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Two Essays on Stock Preference and Performance of Institutional Investors

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Two Essays on Stock Preference and Performance of Institutional Investors

by

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To my son Derek, my wife and my parents

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Two Essays on Stock Preference and Performance of Institutional Investors

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Two essays on the stock preference and performance of institutional investors are included in the dissertation.

In the first essay, I document that mutual fund managers and other institutional investors tend to hold stocks with higher betas. This effect holds even after precisely controlling for stocks' risk characteristics such as size, book-to-market equity ratio and momentum. This is contrary to the widely accepted view that betas are no longer associated with expected returns. However, these results support my simple model where a fund manager's payoff function depends on returns in excess of a benchmark. For the manager, on the one hand, he tends to load up with high beta stocks since he wants to co-move with the market and other factors as much as possible. On the other hand, the manager faces a trade-off be-

tween expected performance and the volatility of tracking error. My model thus shows that the manager prefers to choose higher beta than his benchmark, and that his beta choice has an optimal level which depends on his perceived factor returns and volatility. My empirical findings further confirm the model results. First, I show that the effect of managers holding higher beta stocks is robust to a number of alternative explanations including the effects of their liquidity selection or trading activities. Second, consistent with the model predictions of managers sticking close to their benchmarks during risky periods, I demonstrate that the average beta choice of mutual fund managers can predict future market volatility, even after controlling for other common volatility predictors, such as lagged volatility and implied volatility.

The second essay is the first to explicitly address the performance of actively managed mutual funds conditioned on investor sentiment. Almost all fund size quintiles subsequently outperform the market when sentiment is low while all of them underperform the market when sentiment is high. This also holds true after adjusting the fund returns by various performance benchmarks. I further show that the impact of investor sentiment on fund performance is mostly due to small investor sentiment. These findings can partially validate the existence of actively managed mutual funds which underperform the market overall (Gruber 1996). In addition, when conditioning on investor sentiment, the pattern of decreasing returns to scale in mutual funds, recently documented in Chen, Hong, Huang, and Kubik (2004), is fully reversed when sentiment is high while the pattern persists and is more pronounced when sentiment is low. Further results suggest that smaller funds tend to hold smaller stocks, which is shown to drive the above patterns. I also document that smaller funds have more sentiment timing ability or feasibility than larger funds. These findings have many important implications including persistence of fund performance which may not exist under conventional performance measures.

Contents

List of Tables

List of Figures

Chapter 1

Beta Choice of Institutional Investors

1.1 Introduction

Research on how to evaluate the performance of a fund manager can be dated back to as early as the 1930s when Cowles (1933) published his work 'Can stock market forecasters forecast?' Numerous performance measures have been introduced since then. However, as noted by Roll (1992), "Today's professional money manager is often judged by total return performance relative to a prespecified benchmark, usually a broadly diversified index of assets." This is understandable for three reasons. First, as argued by Roll (1992), "This is a sensible approach because the sponsor's most direct alternative to an active manager is an index fund matching the benchmark." Second, this benchmarking method is the easiest for an average investor of a fund to understand. Thus, if a fund manager fails to beat his benchmark, marketing will barely talk to him.[1] Third, the payoff function of a fund manager is often related to his ability to beat the benchmark. For example, some funds adjust their fees "depending on whether they lead or trail the returns of market benchmarks

[1] See the article "Fund Manager's Diary: The dollar calls - but watch out for growling bears" on Page 32 in *Investors Chronicle* of December 18 1998.

over a certain period of time." [2]

Although previous research has examined institutional investors' stock preference, few papers have exclusively focused on their beta choices, especially when investors are subject to a benchmark. In this study, we address three important economic questions. First, Do institutional investors hold securities with higher beta risk than their benchmarks? Second, What are the determinants of the strength of this preference if they do so? Third, How does their beta preference reflect their perspective on the future market?

If a fund manager is properly benchmarked in the risk-adjusted sense (for example, Jenson's Alpha (Jensen 1968)), his abnormal return, alpha, should not be affected by his beta choice. However, if the manager has a big concern on beating the benchmark, on the one hand, he would choose a portfolio to co-move with the factors [3] as much as possible. In this way the manager can earn higher factor premium than the benchmark if the factor premium is positive.[4] On the other hand, the more the manager chooses to co-move with the factors, the farther he is from the benchmark, which fund managers do not like.[5] Therefore, there is a trade-off between expected performance and the volatility of tracking error. Thus, the manager's beta choice has an optimal level, which depends on his perceived future factor returns and volatilities as suggested by my simple model. Furthermore, controlling for factors like size, book-to-market-ratio and momentum and focusing only on his market beta choice, my simple model shows that a fund manager's chosen market beta for his portfolio will be bigger than that of his benchmark and is positively correlated with his expected market return and negatively correlated with his expected market volatility.

[2]See the article "Some Fund Firms Tie Pay to Performance" in the section of C19 of *The Wall Street Journal* on March 20, 2002.

[3]For example, factors in the Carhart 4-factor model (Carhart 1997).

[4]For example, the manager may tilt his portfolio more than his benchmark toward small stocks, value stocks or momentum stocks. In this way, his loadings on the factors will be higher than those of his benchmark and thus he can earn higher factor premium than on the benchmark portfolio.

[5]As pointed out by Peter L. Bernstein, "Benchmark risk – the prospect that a manager might stray too far from an index – ranks among the greater sins in their morality code." See "Breakthrough: Should fund chiefs be allowed to invest differently? " in *Barron's* on April 7, 2003.

To test these model predictions empirically, I introduce an innovative way to measure how institutional investors choose betas. Basically, I divide all the CRSP stocks into 125 stock groups by triple dependent sorts on size, book-to-market ratio and momentum (in this order), and then compare the beta of a stock chosen by institutional investors with the average beta of the group that the stock belongs to. This sorting procedure is similar in spirit to the pioneering approach of Daniel, Grinblatt, Titman, and Wermers (1997) where they use it to investigate mutual fund performance. The benefit of this sorting procedure is threefold. First, the risk sorted portfolio is a more accurate method of controlling for stock characteristics than the regression approach. Second, characteristic matching allows for benchmarks that gauge more precisely how high or low investors choose betas in a characteristic group and should have more statistical power to detect any pattern of investors' beta choice than regression approaches. Third, the benchmark allows for a more comprehensive and accurate investigation of investors' beta choice, for example, the predictability of beta choice. In addition, calculating a portfolio's beta from the holdings of the portfolio is much more accurate than calculating from the portfolio returns (Jiang, Yao, and Yu 2005).

In this paper, my results show that actively managed mutual funds and institutional investors tend to hold stocks with higher betas even after controlling for their characteristics. Specifically, controlling for size, book-to-market ratio and momentum, mutual funds and other institutional investors each quarter choose stocks with betas on average 5.872% and 5.375% higher than their corresponding benchmark betas, respectively. These results hold whether I use daily or monthly returns to measure betas, or I use the value weighted CRSP index or the S&P 500 index as a benchmark.

Alternatively, two other explanations for these results are also possible. First, as pointed out by Chen, Jegadeesh, and Wermers (2000), institutional investors (specifically mutual funds) tend to pick stocks with greater liquidity. If a stock's liquidity is positively correlated to its beta, we may observe the previous trading pattern of institutional investors.

For this hypothesis, I test the liquidity selections of institutional investors under the same framework as I test their beta choices. Using Amihud (2002) measure of illiquidity, I confirm that institutional investors tend to pick more liquid stocks even after controlling for stocks' risk characteristics such as size, book-to-market ratio and momentum. This shows that institutional investors tend to demand liquidity instead of providing liquidity. I also find that the liquidity of a stock is not highly correlated with its beta and the average correlation is only 0.02. Moreover, the beta choice of institutional investors is not correlated with their liquidity selection after I control for the lagged beta choice and investor characteristics. Thus, the first explanation of beta choice is not valid.

Second, since investor trading activities may change the beta of a stock, the pattern of high beta stock preference may be caused by heavy institutional investor inflows. For this hypothesis, I indeed find that institutional investors' trading activities in a stock affect its beta. That is, a stock's beta is positively correlated with its institutional investor inflows. My results show that this is true not only for the level of beta but also the change of (adjusted) beta. However this still can not explain why institutional investors hold stocks until their betas go above the characteristic group averages. In particular, I do not find that there have been significant changes of the betas of stocks since one quarter or one year before investors hold them.

Campbell and Vuolteenaho (2004a) decompose the beta into cash-flow beta and discount-rate beta. They claim that the cash-flow beta is bad since overloading on high cash-flow beta can not increase a long-term investor's portfolio return but increase its return variation, thus its risk. On the other hand, discount-rate beta is good since the risk of a stock for a long-term investor is determined not by the stock's overall beta with market but by its bad cash-flow beta with a secondary influence from its discount-rate beta. Therefore, a natural robustness check is to investigate the institutional investors' choices of good and bad betas. My results show that institutional investors overweight in both high good beta stocks and high bad beta stocks. This further reinforces my findings of the higher overall beta choice of institutional investors.

The above results confirm the first prediction of my model that generally a benchmark investor would choose higher beta stocks than his benchmark. The second prediction is that the magnitude of beta difference he would choose relative to the benchmark will depend on his expected future market return and volatility. Specifically, my model predicts that if institutional investors are subject to a benchmark, their beta choice will negatively correlate with expected market volatility. The intuition is that if he thinks that the future market is more volatile, she'd better stay with the benchmark, thus his chosen beta within a stock characteristic group will be close to the group average. On the other hand, if he expects that the future market is less volatile, he would be less risk averse and dare to deviate from the benchmark. My results confirm this prediction. I find that the average beta choice measure has the strong predictability for the future market volatility. That is, low average beta choice measure can predict high volatility in the future and vice versa.

I am not the first to investigate the beta preference of institutional investors. The evidence in the literature on the beta choice of institutional investors is conflicting. On the one hand, Falkenstein (1996) shows that there is a negative but not statistically significant relationship between mutual fund ownership and stock beta. On the other hand, Karceski (2002) finds that equity mutual fund managers in aggregate overweight high-beta stocks relative to the overall market. Frieder and Subrahmanyam (2005) also document that institutional investors have a statistically and economically significantly strong preference for high beta stocks. Bennett, Sias, and Starks (2003) also have similar findings. However, my findings are different from the above results in three important ways. First, I am talking about the high beta preference in a different framework. Most of the above results show that institutional investors prefer higher beta stocks relative to the cross-sectional average. There is only one benchmark beta for their comparisons. That is the average beta in the market. In my paper, I have different benchmark betas for different stocks such that I can more precisely and explicitly control for stock characteristics. The result is more puzzling considering beta's death. Second, none of them use holdings data as I do to calculate the betas of institutional investors' portfolios, thus my approach has more statistical power and can impose more precise controls. Third, my results show that the magnitude of institutional investors' high beta preference can predict the future market mean-variance ratio and volatility – one connection that no one has established before.

The rest of the paper is structured as follows. In Section 1.2, I introduce a simple model to illustrate why fund managers care about beta and further discuss the motivation for the investigation. In Section 1.3, I describe the data I use and variables of interest and lay out my hypothesis and describe my empirical methodology. In Section 1.4, I report the results of empirical tests. Section 1.5 concludes this paper.

1.2 Model

Before I go to the formal model, the basic intuition of why a fund manager chooses high beta can be illustrated in Figure 1. If a fund manager wants to beat the market, he would choose a stock that can deliver higher expected return than the market return, i.e., above the line m in Figure 1. However, if it is prohibitively costly to deliver a positive alpha, a fund manager will not choose the area above the security market line l. Thus only the area that is right to $\beta = 1$ and below line l and above m is feasible to a fund manager. In this area, $\beta > 1$.

