r_{f,t} = \alpha_f + \beta_f^M r_{M,t} + \beta_f^{SMB} r_{SMB,t} + \beta_f^{HML} r_{HML,t} + \beta_f^{MOM} r_{MOM,t} + \varepsilon_{f,t}$$

where $r_{f,t}$ is the historic gross-return on fund f in month t and $r_{M,t}$ the return on the CRSP value weighted market portfolio in month t. All returns are expressed in excess of the risk-free interest rate. The gross returns on the fund portfolios computed from from data of the CRSP Survivorship-Bias-Free Mutual Fund Database©, and are calculated by adding the monthly increment of the expense ratio to the net returns provided in the database. The regressors $r_{SMB,t}$ and $r_{HML,t}$ are returns on zero-cost portfolios capturing the small-firm and value-effects. The momentum factor $r_{MOM,t}$ is the return on a zero-cost portfolio long in winning stock and short in losing stock during the 6 month prior to its formation. Mutual fund portfolios with positive point estimates of α_f are classified as skilled (S), while fund portfolios with negative point estimates of α_f are classified as unskilled (U). $N_S - N_U$ refers to a portfolio long in new additions to fund portfolios of skilled managers and short in new additions to fund portfolios of unskilled managers. $A_S - A_U$ refers to a portfolio long in additions to existing positions in fund portfolios of skilled managers and short in additions to existing positions of fund portfolios of unskilled managers. $D_S - D_U$ refers to a portfolio long in deletions from fund portfolios of skilled managers and short in deletions from fund portfolios of unskilled managers. $R_S - R_U$ refers to a portfolio long in reductions of existing positions in fund portfolios of skilled managers and short in reductions of existing positions of fund portfolios of unskilled managers. The left section of the table presents the results when equally weighting each stock in the long and short side of the portfolio. The right section refers to the results when weighting each stock by the average change in the portfolio weight of managers in a particular skill-group. All the portfolio returns calculated are then risk adjusted by estimating the four factor Carhart model described above over two non-overlapping 10 year periods. The first sample covers the time span from July 1985 to June 1995, while the second one covers the period from July 1995 to June 2005. The statistics in bold refer to the later period. The t-statistics in parenthesis below the coefficients are calculated using the Newey-West procedure.

Table A.26: **4-Factor Fama-French Regressions on Spread Portfolios across Skill Groups**