My formal model is as follows. Suppose that a fund manager is subject to a benchmark M in the sense that his payoff function depends on returns in excess of the benchmark. In order to make the model on focus and simple, I do not impose a complex performance measure for the manager. I only use the excess return of the fund portfolio to measure the manager's performance. This is reasonable since it is the easiest benchmarking method that can be understood by average investors of a fund. Assume that the fund manager is risk averse and has an exponential utility function which can be simply described as a mean variance format if returns are normally distributed. I also assume that it is costly to generate a positive alpha. The cost function is as denoted as $c(\alpha)$.

Denote a fund manager's benchmark return as r_b, and portfolio return as r_p. Suppose that the return generating process is as follows.

$$r = \alpha + \beta' f + \varepsilon$$

where f is a vector of factor returns and β is a vector of factor loadings.

A fund manager chooses the alpha and factor loadings to maximize his utility function, which is similar to the factor approach in Admati, Bhattacharya, Pfliederer, and Ross (1986). Then, we have,

$$\max_{\alpha_p, \beta_p} E\left(U(\alpha_p + \beta_p' f - (\alpha_b + \beta_b' f))\right) - c(\alpha_p - \alpha_b)$$

Solve this problem, we have,

$$\Delta\beta = \beta_p - \beta_b = \frac{1}{\gamma} V(f)^{-1} E(f)$$

where $V(f)$ is the variance covariance matrix of the factor returns, and the constant γ represents the risk aversion coefficient of the fund manager.

Suppose we have four factors—excess market return, size (SMB), value (HML) and momentum (UMD). Plug in their variance covariance matrix and their means from the historical data (1928-2004) which are shown in the appendix, we have $\Delta\beta = (2.97, 1.48, 5.41, 6.32)'/\gamma$. This shows that fund managers will choose higher factor loadings than their benchmark portfolios. And if we can estimate the difference between the beta chosen by investors and the benchmark beta, we can estimate their risk aversion coefficient γ.

If we control for size, book-to-market ratio and momentum, the manager's portfolio and the benchmark portfolio would have similar loadings on those factors. His problem is narrowed down to the choice of the market beta. That is, the fund manager solves the following problem.

$$\max_{\alpha,\beta} \quad E\left(U(r_p - r_b)\right) - c(\alpha) \tag{1.1}$$

where r_b is the group average return, i.e., group benchmark return.

Since we have controlled for size, book-to-market ratio and momentum here, the return difference between the manager portfolio and the group average is mostly due to their difference of alpha's and beta's. Thus, the above problem can be transformed as follows.

$$\max_{\alpha,\beta} \quad \alpha + (\beta - \beta_b)E(r_m) - \frac{\gamma}{2}\left(\sigma_\varepsilon^2 + (\beta - \beta_b)^2\sigma_m^2\right) - c(\alpha) \tag{1.2}$$

where β_b is the market beta of the benchmark portfolio and r_m is the market return.

Solve this problem, and we obtain that $\Delta\beta = \beta - \beta_b = \frac{E(r_m)}{\gamma\sigma_m^2}$, which delivers two messages. One is that the fund manager will choose higher beta relative to the group average, and the other is that the beta difference is negatively correlated with the manager's perceived market volatility and positively correlated with the expected market return.

1.3 Data and Methodology

1.3.1 Data

The institutional investor holdings data is from Thomson Financial CDA/Spectrum Institutional 13(f) Common Stock Holdings and Transactions database which covers the quarterly trading and holdings of institutions with over $100 million under management from 1980 to 2004. My data on mutual fund holdings come from CDA/Spectrum Mutual Funds Holdings data at Wharton Research Data Services (WRDS) which span from 1978 to 2004. The funds that I include have the following self-declared investment objective: Aggressive Growth, Growth, Growth and Income, and Balanced–codes 2, 3, 4 and 7 respectively. Sector, bond, preferred, international, and any fund with an investment objective that is not oriented to general equity is excluded. That is, only actively managed mutual funds are included in my data.

Both holdings databases have some reporting issues, as addressed in the previous literature (See, for example, Gompers and Metrick (2001), Jiang, Yao, and Yu (2005) and Griffin, Harris, and Topaloglu (2004)). I am aware of these issues and carefully address them.

I obtain all the stock information from the Center for Research in Security Prices (CRSP) and firm accounting information from COMPUSTAT. The data range for both data I use in the paper is from 1980 to 2004.

I obtain from Professor John Campbell's website the cash flow news and discount rate news in order to calculate the cash flow beta ("bad" beta) and discount rate bate ("good" beta) of each stock. Also, the volatility index data, VIX data is obtained from CBOE (Chicago Board Options Exchange) website.

1.3.2 Methodology

In this section, I will introduce the measures I have used in the paper, including the measures of stock beta, liquidity, Beta Choice Measure and Liquidity Selection Measure. After that, I will lay out my hypotheses to be tested.

The Measure of Stock Beta

The betas of individual stocks are estimated on a rolling basis using the 12-month daily returns prior to the date of portfolio holdings. To account for the effect of non-synchronous trading, I estimate the market model for each stock using market returns up to five daily leads and five daily lags, in addition to the contemporaneous term. That is,

$$r_{j,t} = a_j + \sum_{q=-5}^{5} b_{j,q} r_{m,t-q} + e_{j,t}$$

Following Dimson (1979), the stock beta is the sum of the estimated coefficients $\hat{b}_{jq}, q = -5, ..., 5$:

$$\hat{b}_j = \sum_{q=-5}^{5} \hat{b}_{jq}$$

I require a stock to have at least 60 daily observations during the estimation period, otherwise I assume a value of one for the stock beta. Non-stock securities are assumed to have a beta of zero.

For a robustness check, I also use monthly returns to estimate betas. Under this situation, a backward 60-month rolling window is used for the beta estimation. The formula I use is as follows.

$$r_{jt} = a_j + b_{j1} r_{m,t} + b_{j2} r_{m,t-1} + e_{j,t}$$

The stock beta is the sum of the estimated coefficients b_{j1} and b_{j2} :

$$\hat{b}_j = b_{j1} + b_{j2}$$

For the market index, I use the value-weighted CRSP return index and S&P 500 index.

The Measure of Beta Choice

In order to measure how institutional investors choose stocks based on beta after controlling for size, book-to-market ratio and momentum, I sort all the CRSP stocks into five quintiles according to their size first. Size breaking points are based on NYSE stocks. Then within each size quintile, I further sort stocks into five smaller quintiles according to their book-to-market ratios, and finally within each book-to-market quintile, I sort stocks into five quintiles according to their prior year returns. Thus I obtain 125 stock groups after this triple dependent sorts.

I measure the Beta Choice (BC) of a portfolio during quarter t as follows.

$$BC_t = \sum_{j=1}^{N} \omega_{j,t} \left[\tilde{\beta}_{j,t} - \tilde{\beta}_t^{b_{j,t}} \right]$$

where $\omega_{j,t}$ is the portfolio weight for stock j at the beginning of period t, and $\tilde{\beta}_{j,t}$ is the estimated beta for stock j at time t, and $\tilde{\beta}_t^{b_{j,t}}$ is the group average of betas within the group which stock j belongs to at time t;

Intuitively, if an investor always choose the average beta stock within a group, the measure will be zero. On the other hand, if on average, an investor always choose stocks with higher betas than the groups, his BC measure will be positive and vice versa. That is, the higher the beta of the stock he chooses relative to the group average, the higher the BC measure.

The Measure of Liquidity

Based on Amihud (2002), during each quarter t, I measure the liquidity as follows.

$$LIQ_{i,d,t} = -\frac{1}{D_t}\sum_{d=1}^{D_t}\frac{R_{i,d}}{VOL_{i,d}}$$

where D_t is the number of trading days in quarter t (approximately 63 days), $R_{i,d}$ and $VOL_{i,d}$ are, respectively, stock i's daily return and its dollar volume in day d of quarter t. I may use other measures of liquidity based on microstructure variables, like bid-ask spread, but according to Amihud (2002), this measure has high correlation with measures constructed using microstructure variables.

The Measure of Liquidity Selection

I measure the Liquidity Selection (LS) of a portfolio during quarter t as follows.

$$LS_t = \sum_{j=1}^{N}\omega_{j,t}\left[L\tilde{I}Q_{j,t} - L\tilde{I}Q_t^{b_{j,t}}\right]$$

where $\omega_{j,t}$ is the portfolio weight for stock j at the beginning of period t, and $L\tilde{I}Q_{j,t}$ is the estimated liquidity for stock j at time t, and $L\tilde{I}Q_t^{b_{j,t}}$ is the group average liquidity within the group which stock j belongs to at time t;

1.4 Results

1.4.1 Beta Choice of Institutional Investors

Table 1.1 reports the average Beta Choice (BC) measures of institutional investors. As described in the methodology section, the Beta Choice (BC) of a portfolio during quarter t is measured as follows.

$$BC_t = \sum_{j=1}^{N} \omega_{j,t} \left[\tilde{\beta}_{j,t} - \tilde{\beta}_t^{b_{j,t}} \right]$$

where $\omega_{j,t}$ is the portfolio weight for stock j at the beginning of period t, and $\tilde{\beta}_{j,t}$ is the estimated beta for stock j at time t, and $\tilde{\beta}_t^{b_{j,t}}$ is the group average of betas within the group which stock j belongs to at time t.

Panel A of Table 1.1 reports average Beta Choice Measures based on betas derived from daily returns. Each quarter, I check whether cross sectionally, the average Beta Choice Measure is positive or not. The panel shows that if betas are calculated based on the value-weighted CRSP index, out of 100 quarters in my data, the number of positive quarters for mutual funds is 97 and 96 of them are statistically significant (at the 5% significance level). On the other hand, during only 3 quarters, the average BC measures are negative and none of them are statistically significant. For Institutions (i.e., firms in 13f database), the number of positive quarters for mutual funds is 98 and 93 of them are statistically significant. Similar to mutual funds, institutions have only 2 negative quarters, but none of them are statistically significant. The quarterly average of the cross-sectional average BC measures of mutual funds is 5.872% and the t-statistic is 17.07. That means, on average, mutual fund managers pick stocks with betas that are 5.872% higher than the group average. For institutions, they choose 5.375% higher beta than the group average. The difference between the average BC measures of mutual funds and institutions is 0.497% and statistically significant, which means that mutual fund managers have a greater tendency to pick higher beta stocks than other institutions. If betas are based on S&P 500 index, the results are similar.

Panel B of Table 1.1 reports average Beta Choice Measures based on betas derived from monthly returns. I obtain similar results.

To further illustrate the betas chosen by institutional investors and benchmark betas, I tabulate the average betas chosen by mutual funds across two characteristic dimensions and their corresponding benchmark betas in Table 1.2. Specifically, I obtain three groups of 25 time series average benchmark betas as reported in brackets in Table 1.2 by averaging benchmark betas along any two of the size, book-to-market ratio and momentum dimensions over time. Also, each quarter, in each stock group (i.e., a group of stocks with the same size, book-to-market ratio and momentum rank), I calculate the average betas of the stocks chosen by mutual funds, then I report time-series average of this average along any two of the size, book-to-market ratio and momentum dimensions. As shown in Panel A, along size and book-to-market ratio dimensions, mutual funds always choose higher beta stocks than the group benchmarks. This can be seen more clearly in Figure 4, which plots the average percentage difference between betas chosen by mutual funds and benchmark betas along any two of the size, book-to-market ratio and momentum dimensions. These results confirm further that institutional investors prefer higher beta stocks. Panel B and Panel C describe similar results. Moreover, one interesting pattern in Panel B and Panel C of Figure 4 is worth mentioning. We note that mutual funds tend to pick even higher beta stocks in the higher momentum groups.