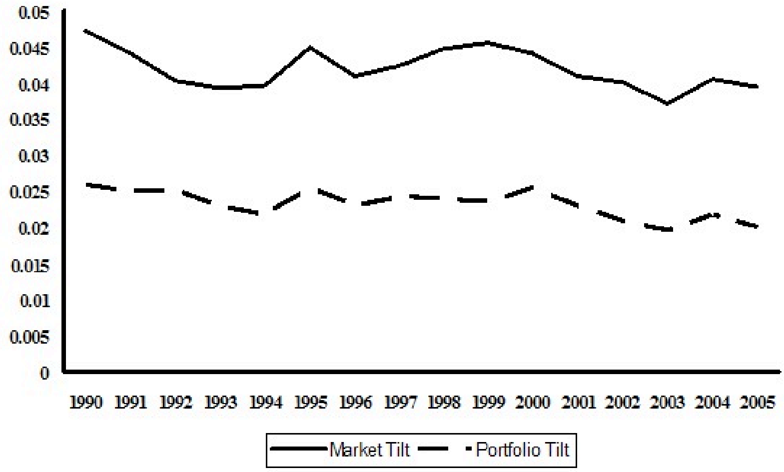
	Equally Weighted							
	$N_S - N_U$		$A_S - A_U$		$D_S - D_U$		$R_S - R_U$	
α	0.0010	**0.0075**	0.0019	**0.0015**	-0.0013	**-0.0008**	0.0004	**0.0004**
	(0.59)	**(2.11)**	(2.83)	**(2.21)**	(-0.67)	**(-0.20)**	(0.60)	**(0.41)**
β_{MKT}	0.030	**-0.811**	0.012	**-0.001**	-0.023	**0.051**	-0.022	**-0.016**
	(0.81)	**(-0.86)**	(0.62)	**(-0.02)**	(-0.47)	**(0.45)**	(-1.28)	**(-0.62)**
β_{SMB}	-0.110	**0.026**	-0.119	**-0.052**	-0.077	**-0.191**	-0.081	**0.081**
	(-1.87)	**(0.27)**	(-4.54)	**(-3.71)**	(-0.86)	**(-2.16)**	(-2.17)	**(2.88)**
β_{HML}	0.024	**-0.254**	-0.074	**0.061**	-0.213	**-0.285**	-0.079	**-0.069**
	(0.33)	**(-2.41)**	(-3.19)	**(3.08)**	(-2.13)	**(-2.19)**	(-2.59)	**(-2.12)**
β_{MOM}	0.034	**-0.402**	-0.005	**-0.079**	0.023	**-0.167**	0.004	**0.030**
	(0.55)	**(-4.07)**	(-0.18)	**(-6.10)**	(0.32)	**(-2.42)**	(0.16)	**(0.85)**
R^2	0.03	**0.33**	0.2	**0.53**	0.05	**0.16**	0.13	**0.31**
	Trade-Size-Weighted							
	$N_S - N_U$		$A_S - A_U$		$D_S - D_U$		$R_S - R_U$	
α	0.0022	**0.0112**	0.0039	**0.0037**	0.0068	**-0.0174**	-0.0011	**-0.004**
	(0.45)	**(1.69)**	(2.33)	**(1.94)**	(1.11)	**(-1.64)**	(-0.59)	**(-1.35)**
β_{MKT}	0.141	**0.125**	0.048	**0.035**	-0.060	**0.345**	-0.018	**0.1015**
	(1.15)	**(0.56)**	(1.37)	**(0.78)**	(-0.36)	**(1.52)**	(-0.45)	**(1.37)**
β_{SMB}	-0.143	**0.244**	-0.178	**-0.039**	-0.034	**-0.330**	0.018	**-0.002**
	(-0.88)	**(1.41)**	(-3.23)	**(-0.70)**	(-0.15)	**(-1.25)**	(0.27)	**(-0.02)**
β_{HML}	0.070	**-0.209**	-0.072	**-0.137**	-0.288	**0.258**	-0.008	**-0.188**
	(0.35)	**(-0.75)**	(-0.98)	**(-1.71)**	(-0.90)	**(0.84)**	(-0.11)	**(-1.59)**
β_{MOM}	0.223	**0.075**	-0.083	**-0.073**	0.517	**0.253**	-0.163	**0.0911**
	(1.49)	**(0.72)**	(-1.38)	**(-1.81)**	(1.83)	**(0.73)**	(-2.28)	**(2.00)**
R^2	0.04	**0.08**	0.07	**0.13**	0.06	**0.17**	0.06	**0.15**

Figure A.1: **Popularity**

This figure displays the histogram of the popularity of the stocks that we select as manager's best ideas from 1990-2005. Popularity is defined as the number of managers at any point in time which consider a particular stock their best idea. Best ideas are determined within each fund as the stock with the maximum value of $market\_tilt_{ijt} = \lambda_{ijt} - \lambda_{iMt}$, where λ_{ijt} is manager j's portfolio weight in stock i and λ_{iMt} is the weight of stock i in the market portfolio.

Figure A.2: **Measures**

This figure graphs the value of the various measures we use to identify the best idea of a portfolio for the median manager over the time period in question. Best ideas are determined within each fund as the stock with the maximum value of one of four possible measures: 1) $market\_tilt_{ijt} = \lambda_{ijt} - \lambda_{iMt}$, 2) $CAPM\_tilt_{ijt} = \sigma^2_{it}(\lambda_{ijt} - \lambda_{iMt})$, 3) $portfolio\_tilt_{ijt} = \lambda_{ijt} - \lambda_{ijtV}$, and 4) $CAPM\_portfolio\_tilt_{ijt} = \sigma^2_{it}(\lambda_{ijt} - \lambda_{ijtV})$ where λ_{ijt} is manager j's portfolio weight in stock i, λ_{iMt} is the weight of stock i in the market portfolio, λ_{ijtV} is the value weight of stock i in manager j's portfolio, and σ^2_{it} is the most-recent estimate (as of the time of the ranking) of a stock's CAPM idiosyncratic variance.