1.4.2 Good Beta And Bad Beta

Campbell (1991) argues that the unexpected market return can be decomposed into two components as follows.

$$
\begin{aligned}
r_{t+1} - E_t r_{t+1} &= \Delta E_{t+1} \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} - \Delta E_{t+1} \sum_{j=0}^{\infty} r_{t+1+j} \\
&= N_{CF,t+1} - N_{DR,t+1} \qquad (1.3)
\end{aligned}
$$

where r_{t+1} is a log stock return, d_{t+1} is the log dividend paid by the stock, Δ denotes a period change. They call the two terms in the equation $N_{CF,t+1}$ and $N_{DR,t+1}$ as cash flow news and discount rate news respectively. These two components can be backed out using a VAR methodology. Assume that the data are generated by a first-order VAR model.

$$
\mathbf{z}_{t+1} = \mathbf{a} + \Gamma \mathbf{z}_t + \mathbf{u}_{t+1} \qquad (1.4)
$$

where $\mathbf{z}_{t+1}$ is a 4-by-1 vector with the *excess market return* (measured as the log excess return on the value-weighted CRSP index over T-bills) as its first element. The other three state variables are *term spread* (measured as the difference between the ten-year constant maturity taxable bond yield and the yield on short-term taxable notes), *the market's smoothed price-earnings ratio* (measured as the log ratio of S&P 500 index to a ten year trailing moving average of the aggregate S&P 500 earnings), and the *small-stock value spread* (measured as the difference between the log book-to-market ratios of small value and small growth stocks).

The cash flow news and discount rate news can be backed out as follows.

$$
\begin{aligned}
N_{CF,t+1} &= (\mathbf{e1}' + \mathbf{e1}'\lambda)\mathbf{u}_{t+1} \qquad (1.5) \\
N_{DR,t+1} &= \mathbf{e1}'\lambda\mathbf{u}_{t+1}.
\end{aligned}
$$

where $\lambda \equiv \rho\Gamma(\mathbf{I} - \rho\Gamma)^{-1}$.

Then a stock cash flow beta and discount rate beta can calculated as follows.

$$\hat{\beta}_{i,CF} = \frac{\widehat{Cov}\left(r_{i,t},\hat{N}_{CF,t}\right)}{\widehat{Var}\left(\hat{N}_{CF,t},\hat{N}_{DR,t}\right)} + \frac{\widehat{Cov}\left(r_{i,t},\hat{N}_{CF,t-1}\right)}{\widehat{Var}\left(\hat{N}_{CF,t},\hat{N}_{DR,t}\right)} \tag{1.6}$$

$$\hat{\beta}_{i,DR} = \frac{\widehat{Cov}\left(r_{i,t},\hat{N}_{DR,t}\right)}{\widehat{Var}\left(\hat{N}_{CF,t},\hat{N}_{DR,t}\right)} + \frac{\widehat{Cov}\left(r_{i,t},\hat{N}_{DR,t-1}\right)}{\widehat{Var}\left(\hat{N}_{CF,t},\hat{N}_{DR,t}\right)} \tag{1.7}$$

where $\hat{\beta}_{i,CF}$ is the cash flow beta, and $\hat{\beta}_{i,DR}$ is the discount rate beta.

If the equity premium stays in a steady state, a long-term investor should care less about future cash flow news which affects the investor's wealth but not the investment opportunities. Therefore, high loading on the cash flow betas can only increase the risk of the portfolio but not the return in the long run. In this sense, the cash flow beta is bad. On the other hand, the change of discount rate can affect wealth and predict the enhancement of future investment opportunities. Therefore the discount rate beta is good.

Here, I want to investigate whether the high beta choice of institutional investors is due to their high loadings on good betas. Table 1.3 reports the decomposition of the Beta Choice (BC) measures into Good Beta Choice and Bad Beta Choice. Good Beta is a stock's sensitivity to discount rate news and bad beta is the sensitivity to cash flow news.

The left panel of Table 1.3 reports average Good Beta Choice Measures based on betas derived from monthly returns. Each quarter, I check whether cross sectionally, the average Good Beta Choice Measure is positive or not. The panel shows that out of 88 quarters in my data, 83 quarters for mutual funds is positive and 74 of them are statistically significant (at the 5% significance level). On the other hand, only 5 quarters are negative, and only one of them is statistically significant. For Institutions (i.e., firms in 13f database), the number of positive quarters for mutual funds is 74 and 64 of them are statistically significant. Similar to mutual funds, institutions have only 14 negative quarters, and five of them are statistically significant. The quarterly average of the cross-sectional average BC measures of mutual funds is 4.408% and the t-statistic is 17.07, which means that on average, mutual fund managers pick stocks with good betas that are 5.872% higher than the group average. For institutions, they choose 1.695% higher good beta than the group average. The difference between the average BC measures of mutual funds and institutions is 2.713% and statistically significant, which means that mutual fund managers have a greater tendency to pick higher good beta than institutions. The results are similar for the bad betas (cash-flow betas) except that mutual funds and other institutional investors have no significant difference in their preference for bad betas.

The above results show that institutional investors prefer both higher good betas and bad betas relative to the group averages. Since beta can be decomposed into good beta and bad beta, these results further demonstrate that institutional investors tend to pick higher beta stocks than the group benchmarks.

1.4.3 Beta Choice and Liquidity Selection

In order to check the hypothesis that the high beta choice of institutional investors may be due to their liquidity selection. I design a measure to calculate the average Liquidity Selection (LS) of institutional investors. I measure the Liquidity Selection (LS) of a portfolio during quarter t as follows.

$$LS_t = \sum_{j=1}^{N} \omega_{j,t} \left[L\tilde{I}Q_{j,t} - L\tilde{I}Q_t^{b_{j,t}} \right]$$

where $\omega_{j,t}$ is the portfolio weight for stock j at the beginning of period t, and $L\tilde{I}Q_{j,t}$ is the estimated liquidity for stock j at time t, and $L\tilde{I}Q_t^{b_{j,t}}$ is the group average liquidity within the group which stock j belongs to at time t. This measure is similar in spirit to the Beta Choice measure.

I find that out of 100 quarters in my data, 77 quarters have positive average LS measures across mutual funds, and 59 of them are significantly positive. And 23 quarters have negative average LS measures across mutual funds, only one quarter is significantly negative. The time series average of the cross-sectional average LS measures across mutual funds is 0.413, which is statistically significant. I find similar results for institutions. Mutual funds slightly prefer more liquid stocks than institutions. These results show that on average institution investors prefer liquid stocks instead of illiquid stocks. To investigate how their liquidity selection affects their beta selection. I run the following Fama-Macbeth regressions for mutual funds and institutional investors.

$$BC_{it} = a + \sum_{p=1}^{4} b_{ip} \cdot BC_{i,t-p} + \sum_{q=0}^{4} c_{iq} \cdot LS_{i,t-q} + \varepsilon_{it}$$

Coefficients are estimated using Fama-Macbeth method. That is, every quarter, I run the BC measure of each fund (firm) on its LS measure and lagged BC and LS measures, then I calculate the time-series average.

The left panel of Table 1.6 reports the relationship between Beta Choice (BC) and Liquidity Selection (LS) Measures of Mutual Funds, and the right panel reports that of Institutional Investors. I can see that the coefficient on the contemporaneous liquidity selection measure is significantly positive for mutual funds in different regression specifications. However, the adjusted R^2 is pretty low for the univariate regression. For the institutional investors, the coefficient is significant only in the univariate regression.

1.4.4 Beta Choice and Fund Characteristics

To further investigate what can explain the beta choice of a mutual fund, I run Beta Choice measure on several fund characteristics including age, size, category and turnover. The regression specification is as follows.

$$BC_{it} = a + \sum_{p=1}^{3} b_{ip} BC_{i,t-p} + \sum_{q=0}^{3} c_{iq} LS_{i,t-q} + f(fund\_characteristics_{it}) + u_{it}$$

Age is defined as the number of quarters since a fund appeared in the holdings database. Assets is the quarterly total assets of a fund reported in 13f database. BC(t-1), BC(t-2) and BC(t-3) are the lagged 1, 2, and 3 quarter BC measures. Aggressive Growth, Growth, Growth & Income and Balanced are dummy variables. They are equal to 1 if the fund falls into the corresponding category, and equal to zero otherwise. If these dummy variables are used in the regression, the intercept will not be used to avoid multicollinearity. LS is the Liquidity Selection measure. Its three lags are included. Turnover is fund trading turnover which is defined as the minimum of aggregate purchases and sales of securities divided by the average TNA over the calendar year. Coefficients are estimated using Fama-Macbeth method. That is, every quarter, I run the BC measure of each fund (firm) on the variables listed in the table, then I calculate the time-series average as coefficients.

In Table 1.7, I can find that the coefficient on the contemporaneous liquidity selection is no longer significant after controlling for fund characteristics. This further shows that liquidity selection is hard to justify the beta choice. It is interesting to note that funds in the aggressive growth category tend to have even stronger preference for high beta even after controlling for size, book-to-market and momentum.

1.4.5 DGTW Performance Sorted on BC Measure

In the Table 1.8, I investigate how the choice of beta affect the performance of mutual funds. I use DGTW measures to evaluate the performance of mutual funds. DGTW performance measure includes CS (Characteristic Selection) and CT (Characteristic Timing) measure here. *CS* is a measure of stock selection ability and uses as a benchmark the return of portfolio of stocks that is matched to each of the fund's holdings every quarter along three characteristic dimensions of stocks—size, book-to-market ratio, and momentum:

$$CS_t = \sum_{j=1}^{N} \tilde{\omega}_{j,t-1} \left[\tilde{R}_{j,t} - \tilde{R}_t^{b_{j,t-1}} \right]$$

where $\omega_{j,t-1}$ is the portfolio weight on stock j at the end of quarter $t-1$, $\tilde{R}_{j,t}$ is the quarter t buy-and-hold return of stock j, and $\tilde{R}_t^{b_{j,t-1}}$ is the quarter t buy-and-hold return of the characteristic-based benchmark portfolio that is matched to stock j at the end of quarter $t-1$. CT is a measure of style timing ability. It is defined as follows.

$$CT_t = \sum_{j=1}^{N} \left[\tilde{\omega}_{j,t-1} \tilde{R}_t^{b_{j,t-1}} - \tilde{\omega}_{j,t-5} \tilde{R}_t^{b_{j,t-5}} \right]$$

where the terms are defined similarly as in CS measure.

At the end of each quarter, I sort all the mutual funds into ten deciles according to their Beta Choice measure, then I examine the return of each decile next quarter. The table reports the quarterly average of the performance of each decile. As shown in the table, no monotonic pattern is found for the performance measures. The difference of CS performance between Low BC and High BC decile is negative but not significant. Actually, the CS performance is U-shaped. Decile 8 and 9 have higher performance than others. When use monthly returns, I obtain the similar pattern. At the same time, I do not observe any pattern of CT measures. According to the above results, we can conclude that beta choice actually does not affect performance. This is reasonable and consistent with the empirical evidence that beta is no longer associated with expected return after controlling for size, book-to-market ratio and momentum.

1.4.6 Mutual Fund Trades and BC Measure

Table 1.9 reports how mutual fund trading activities affect a stock's beta. I define mutual fund trades on a stock as the change of the aggregate mutual fund ownership of the stock. The dependent variables are the change of beta of a stock and the change of its adjusted beta. The adjusted beta is the difference between the beta and the average beta in the risk group which the stock belongs to. Each quarter, I run the beta change or the adjusted beta change on its lags and lagged mutual fund trades, then I calculate the time series average as coefficients. The variance-covariance matrices are adjusted using Newey-West method with 6 lags.