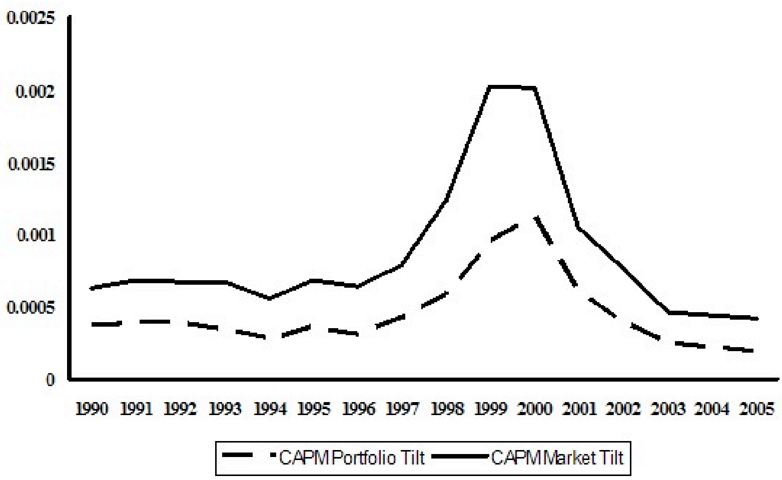


Figure A.3: **Six-Factor Alpha**

This figure graphs the six-factor alpha along with the accompanying two standard deviation bounds of trading strategies based on the $portfolio\_tilt_{ijt}$ measure of Table 2 Panel A for managers' best idea, second-best idea, down to their worst idea.

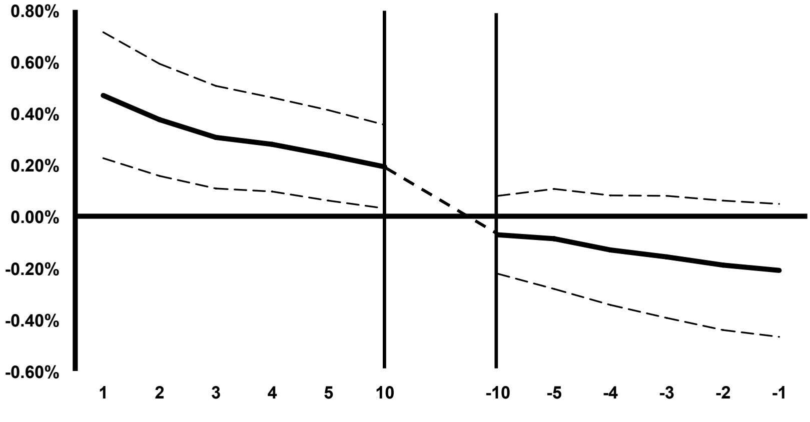


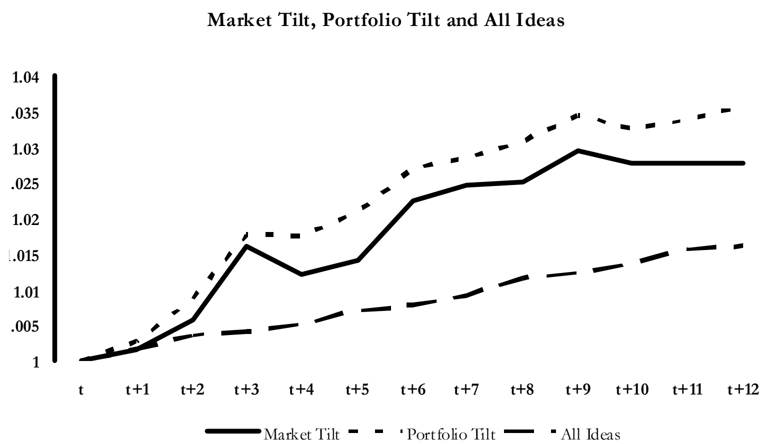
Figure A.4: **Performance of best ideas**