Table 1.9 shows that mutual fund trades can strongly affect both the change of beta and the change of the adjusted beta. That is, the coefficients on the lagged trades and lagged two period trades are significantly positive. This raises a concern that the fact of higher beta choice of institutional investors may be caused by their trading activities.

To address this issue, I make a comparison of current beta and past betas of stocks chosen by institutional investors. Table 1.10 reports this comparison. For a stock held by an institutional investor, I compare its beta at the time when it is picked with its beta a quarter or year before it is picked. Every quarter, for each institutional investor, I calculate the weighted average of the difference between the current beta and past beta of each stock in his holdings. Thus, I obtain a BD (Beta Difference) measure for each institutional investor. Formally, the BD measure is defined as follows.

$$BD_t = \sum_{j=1}^{N} \omega_{j,t} \left[\tilde{\beta}_{j,t} - \tilde{\beta}_{j,t-i} \right] \tag{1.8}$$

where $\omega_{j,t}$ is the portfolio weight for a stock j at the beginning of period t, and $\tilde{\beta}_{j,t}$ is the estimated beta for the stock j at time t, and $\tilde{\beta}_{j,t-i}$ is the beta of the stock j at time $t-i$, where

i can be 1 (i.e., a quarter ago) or 4 (i.e., a year ago). In the table, Panel A reports average Beta Difference Measures based on current betas and one-quarter-ago betas, and Panel B reports average Beta Difference Measures based on current betas and one-year-ago betas. All betas are calculated based on daily returns and the benchmark used is value weighted CRSP index.

From the table, I find that the number of positive quarters is almost the same with that of negative quarters for mutual funds and the average BD measure is not significant, which means that the betas of stocks chosen by mutual funds have no significant changes since one quarter or one year ago. I obtain similar results for other institutional investors. These results show that the pattern of the beta choice is not driven by the trading activities of institutional investors.

1.4.7 Predictability

As my model suggests, the beta difference is proportional to the mean variance ratio of the market return. That is, $\Delta\beta = \beta - \beta_b = \frac{E(r_m)}{\gamma\sigma_m^2}$. Thus, the beta choice of a fund manager can reflect how he thinks about future mean variance ratio of the market return.

Table 1.11 describes the predictability of Beta Choice measures on the mean variance ratio of the market return, which is defined as the ratio of average market return to the variance of the market return, i.e., $MVRation = \bar{r_m}/\sigma_m^2$. The following regression is run on BC measures, lagged market volatility and implied volatility VIX measures.

$$MVRatio_t = b_0 + b_1 BC_{t-1} * 100 + b_2 MVRatio_{t-1} + b_3 VIX_{m-1} + b_4 VIX_{m-2} + b_5 VIX_{m-3} \tag{1.9}$$

where $MVRatio_t$ is the mean variance ratio of the market return at quarter t, and BC_{t-1} is the average BC measure at quarter $t-1$. VIX_{m-1} is the VIX measure one month before the quarter t end. VIX_{m-2} and VIX_{m-3} are the VIX measure two or three months before the quarter t end, respectively. Coefficients are estimated using GMM method and co-variance matrices are adjusted using Newey-West method.

We can find from Table 1.11 that the coefficients on the BC measure are significantly positive, which means that the average BC measure can indeed predict the mean variance ratio of the future market return. According to my model, the coefficient on the average BC measure is actually the risk aversion coefficient of mutual funds and shown in the table to be above 100, which shows that mutual funds are extremely risk averse. This result is consistent with Becker, Ferson, Myers, and Schill (1999a).

In order to further investigate whether the predictability of the mean variance ratio by the average BC measure is from the predictability of the future market return or the predictability of the future market volatility, I run two additional predictive regressions. One is to check on the predictability of the future market return and the other on the predictability of the future market volatility.

Table 1.12 exams the predictability of Beta Choice measures on market return. The following regression is run on BC measures, lagged market volatility and implied volatility VIX measures.

$$Mktret_t = b_0 + b_1 \cdot BC_{t-1} + b_2 \cdot Mktret_{t-1} + b_3 \cdot VIX_{m-1} + b_4 \cdot VIX_{m-2} + b_5 \cdot VIX_{m-3} \quad (1.10)$$

where $Mktret_t$ is the market return at quarter t, and BC_{t-1} is the average BC measure at quarter $t-1$. The left panel reports the results using BC measures based on daily market returns and the right panel reports the results using BC measures based on monthly market returns. In this table, I find that after controls for implied volatility and lagged market return, the average BC measure can not predict the future market return.

Table 1.13 describes the predictability of Beta Choice measures on market volatility. The following regression is run on BC measures, lagged market volatility and implied volatility VIX measures.

$$MktVol_t = b_0 + b_1 \cdot BC_{t-1} + b_2 \cdot MktVol_{t-1} + b_3 \cdot VIX_{m-1} + b_4 \cdot VIX_{m-2} + b_5 \cdot VIX_{m-3} \tag{1.11}$$

where $MktVol_t$ is the market volatility at quarter t, and BC_{t-1} is the average BC measure at quarter $t-1$.

As shown in the table, the lagged BC measure can strongly predict future market volatility. I also find that, not reported here, the significance is persistent during both half sample periods.

In summary, the average BC measure of mutual funds can predict the mean variance ratio of the future market return and this predictability seems to come from the strong predictability of the future market volatility.

1.5 Conclusion

It's understandable that institutional investors seek alpha, but it is hard to believe that they also seek beta, especially given the beta's death. In this paper, I design an innovative measure to investigate the beta choice of institutional investors. This measure can carefully and accurately control for a stock's risk characteristics such as size, book-to-market ratio and momentum. I find that institutional investors prefer high beta stocks within the same characteristic group. That is, given similar size, book-to-market ratio, and momentum, an institutional investor tend to choose the stock with higher beta. This result is robust whether I use daily or monthly returns, and whether I use the value-weighted CRSP index or S&P 500 index as the benchmark.

Further results show that investors' liquidity selection is hard to justify their beta choice although there is some evidence that these two choices are positively correlated.

Another possible explanation is that institutional investors' trading activities will affect beta. That is, big institutional investor inflows (outflows) will push up (down) a stock's beta. My results show that it is indeed the case. The increase (decrease) of institutional ownership can drive up (down) not only the level of beta but also the change of (adjusted) beta. However by checking the change of betas for each fund, I do not find evidence that the betas of stocks chosen by institutional investors have significant changes since one quarter or one year before institutional investors hold them.

I also find that institutional investors not only overweight in good beta (discount-rate beta) stocks, but also bad beta (cash-flow beta) stocks, thus the explanation that investors choose high overall beta is just because they choose high good beta is not the case here.

Additionally, I find that institutional investors' performance sorted based on Beta Choice measure does not exhibit a monotonic pattern, which shows that their beta choice is not motivated by their outperforming concern. Therefore, the only plausible explanation for the high beta choice of institutional investors is that they are subject to a benchmark which is consistent with my simple model.

I also confirm the second prediction of our model that the average beta choice of mutual funds can predict future market mean variance ratio and volatility. This predictability can be also explained by the fact that they are benchmark followers. Suppose there is a storm predicted, everyone will stay at their home or a shelter, but if weather is good, the tendency to stay home will be substantially reduced. This analog can apply to the beta choice of institutional investors. If they expect that the future market will be very volatile, they'd better stay close to their benchmarks, but in less volatile conditions managers load up more risky securities.

Some future work is interesting and promising. First, future research may investigate the time varying beta choice of institutional investors in this framework, that is, see more closely how they time the market. Second, we may investigate more closely how the beta choice of investigations affect individual stock returns. Finally, the degree of the deviation from a benchmark may proxy for an investor's confidence. Future work can investigate this linkage of investor optimism to other phenomena hypothesized to be related to overconfidence like momentum.

Figure 1.1: An illustration of Beta Choice

This figure illustrates why fund managers choose stock with higher beta than one. The line l depicts the relationship between stock excess return and beta. The point M is for the market.

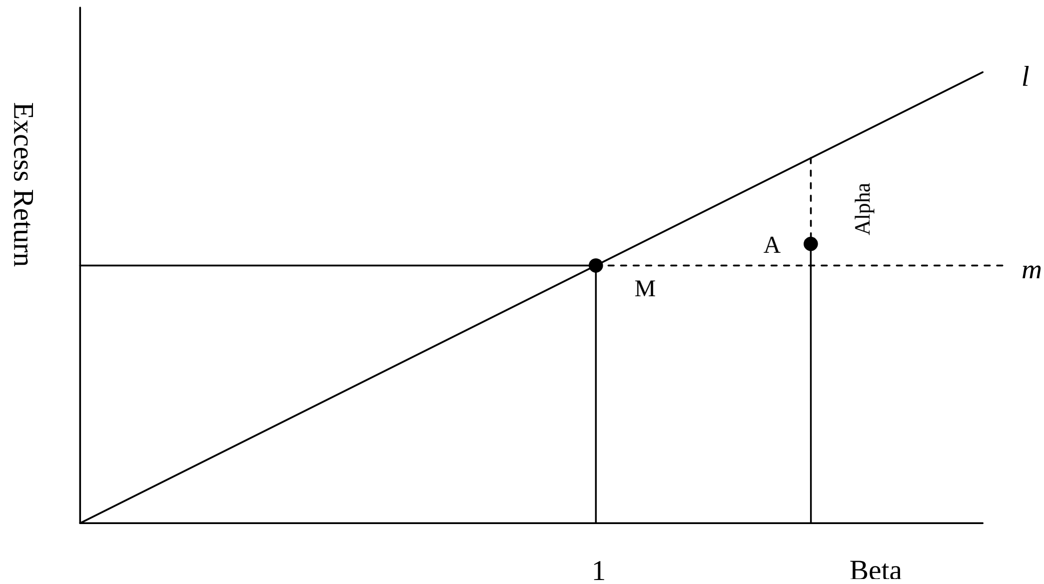


Figure 1.2: Average BC measure over time

This figure plots the quarterly cross-sectional average BC measures of mutual funds and institutional investors from 1980:Q1 to 2004:Q4. Market volatility is also plotted. Market volatility is calculated as the volatility of daily returns of the value weighted CRSP index during each quarter. The plotted volatility has been multiplied by 10.