This figure graphs the risk-adjusted cumulative buy-and-hold abnormal returns of the best ideas portfolio as identified by our various tilt measures. The performance of the best ideas portfolios is contrasted with the performance of all stocks held by the mutual fund industry at the same points in time. All cumulative abnormal returns are adjusted using the six factor model

$r_{p,t} - r_{f,t} =$

$= a_6 + bRMRF_t + sSMB_t + hHML_t + mMOM_t + iIDI_t + rSTREV_t + \varepsilon_{p,t}$

where $r_{p,t}$ is the equal-weight return on the portfolio of the stocks that represent the best idea of each active manager. The best idea is determined within each fund as the stock with the maximum value of one of four possible tilt measures: The explanatory variables in the regression are all from Ken French's website except for IDI which we construct following Ang, Hodrick, and Xi (2004). We restrict the analysis to those managers whose maximum tilt is in the top 25% of all maximum tilts at the time. The sample period for the dependent variables is January 1991 - December 2005.



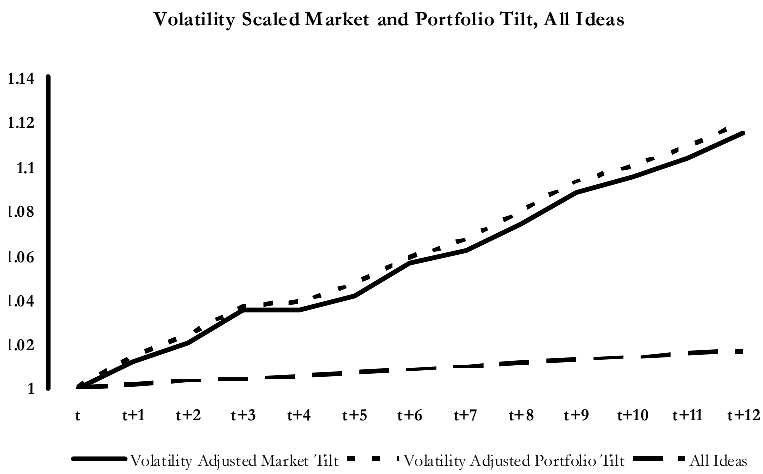


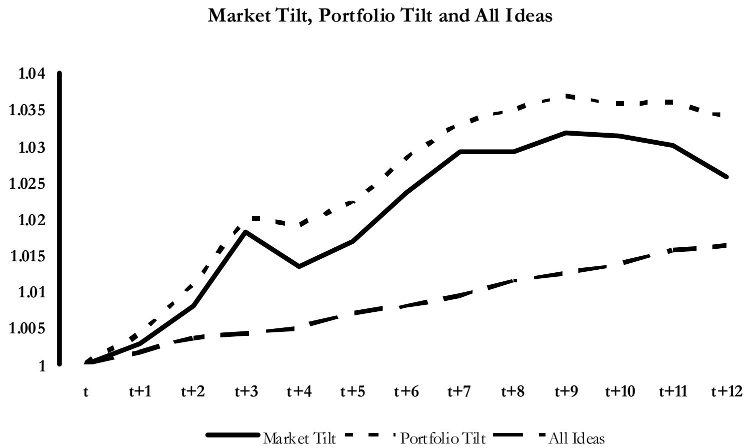
Figure A.5: **Performance of best fresh ideas**

This figure graphs the risk-adjusted cumulative buy-and-hold abnormal returns of the best fresh ideas portfolio as identified by our various tilt measures. The performance of the best fresh ideas portfolios is contrasted with the performance of all stocks held by the mutual fund industry at the same points in time. All cumulative abnormal returns are adjusted using the six factor model

$r_{p,t} - r_{f,t} =$

$= a_6 + bRMRF_t + sSMB_t + hHML_t + mMOM_t + iIDI_t + rSTREV_t + \varepsilon_{p,t}$

where $r_{p,t}$ is the equal-return on the portfolio of the stocks that represent the best idea of each active manager. The best idea is determined within each fund as the stock with the maximum value of one of four possible tilt measures: The explanatory variables in the regression are all from Ken French's website except for IDI which we construct following Ang, Hodrick, and Xi (2004). We restrict the analysis to those managers whose maximum tilt is in the top 25% of all maximum tilts at the time. The sample period for the dependent variables is January 1991 - December 2005



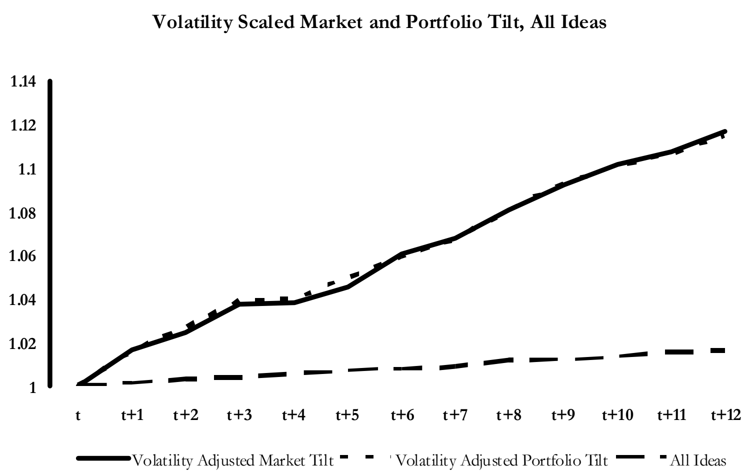


Figure A.6: **Sharpe Ratios**

This figure shows the Sharpe ratios obtained from different allocations to the market (M), a best idea (X), and a second-best idea (Y). In particular, we consider the Sharpe ratio of portfolios where an investor allocates a fixed percentage to an active manager choosing a portfolio of X and Y and puts the remaining capital in M. The riskless rate is zero and the expected returns on the three assets in question are: $E[R_M] = 7\%$, $E[R_X] = 2\%$, and $E[R_Y] = 1\%$. All three assets are uncorrelated and each has the same volatility. Each line on the graph shows the results for a different constraint on the total fraction of assets that are managed by the active manager (i.e. invested in either X or Y).