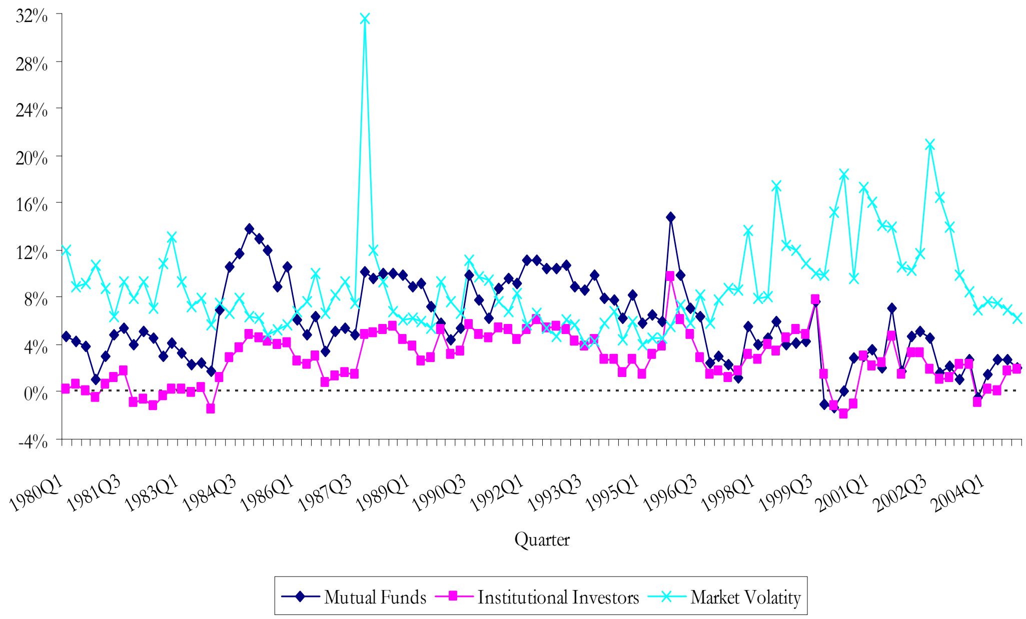


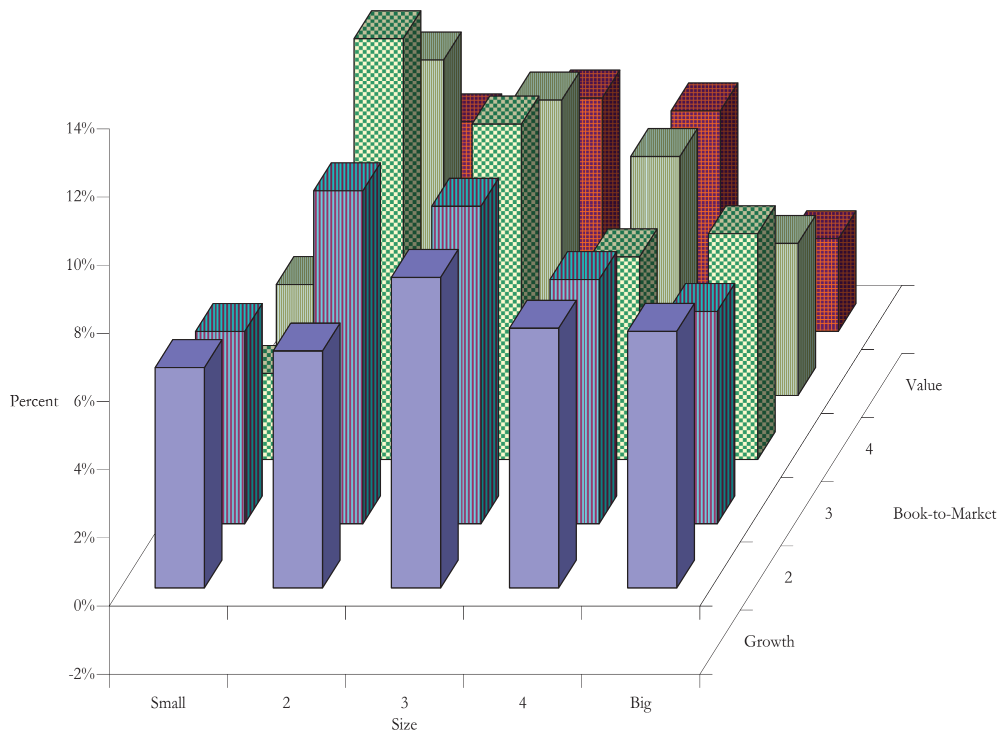
Figure 1.3: Average BC measure as a percentage of benchmark betas over time

This figure plots the quarterly cross sectional average BC measure as a percentage of benchmark betas from 1980:Q1 to 2004:Q4. Each quarter, for each fund (firm), we divide its BC measure over its benchmark betas, and then calculate the cross sectional average as reported below.

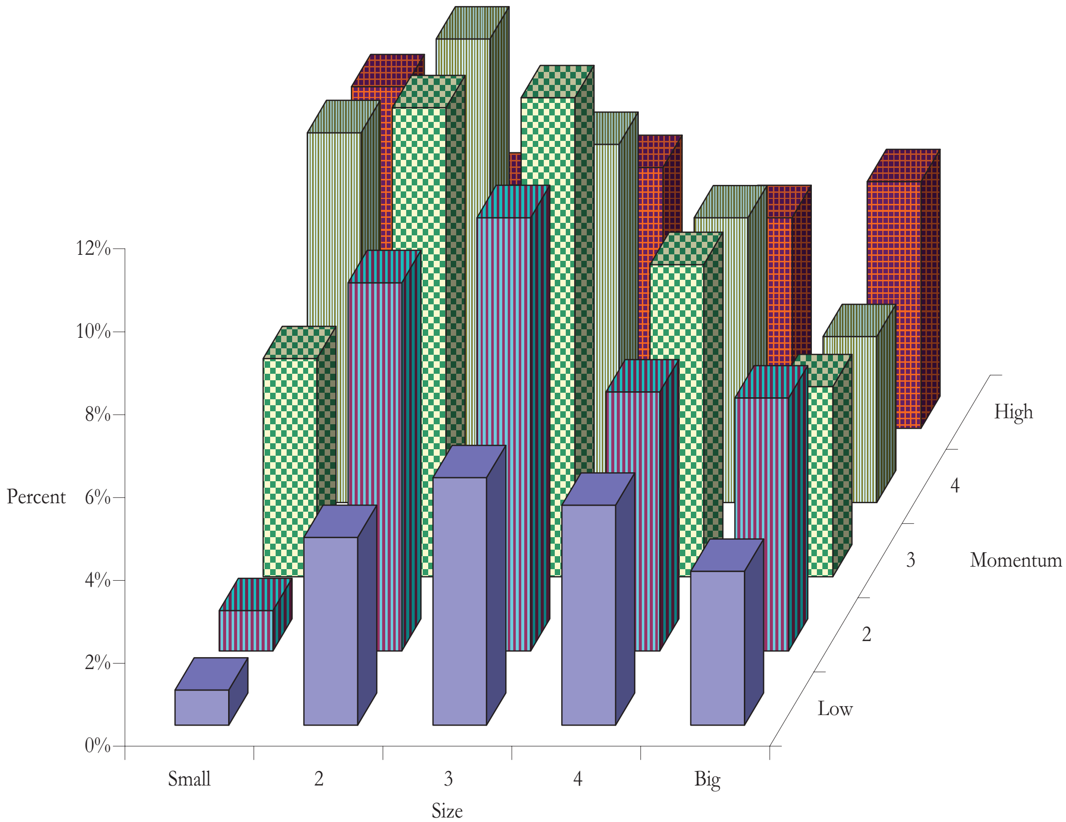
Figure 1.4: Average BC Measures as a percentage of benchmark betas across stock characteristics

The figures below plot the average percentage difference between betas chosen by mutual funds and benchmark betas along any two of the size, book-to-market ratio and momentum dimensions. We form benchmark portfolios as follows. First we sort all the qualified stocks on CRSP into five size quintiles, then within each size quintile sort according book-to-market ratio into five smaller quintiles, and finally within each smaller five quintiles (total 25 quintiles), sort into five even smaller quintiles based on momentum (piror year's return). Thus, we have 125 benchmark portfolios, each of which has its own size, book-to-mark ratio and momentum rank. Each quarter, we calculate the benchmark beta of a portfolio as the value-weighted average of the betas of all stocks in the portfolio. Thus we have 125 benchmark betas each quarter. By averaging benchmark betas along any two of the size, book-to-market ratio and momentum dimensions over time, we obtain 25 time series average benchmark betas. Each quarter, in each stock group (i.e., a group of stocks with the same size, book-to-market ratio and momentum rank), we calculate the average betas of the stocks chosen by mutual funds, then we further calculate time-series average of this average along any two of the three characteristic dimensions of stocks?size, book-to-market ratio and momentum. The figures below plot the percentage difference between average beta chosen by mutual funds and the corresponding benchmark betas. Mutual funds are actively managed (excluding sector, index, and other passive funds).

Panel A: Average BC Measures as a percentage of benchmark betas across size and book-to-market ratio dimensions



Panel B: Average BC Measures as a percentage of benchmark betas across size and momentum dimensions



Panel C: Average BC Measures as a percentage of benchmark betas across book-to-market ratio and momentum dimensions

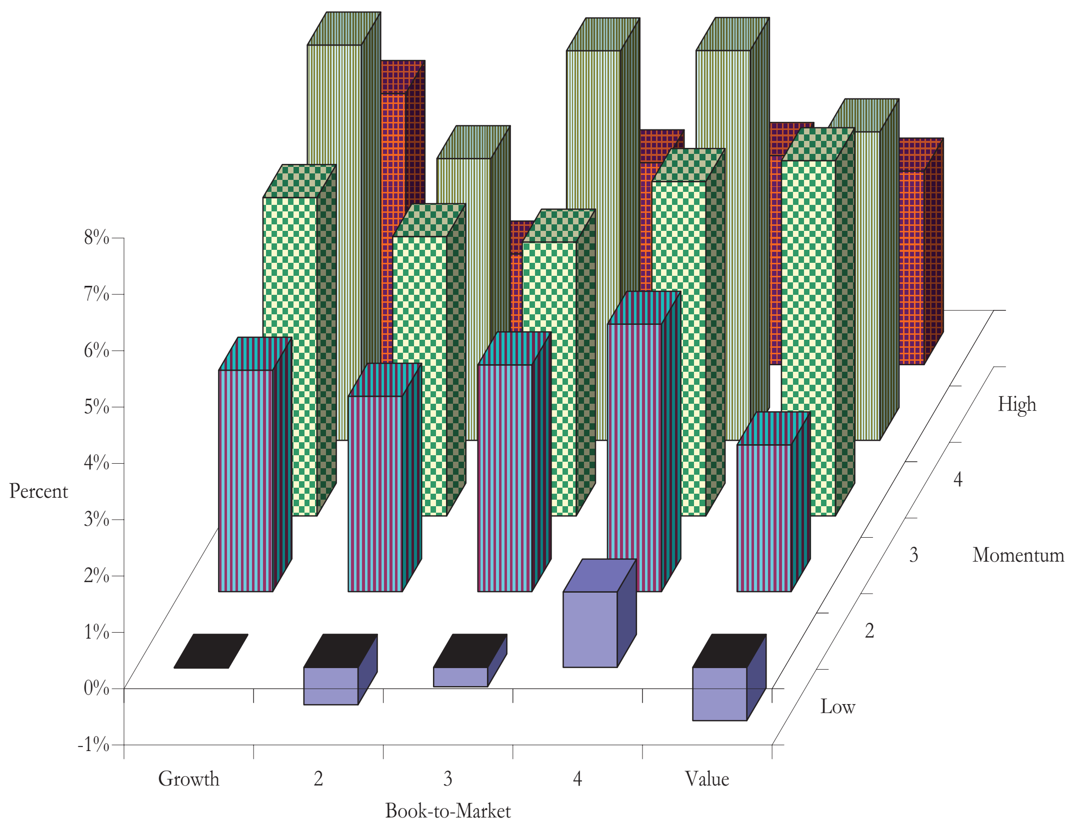
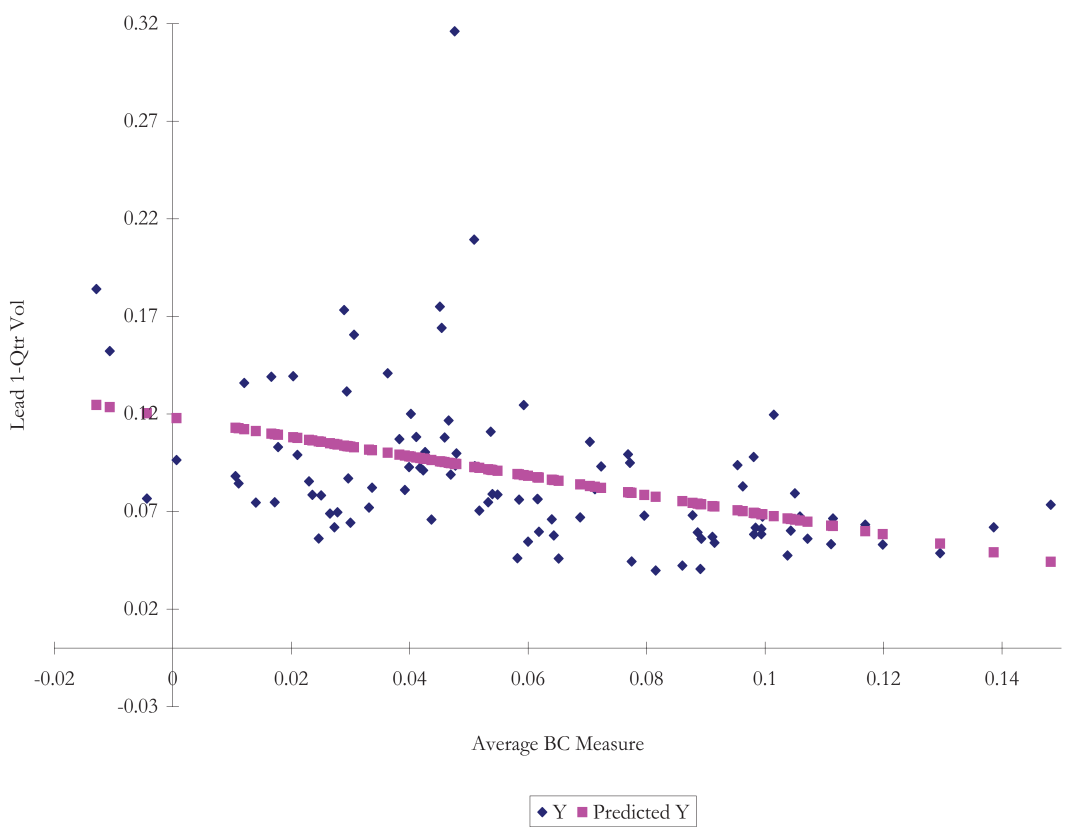