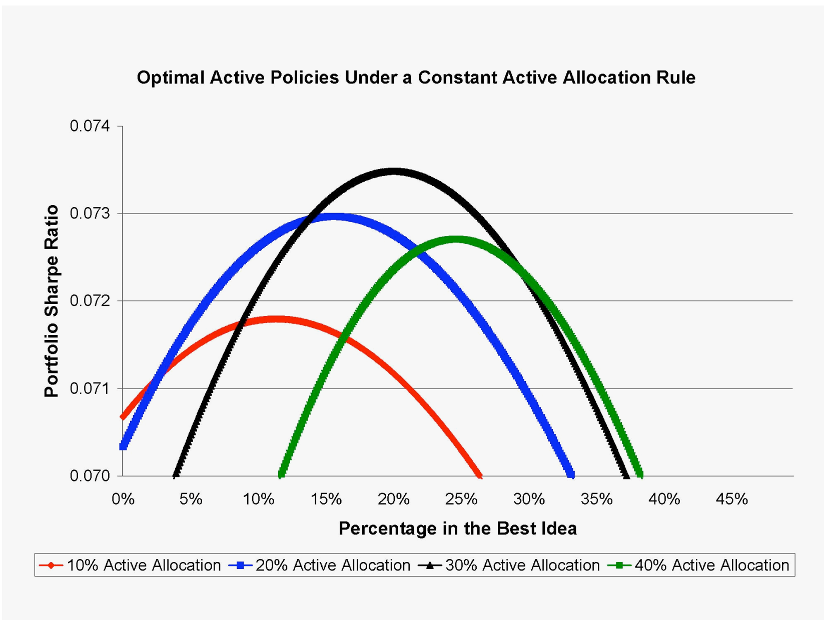


Figure A.7: **Sharpe Ratios**

This figure shows the Sharpe ratio of equal-weight portfolios of active managers. We assume that there are N managers, each of whom has one best idea so that each manager's portfolio consists of a combination of the best idea and the market portfolio. For simplicity, we assume that each manager's idea has the same expected return, volatility, and beta and that the unsystematic components of managers' best ideas are uncorrelated. The figure displays the Sharpe ratios for such portfolios based on the following set of assumptions. Suppose that each investment X has 4% annual alpha and that the market premium is 6%; let the market's annual volatility be 15% and X's be 40% (with the assumption of unit beta, every X must have a correlation of .375 with M, where M again represents the market portfolio). The risk-free rate is zero. The top line in Figure 7 shows the Sharpe ratio that would result if managers followed this optimal policy. The lowest line shows the Sharpe ratio the investor will obtain if each manager instead mean-variance optimizes his own portfolio. The middle line gives the resulting Sharpe ratios if managers choose the portfolio that is best for the investor but with the constraint that they cannot sell the market short.

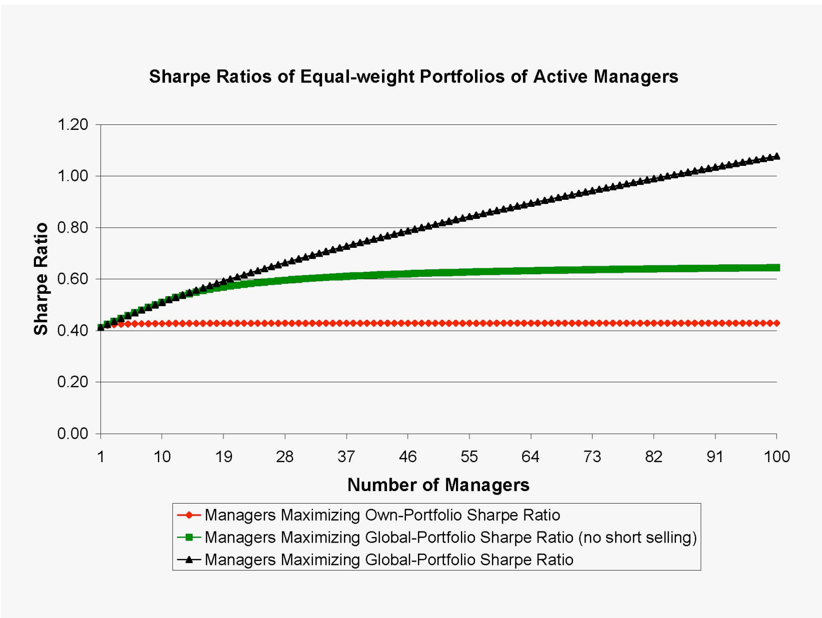


Figure A.8: **Portfolio Weight Distribution**

This figure illustrates the cumulative distribution of portfolio weights in mutual during the period of January 1991 to December 2005. The graph is a result of first sorting each portfolio in the sample in descending order by the weight it allocates to each stock and then plotting the rolling cumulation of these weights against the rolling cumulation of (hypothetical) equal weights in each stock. A portfolio that allocates equal weights to each holding would be characterized by the 45 degree line in this plot. Stronger convexity implies stronger concentration of a portfolio's capital into a limited number of names. The bold line depicts the median portfolio in the sample. The thinner solid lines in Figure trace out the inter-quartile range around the median, while the broken lines are the 5th and 95th cross-sectional percentiles, respectively.