Figure 1.5: Average BC Measure and Future Market Volatility

This figure plots the linear regression of lead 1-Qtr market volatility on average BC measure. Panel A plots the full sample with 1987Q4. Panel B doesn't include 1987Q4. Market volatility is also plotted. Market volatility is calculated as the volatility of daily returns of the value weighted CRSP index during each quarter. The plotted volatility has been multiplied by 10.

Panel A: Full Sample with 1987Q4



Panel B: Full Sample Without 1987Q4

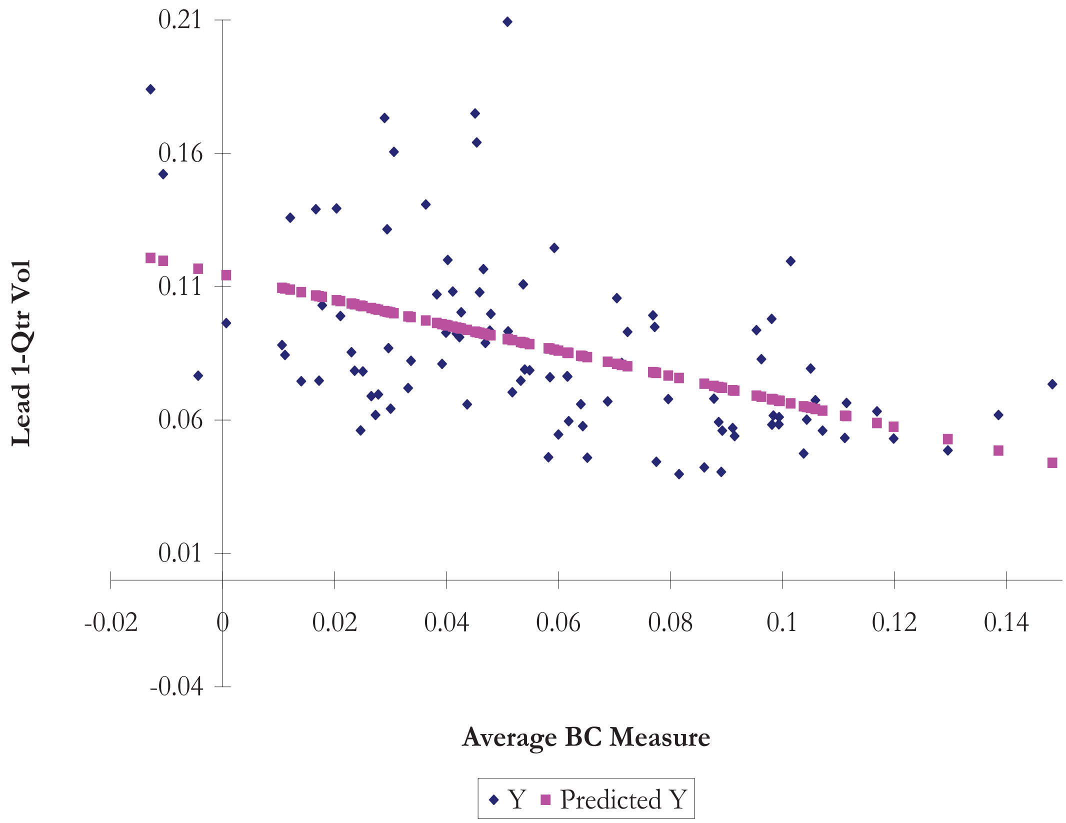


Table 1.1: Average Beta Choice Measures of Institutional Investors

This table reports the average Beta Choice (BC) measures of institutional investors. Negative quarters is the number of quarters that have negative average BC measures across funds (firms). Positive Quarters is the number of quarters that have non-negative average BC measures across funds (firms). The numbers in square brackets are the number of quarters that is statistically significant. "Average BC" is the quarterly average of the average BC measures across funds (firms). "Average BC" is multiplied by 100 in the table. T-statistics are in brackets. I measure the Beta Choice (BC) of a portfolio during quarter t as follows.

$$BC_t = \sum_{j=1}^{N} \omega_{j,t} \left[\tilde{\beta}_{j,t} - \tilde{\beta}_t^{b_{j,t}}\right]$$

where $\omega_{j,t}$ is the portfolio weight for stock j at the beginning of period t, and $\tilde{\beta}_{j,t}$ is the estimated beta for stock j at time t, and $\tilde{\beta}_t^{b_{j,t}}$ is the group average of betas within the group which stock j belongs to at time t. Panel A reports average Beta Choice Measures based on betas derived from daily returns, and Panel B reports average Beta Choice Measures based on betas derived from monthly returns.

Panel A: Average Beta Choice (BC) measures based on betas derived from daily returns

	Beta Based on VW CRSP index			Beta Based on S&P 500 index		
	Mutual Funds	Institutions	Difference	Mutual Funds	Institutions	Difference
Total Quarters	100	100		100	100	
Positive	97	89		98	93	
	[95]	[79]		[94]	[76]	
Negative	3	11		2	7	
	[1]	[3]		[0]	[1]	
Average BC	5.875	2.708	3.167	5.371	2.557	2.815
	(16.88)	(12.29)	(13.80)	(16.33)	(13.05)	(11.96)

Panel B: Average Beta Choice (BC) measures based on betas derived from monthly returns

	Beta Based on VW CRSP index			Beta Based on S&P 500 index		
	Mutual Funds	Institutions	Difference	Mutual Funds	Institutions	Difference
Total Quarters	100	100		100	100	
Positive	99	87		96	87	
	[93]	[72]		[85]	[70]	
Negative	1	13		4	13	
	[0]	[3]		[0]	[3]	
Average BC	4.868	2.155	2.713	4.544	2.083	2.461
	(19.57)	(11.77)	(16.41)	(17.52)	(12.07)	(13.90)

Table 1.2: Betas Chosen by Mutual Funds and Benchmark Betas

This table reports the average betas chosen by mutual funds and benchmark betas along any two of the size, book-to-market ratio and momentum dimensions. I form benchmark portfolios as follows. First I sort all the qualified stocks on CRSP into five size quintiles, then within each size quintile sort according book-to-market ratio into five smaller quintiles, and finally within each smaller five quintiles (total 25 quintiles), sort into five even smaller quintiles based on momentum (piror year's return). Thus, I have 125 benchmark portfolios, each of which has its own size, book-to-mark ratio and momentum rank. Each quarter, I calculate the benchmark beta of a portfolio as the value-weighted average of the betas of all stocks in the portfolio. Thus I have 125 benchmark betas each quarter. By averaging benchmark betas along any two of the size, book-to-market ratio and momentum dimensions over time, I obtain 25 time series average benchmark betas as reported below in brackets. Each quarter, in each stock group (i.e., a group of stocks with the same size, book-to-market ratio and momentum rank), I calculate the average betas of the stocks chosen by mutual funds, then I report time-series average of this average along any two of the size, book-to-market ratio and momentum dimensions as below. Mutual funds are actively managed (excluding sector, index, and other passive funds).

Panel A: Average Betas Chosen by Mutual Funds (Benchmark Betas in Brackets) across Size and BM/ME Quintiles

	Beta based on daily VW CRSP index returns					Beta based on monthly VW CRSP index returns				
	Growth	2	3	4	Value	Growth	2	3	4	Value
Small	1.27	1.13	1.03	0.98	0.98	1.16	1.04	0.94	0.90	0.90
	[1.19]	[1.07]	[1.00]	[0.95]	[0.98]	[1.07]	[0.97]	[0.90]	[0.86]	[0.88]
2	1.36	1.24	1.21	1.15	1.15	1.27	1.18	1.15	1.09	1.09
	[1.27]	[1.13]	[1.07]	[1.05]	[1.08]	[1.18]	[1.07]	[1.02]	[0.98]	[1.02]
3	1.38	1.25	1.16	1.14	1.17	1.31	1.20	1.13	1.09	1.13
	[1.26]	[1.14]	[1.06]	[1.04]	[1.09]	[1.20]	[1.09]	[1.02]	[1.00]	[1.06]
4	1.32	1.19	1.11	1.10	1.16	1.29	1.18	1.10	1.10	1.14
	[1.23]	[1.11]	[1.05]	[1.03]	[1.09]	[1.20]	[1.10]	[1.04]	[1.03]	[1.07]
Big	1.18	1.00	0.97	0.98	1.02	1.20	1.04	1.01	1.02	1.05
	[1.09]	[0.94]	[0.91]	[0.94]	[0.99]	[1.13]	[0.99]	[0.96]	[0.98]	[1.02]

Panel B: Average Betas Chosen by Mutual Funds (Benchmark Betas in Brackets) across Size and Momentum Quintiles

	Beta based on daily VW CRSP index returns					Beta based on monthly VW CRSP index returns				
	Low	2	3	4	High	Low	2	3	4	High
Small	1.23	1.03	0.95	0.97	1.24	1.11	0.94	0.88	0.89	1.15
	[1.22]	[1.02]	[0.90]	[0.89]	[1.15]	[1.08]	[0.92]	[0.83]	[0.81]	[1.04]
2	1.28	1.09	1.05	1.16	1.47	1.21	1.04	1.00	1.10	1.38
	[1.23]	[1.00]	[0.94]	[1.04]	[1.39]	[1.15]	[0.95]	[0.89]	[0.98]	[1.30]
3	1.27	1.08	1.07	1.18	1.47	1.22	1.05	1.05	1.14	1.38
	[1.20]	[0.97]	[0.96]	[1.09]	[1.38]	[1.15]	[0.95]	[0.93]	[1.04]	[1.29]
4	1.20	1.04	1.07	1.13	1.40	1.18	1.03	1.08	1.13	1.35
	[1.14]	[0.98]	[1.00]	[1.06]	[1.33]	[1.12]	[0.97]	[1.00]	[1.06]	[1.28]
Big	1.02	0.92	0.93	1.03	1.21	1.06	0.97	0.97	1.06	1.22
	[0.99]	[0.87]	[0.89]	[0.99]	[1.15]	[1.03]	[0.92]	[0.94]	[1.03]	[1.17]

Panel C: Average Betas Chosen by Mutual Funds (Benchmark Betas in Brackets) across BM/ME and Momentum Quintiles

	Beta based on daily VW CRSP index returns					Beta based on monthly VW CRSP index returns				
	Low	2	3	4	High	Low	2	3	4	High
Growth	1.20	1.11	1.13	1.29	1.58	1.18	1.10	1.13	1.26	1.50
	[1.20]	[1.06]	[1.07]	[1.20]	[1.51]	[1.15]	[1.03]	[1.04]	[1.15]	[1.41]
2	1.13	0.98	0.98	1.10	1.34	1.13	0.99	0.99	1.10	1.29
	[1.14]	[0.95]	[0.94]	[1.05]	[1.32]	[1.10]	[0.93]	[0.92]	[1.02]	[1.24]
3	1.15	0.95	0.90	1.01	1.26	1.13	0.95	0.92	1.01	1.23
	[1.15]	[0.92]	[0.86]	[0.95]	[1.21]	[1.10]	[0.90]	[0.85]	[0.93]	[1.16]
4	1.13	0.98	0.94	0.96	1.21	1.11	0.97	0.95	0.96	1.19
	[1.11]	[0.94]	[0.89]	[0.90]	[1.17]	[1.06]	[0.90]	[0.88]	[0.88]	[1.12]
Value	1.16	1.00	0.99	1.01	1.23	1.14	1.00	0.99	1.01	1.20
	[1.17]	[0.98]	[0.93]	[0.96]	[1.19]	[1.12]	[0.95]	[0.91]	[0.94]	[1.14]

Table 1.3: Bad Beta and Good Beta

This table reports the decomposition of the Beta Choice (BC) measures into Good Beta Choice and Bad Beta Choice. Good Beta is a stock's sensitivity to discount rate news and bad beta is the sensitivity to cash flow news. Negative quarters is the number of quarters that have negative average BC measures across funds (firms). Positive Quarters is the number of quarters that have non-negative average BC measures across funds (firms). The numbers in square brackets are the number of quarters that is statistically significant. Mean is the quarterly average of the average BC measures across funds (firms). Mean is multiplied by 100 in the table. T-statistics are in brackets. I measure the Beta Choice (BC) of a portfolio during quarter t as follows.

$$BC_t = \sum_{j=1}^{N} \omega_{j,t} \left[\tilde{\beta}_{j,t} - \tilde{\beta}_t^{b_{j,t}}\right]$$

where $\omega_{j,t}$ is the portfolio weight for stock j at the beginning of period t, and $\tilde{\beta}_{j,t}$ is the estimated beta for stock j at time t, and $\tilde{\beta}_t^{b_{j,t}}$ is the group average of betas within the group which stock j belongs to at time t. Betas are estimated repeatedly in a backward 60-month rolling window using monthly data.

	Discount Rate News Beta			Cash Flow News Beta		
	Mutual Funds	Institutions	Difference	Mutual Funds	Institutions	Difference
Positive Quarters	83	74		57	63	
	[74]	[64]		[48]	[45]	
Negative Quarters	5	14		31	25	
	[1]	[5]		[26]	[12]	
Mean	4.408	1.695	2.713	0.165	0.227	-0.062
	(16.40)	(9.50)	(13.89)	(1.94)	(5.73)	(-1.02)

Table 1.4: Average Liquidity Selection Measures of Institutional Investors

This table reports the average Liquidity Selection (LS) measures of institutional investors. Positive Quarters is the number of quarters that have positive average LS measures across funds (firms). Negative Quarters is the number of quarters that have negative average LS measures across funds (firms). The numbers in square brackets are the number of quarters that is statistically significant. Mean is the time-serial average of the average LS measures across funds (firms) each quarter. T-Statistics are in brackets. P-values less than 0.05 (0.01) are denoted by * (**). I measure the Liquidity Selection (LS) of a portfolio during quarter t as follows.

$$LS_t = \sum_{j=1}^{N} \omega_{j,t} \left[L\tilde{I}Q_{j,t} - L\tilde{I}Q_t^{b_{j,t}} \right]$$

where $\omega_{j,t}$ is the portfolio weight for stock j at the beginning of period t, and $L\tilde{I}Q_{j,t}$ is the estimated liquidity for stock j at time t, and $L\tilde{I}Q_t^{b_{j,t}}$ is the group average liquidity within the group which stock j belongs to at time t.

	Mutual Funds	Institutions	Difference
Positive Quarters	77	72	
	[59]	[51]	
Negative Quarters	23	28	
	[1]	[4]	
Mean	0.413**	0.219**	0.194
	(3.26)	(3.82)	(1.60)

Table 1.5: Beta and Liquidity

This table reports the relation between a stock's beta and liquidity. Panel A reports the regression of beta on liquidity and their lagged terms. Panel B reports the regression of liquidity on beta and their lagged terms. Panel C reports average cross-sectional correlations between beta and liquidity during the whole sample and sub-periods.

Panel A: Regression of Beta on Liquidity

	(1)	(2)	(3)	(4)
Beta (t-1)		0.220		0.219
		(5.74)		(5.71)
Liquidity (t)	0.020		-0.001	0.000
	(2.49)		(-0.07)	(-0.01)
Liquidity (t-1)			0.078	0.067
			(7.91)	(6.24)
Adj. R^2	0.003	0.065	0.007	0.072

Panel B: Regression of Liquidity on Beta

	(1)	(2)	(3)	(4)
Beta	0.023		0.018	0.006
	(3.47)		(2.46)	(0.81)
Beta (t-1)			0.016	0.011
			(2.23)	(1.58)
Liquidity (t-1)		0.451		0.448
		(9.49)		(9.34)
Adj. R^2	0.003	0.098	0.006	0.102

Panel C: Average cross-sectional correlations between beta and liquidity

Year	Correlation
1980-1984	0.039
1985-1989	0.032
1990-1994	-0.008
1995-1999	0.034
2000-2004	0.019
1980-2004	0.023

Table 1.6: Beta Choice and Liquidity Selection

This table reports the regression results on the relationship between Beta Choice (BC) measures and Liquidity Selection (LS) measures. The left panel reports the relationship between Beta Choice (BC) and Liquidity Selection (LS) Measures of Mutual Funds, and the right panel reports that of Institutional Investors. Coefficients are estimated using Fama-Macbeth method. That is, every quarter, I run the BC measure of each fund (firm) on its LS measure and lagged BC and LS measures, then I calculate the time-series average. The variance-covariance matrices are adjusted using Newey-West method with 6 lags. T-statistics are in brackets. P-values less than 0.05 (0.01) are denoted by * (**).

	Mutual Funds				Institutional Investors			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
BC(t-1)			0.69**	0.69**			0.69**	0.68**
			(27.78)	(29.85)			(29.00)	(28.91)
BC(t-2)			0.02	0.02			0.06**	0.06**
			(1.79)	(1.55)			(4.58)	(6.13)
BC(t-3)			0.06**	0.05**			0.01	0.01
			(11.19)	(8.06)			(0.48)	(0.52)
BC(t-4)			0.03**	0.02*			0.00	0.00
			(2.73)	(2.47)			(-0.02)	(-0.24)
LS(t)	0.60**	0.40**		0.25**	0.48**	0.10		0.02
	(3.47)	(3.27)		(3.45)	(4.46)	(0.82)		(0.23)
LS(t-1)		0.11*		-0.12		0.18**		0.09
		(1.96)		(-1.59)		(2.77)		(1.75)
LS(t-2)		0.16*		-0.02		0.18		-0.06
		(2.15)		(-0.44)		(1.22)		(-0.49)
LS(t-3)		0.24 **		0.06		0.29**		0.08
		(3.24)		(0.92)		(3.33)		(0.81)
LS(t-4)		0.16		-0.04		0.41*		0.15**
		(1.76)		(-1.07)		(2.57)		(2.80)
Adj R^2	0.03	0.07	0.59	0.61	0.03	0.07	0.55	0.58

Table 1.7: Beta Choice Measure and Fund Characteristics

This table reports how fund characteristics affect its Beta Choice measure. Age is defined as the number of quarters since a fund appeared in the holdings database. Assets is the quarterly total assets of a fund reported in 13f database. BC(t-1), BC(t-2) and BC(t-3) are the lagged 1, 2, and 3 quarter BC measures. Aggressive Growth, Growth, Growth & Income and Balanced are dummy variables. They are equal to 1 if the fund falls into the corresponding category, and equal to zero otherwise. If these dummy variables are used in the regression, the intercept will not be used to avoid multicollinearity. LS is the Liquidity Selection measure. Its three lags are included. Turnover is fund trading turnover which is defined as the minimum of aggregate purchases and sales of securities divided by the average TNA over the calendar year. Coefficients are estimated using Fama-Macbeth method. That is, every quarter, I run the BC measure of each fund (firm) on the variables listed in the table, then I calculate the time-series average as coefficients reported in the table. The variance-covariance matrices are adjusted using Newey-West method with up to 6 lags. T-statistics are in brackets. P-values less than 0.05 (0.01) are denoted by * (**).

	(1)	(2)	(3)	(4)
Age			-0.002	-0.002
			(-1.01)	(-1.00)
Log(Assets)/100			0.082*	0.073*
			(2.00)	(1.74)
BC(t-1)	0.691**	0.693**	0.691**	0.689**
	(31.19)	(35.06)	(30.55)	(32.82)
BC(t-2)	0.037**	0.034**	0.015	0.017
	(3.28)	(3.31)	(1.03)	(1.45)
BC(t-3)	0.069**	0.068**	0.061**	0.060**
	(9.62)	(8.09)	(4.93)	(4.59)
Aggressive Growth			0.042*	0.041*
			(2.37)	(2.26)
Growth			0.022	0.022
			(1.27)	(1.25)
Growth & Income			0.005	0.006
			(0.26)	(0.30)
Balanced			0.005	0.006
			(0.31)	(0.34)
LS(t)		0.160*		0.167
		(2.33)		(1.49)
LS(t-1)		-0.105		-0.138
		(-1.34)		(-1.33)
LS(t-2)		0.033		0.077
		(0.38)		(0.67)
LS(t-3)		-0.006		-0.037
		(-0.12)		(-0.89)
Turnover/100			-0.042	-0.079
			(-0.67)	(-1.07)
Adj. R^2	0.61	0.62	0.64	0.66

Table 1.8: Quarterly DGTW Performance Sorted on BC Measures

This table reports the DGTW performance of mutual funds sorted on their BC measures. DGTW performance measure includes CS (Characteristic Selection) and CT (Characteristic Timing) measure here. *CS* is a measure of stock selection ability and uses as a benchmark the return of portfolio of stocks that is matched to each of the fund's holdings every quarter along three stock characteristic dimensions of stocks—size, book-to-market ratio, and momentum:

$$CS_t = \sum_{j=1}^{N} \tilde{\omega}_{j,t-1} \left[\tilde{R}_{j,t} - \tilde{R}_t^{b_{j,t-1}} \right]$$

where $\omega_{j,t-1}$ is the portfolio weight on stock j at the end of quarter $t-1$, $\tilde{R}_{j,t}$ is the quarter t buy-and-hold return of stock j, and $\tilde{R}_t^{b_{j,t-1}}$ is the quarter t buy-and-hold return of the characteristic-based benchmark portfolio that is matched to stock j at the end of quarter $t-1$. *CT* is a measure of style timing ability. It is defined as follows.

$$CT_t = \sum_{j=1}^{N} \left[\tilde{\omega}_{j,t-1} \tilde{R}_t^{b_{j,t-1}} - \tilde{\omega}_{j,t-5} \tilde{R}_t^{b_{j,t-5}} \right]$$

where the terms are defined similarly as in *CS* measure.