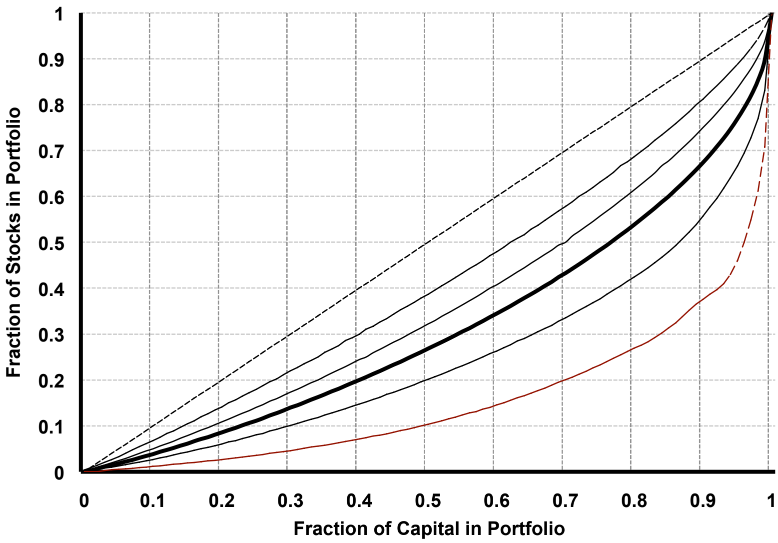


Figure A.9: **Number of assets included in trade portfolio by manager subset**

This figure shows the evolution of the number of stocks in the aggregate trade portfolios of skilled (S)and unskilled (U) fund managers. Mutual fund trades are classified into four groups. Additions to existing positions (A), reductions of existing positions (R), new positions (N) and deletions (D). Management skill is determined *ex ante* by the sign of the alpha in a 48-month rolling regression with the following specification $r_{f,t} = \alpha_f + \beta_f^M r_{M,t} + \beta_f^{SMB} r_{SMB,t} + \beta_f^{HML} r_{HML,t} + \beta_f^{MOM} r_{MOM,t} + \varepsilon_{f,t}$ where $r_{f,t}$ is the historic gross return on the fund portfolio in month t and $r_{M,t}$ the return on the CRSP value-weighted market portfolio in month t. All returns are expressed in excess of the risk-free interest rate. The regressors $r_{SMB,t}$ and $r_{HML,t}$ are returns on zero-cost portfolios capturing the small-firm and value-effects. The momentum factor $r_{MOM,t}$, conceptually following Jegadeesh and Titman (1993), is the return on a zero-cost portfolio long in winning stock and short in losing stock during the 6 month prior to its formation.

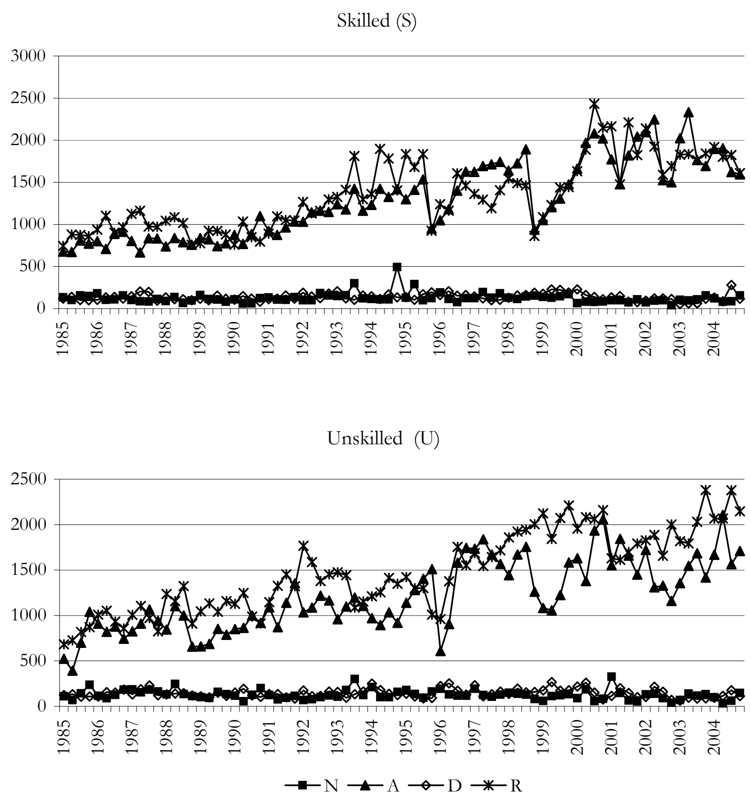


Figure A.10: **Evaluation and portfolio formation**

This graph summarizes how the trade portfolios are constructed for skilled and unskilled managers. At each quarter end, I first divide the cross-section of fund managers into the two skill groups by the sign of the alpha in a 48-month rolling regression with the following specification $r_{f,t} = \alpha_f + \beta_f^M r_{M,t} + \beta_f^{SMB} r_{SMB,t} + \beta_f^{HML} r_{HML,t} + \beta_f^{MOM} r_{MOM,t} + \varepsilon_{f,t}$ where $r_{f,t}$ is the historic gross return on the fund portfolio in month t and $r_{M,t}$ the return on the CRSP value-weighted market portfolio in month t. All returns are expressed in excess of the risk-free interest rate. The regressors $r_{SMB,t}$ and $r_{HML,t}$ are returns on zero-cost portfolios capturing the small-firm and value-effects. The momentum factor $r_{MOM,t}$, conceptually following Jegadeesh and Titman (1993), is the return on a zero-cost portfolio long in winning stock and short in losing stock during the 6 month prior to its formation. Within both skill groups I then classify each manager's trades into additions to existing positions (A), reductions of existing positions (R), new positions (N) and deletions (D) and aggregate them over the skill group. I then evaluate the performance of these trade portfolios over the three month following the quarter end in question.

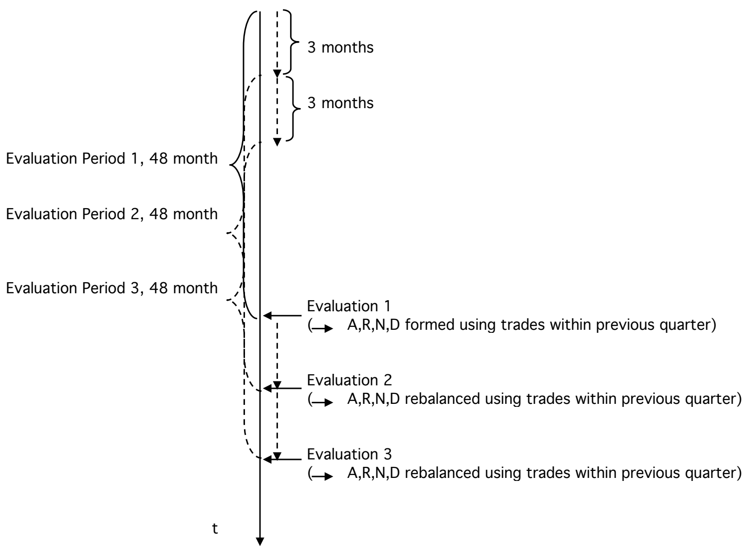


Figure A.11: **Quantile-quantile plots of trading strategies against the CRSP-VW**

This figure depicts QQ-plots of the return distributions of two trading strategies against the distributions of the CRSP value-weighted market index. Both strategy portfolios are constructed following the hedging methodology of Franzoni and Marin (2005). From July 1985 to March 2005, each quarter end a portfolio of assets is identified that is thought to be under-priced. The exposures to market, size and book-to-market factors of the portfolio are then estimated by using the preceding 48-month window of portfolio returns. Subsequently, a trading strategy is pursued over the next quarter that is long in one unit of the under-priced portfolio and short in the three risk-factor-mimicking portfolios in the amounts specified by the previously estimated exposures on the factors. Any leftover is invested in the risk-free rate. The strategy is then pursued until the next quarter end, when a new under-priced portfolio is available due the updated information on the skill distribution of managers and their trades. The process is thereafter repeated in the same fashion for all quarters until March 2005. The two portfolios of under-priced assets are the trade-size-weighted addition of skilled managers (A_S) and the trade-size-weighted reductions portfolio of unskilled managers (R_U) described in the text.