	CS	CT	CS	CT
Low	-0.051	0.077	-0.068	0.031
2	0.195	0.084	0.114	0.040
3	0.184	0.107	0.181	0.076
4	0.219	0.056	0.155	0.060
5	0.165	0.072	0.184	0.079
6	0.182	0.071	0.190	0.056
7	0.222	0.090	0.254	0.098
8	0.340	0.076	0.295	0.084
9	0.402	0.057	0.445	0.092
High	0.015	-0.027	0.122	0.053
Low-High	-0.066	0.104	-0.189	-0.022
	(-0.14)	(0.58)	(-0.41)	(-0.13)

Table 1.9: Mutual Fund Trades and Betas

This table reports how mutual fund trading activities affect a stock's beta. I define mutual fund trades on a stock as the change of the aggregate mutual fund ownership of the stock. The dependent variables are the change of beta of a stock and the change of its adjusted beta. The adjusted beta is the difference between the beta and the average beta in the risk group which the stock belongs to. Each quarter, I run the beta change or the adjusted beta change on its lags and lagged mutual fund trades, then I calculate the time series average as coefficients. The standard errors are adjusted using Newey-West method with up to 6 lags. T-statistics are in brackets. P-values less than 0.05 (0.01) are denoted by * (**).

Panel A: Relation between Changes of Betas of Stocks and the Changes of Mutual Fund Ownership (Dependent variable: Change of Beta (t))

	(1)	(2)	(3)
Change of Beta (t-1)		-0.018	-0.018
		(-1.81)	(-1.44)
Change of Beta (t-2)		0.025	0.032
		(1.71)	(2.07)
Change of Ownership (t-1)	0.221**		0.208**
	(4.47)		(4.61)
Change of Ownership (t-2)	0.315**		0.330**
	(5.35)		(5.62)
Adj. R^2	0.001	0.042	0.046

Panel B: Relation between Changes of Adjusted Betas of Stocks and the Changes of Mutual Fund Ownership (Dependent variable: Change of Adjusted Beta (t))

	(1)	(2)	(3)
Change of Adjusted Beta (t-1)		-0.031**	-0.033**
		(-2.98)	(-2.79)
Change of Adjusted Beta (t-2)		0.007	0.003
		(0.61)	(0.28)
Change of Ownership (t-1)	0.147*		0.122*
	(2.48)		(2.01)
Change of Ownership (t-2)	0.170**		0.168**
	(2.95)		(2.86)
Adj. R^2	0.001	0.039	0.040

Table 1.10: A Comparison of Current Beta and Past Betas of stocks Chosen by Institutional Investors

This table reports a comparison of current beta and past betas of stocks chosen by institutional investors. For a stock held by an institutional investor, I compare its beta at the time when it is picked with its beta a quarter or year before it is picked. Every quarter, for each institutional investor, I calculate the weighted average of the difference between the current beta and past beta of each stock in his holdings. Thus, I obtain a BD (Beta Difference) measure for each institutional investor. Formally, the BD measure is defined as follows.

$$BD_t = \sum_{j=1}^{N} \omega_{j,t} \left[\tilde{\beta}_{j,t} - \tilde{\beta}_{j,t-i}\right]$$

where $\omega_{j,t}$ is the portfolio weight for a stock j at the beginning of period t, and $\tilde{\beta}_{j,t}$ is the estimated beta for the stock j at time t, and $\tilde{\beta}_{j,t-i}$ is the beta of the stock j at time $t-i$, where i can be 1 (i.e., a quarter ago) or 4 (i.e., a year ago). In the table, "Negative" denotes the number of quarters that have negative average BC measures across funds (firms) and "Positive" is defined likewise. The numbers in square brackets are the number of quarters that are statistically significant. "Average BD" is the time-serial average of the average BD measures across funds (firms) each quarter, which has been multiplied by 100. T-Statistics are in brackets. Panel A reports average Beta Difference Measures based on current betas and one-quarter-ago betas, and Panel B reports average Beta Difference Measures based on current betas and one-year-ago betas. All betas are calculated based on daily returns and the benchmark used is value weighted CRSP index.

Panel A: Average Beta Difference (BD) Measures based on Current Betas and One-quarter-ago Betas

	Beta Based on VW CRSP			Beta Based on S&P 500		
	Mutual Funds	Institutions	Difference	Mutual Funds	Institutions	Difference
Total Quarters	100	100		100	100	
Positive	51	47		43	42	
	[45]	[35]		[41]	[39]	
Negative	49	53		57	58	
	[41]	[37]		[48]	[50]	
Average BD	0.376	0.041	0.335	0.437	0.077	0.360
	(0.93)	(0.12)	(1.38)	(0.64)	(0.15)	(1.35)

Panel B: Average Beta Difference (BD) Measures based on Current Betas and One-year-ago Betas

	Beta Based on VW CRSP			Beta Based on S&P 500		
	Mutual Funds	Institutions	Difference	Mutual Funds	Institutions	Difference
Total Quarters	100	100		100	100	
Positive	52	46		51	48	
	[46]	[37]		[49]	[44]	
Negative	48	54		49	52	
	[38]	[40]		[46]	[46]	
Average BD	0.842	0.242	0.599	0.814	0.279	0.535
	(0.86)	(0.27)	(1.41)	(0.52)	(0.23)	(1.16)

Table 1.11: Predict the Mean Variance Ratio of the Market Return

This table describes the predictability of Beta Choice measures on the mean variance ratio of the market return, which is defined as the ratio of average market return to the variance of the market return, i.e., $MVRation = \bar{r_m}/\sigma_m^2$. The following regression is run on BC measures, lagged market volatility and implied volatility VIX measures.

$$MVRatio_t = b_0 + b_1 \cdot BC_{t-1} * 100 + b_2 \cdot MVRatio_{t-1} + b_3 \cdot VIX_{m-1} + b_4 \cdot VIX_{m-2} + b_5 \cdot VIX_{m-3};$$

where $MVRatio_t$ is the mean variance ratio of the market return at quarter t, and BC_{t-1} is the average BC measure at quarter $t-1$. VIX_{m-1} is the VIX measure one month before the quarter t end. VIX_{m-2} and VIX_{m-3} are the VIX measure two or three months before the quarter t end, respectively. The left panel reports the results using BC measures based on daily market returns and the right panel reports the results using BC measures based on monthly market returns. Coefficients are estimated using GMM method and co-variance matrices are adjusted using Newey-West method. T-statistics are in brackets. P-values less than 0.05 (0.01) are denoted by * (**).

	BC Based on Daily Market Returns				BC Based on Monthly Market Returns			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Intercept	3.409	1.675	21.526	21.416	4.432	2.180	24.177	24.600
	(0.97)	(0.53)	(1.92)	(1.32)	(1.13)	(0.66)	(2.40)	(1.67)
$BC_{t-1} * 100$	1.728**	1.683**	1.159**	1.153*	1.702**	1.702**	1.191*	1.178*
	(4.69)	(4.77)	(2.31)	(2.07)	(4.27)	(4.76)	(2.14)	(1.96)
$MVRatio_{t-1}$		0.136	0.137	0.137		0.156	0.153	0.150
		(1.32)	(1.59)	(1.53)		(1.42)	(1.72)	(1.61)
VIX_{m-1}			-3.605	-2.893			-4.080*	-3.101
			(-1.84)	(-0.80)			(-2.18)	(-0.83)
VIX_{m-2}				1.676				1.603
				(0.22)				(0.21)
VIX_{m-3}				-2.368				-2.667
				(-0.28)				(-0.32)

Table 1.12: Predict Market Return

This table exams the predictability of Beta Choice measures on market return. The following regression is run on BC measures, lagged market volatility and implied volatility VIX measures.

$$Mktret_t = b_0 + b_1 \cdot BC_{t-1} + b_2 \cdot Mktret_{t-1} + b_3 \cdot VIX_{m-1} + b_4 \cdot VIX_{m-2} + b_5 \cdot VIX_{m-3};$$

where $Mktret_t$ is the market return at quarter t, and BC_{t-1} is the average BC measure at quarter $t-1$. VIX_{m-1} is the VIX measure one month before the quarter t end. VIX_{m-2} and VIX_{m-3} are the VIX measure two or three months before the quarter t end, respectively. The left panel reports the results using BC measures based on daily market returns and the right panel reports the results using BC measures based on monthly market returns. Coefficients are estimated using GMM method and co-variance matrices are adjusted using Newey-West method. T-statistics are in brackets. P-values less than 0.05 (0.01) are denoted by * (**).

	BC Based on Daily Market Returns				BC Based on Monthly Market Returns			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Intercept	0.012	0.010	-0.061	-0.134	0.011	0.009	-0.043	-0.104
	(0.70)	(0.55)	(-1.27)	(-1.31)	(0.64)	(0.50)	(-0.97)	(-1.19)
BC_{t-1}	0.396	0.414*	0.503	0.635	0.456*	0.466*	0.486	0.603
	(1.87)	(2.03)	(1.64)	(1.58)	(2.14)	(2.21)	(1.34)	(1.39)
$Mktret_{t-1}$		0.013	-0.036	0.044		0.017	-0.038	0.033
		(0.17)	(-0.61)	(0.42)		(0.22)	(-0.61)	(0.31)
VIX_{m-1}			0.014	-0.001			0.011	-0.002
			(1.86)	(-0.05)			(1.51)	(-0.09)
VIX_{m-2}				0.040				0.038
				(1.63)				(1.62)
VIX_{m-3}				-0.012				-0.014
				(-0.34)				(-0.41)

Table 1.13: Predict Market Volatility

This table describes the predictability of Beta Choice measures on market volatility. The following regression is run on BC measures, lagged market volatility and implied volatility VIX measures.

$$MktVol_t = b_0 + b_1 \cdot BC_{t-1} + b_2 \cdot MktVol_{t-1} + b_3 \cdot VIX_{m-1} + b_4 \cdot VIX_{m-2} + b_5 \cdot VIX_{m-3};$$

where $MktVol_t$ is the market volatility at quarter t, and BC_{t-1} is the average BC measure at quarter $t-1$. VIX_{m-1} is the VIX measure one month before the quarter t end. VIX_{m-2} and VIX_{m-3} are the VIX measure two or three months before the quarter t end, respectively. The left panel reports the results using BC measures based on daily market returns and the right panel reports the results using BC measures based on monthly market returns. Coefficients are estimated using GMM method and co-variance matrices are adjusted using Newey-West method. T-statistics are in brackets. P-values less than 0.05 (0.01) are denoted by * (**).

	BC Based on Daily Market Returns				BC Based on Monthly Market Returns			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Intercept	0.111	0.070	0.082	-0.011	0.107	0.065	0.072	-0.022
	(9.42)	(3.79)	(1.84)	(-0.34)	(9.21)	(3.73)	(1.72)	(-0.76)
BC_{t-1}	-0.46**	-0.33**	-0.40**	-0.34**	-0.42**	-0.31**	-0.41**	-0.35**
	(-3.71)	(-2.80)	(-2.52)	(-2.45)	(-3.45)	(-2.81)	(-2.67)	(-2.68)
$MktVol_{t-1}$		0.401**	0.413**	0.057		0.430	0.434**	0.063
		(3.23)	(3.86)	(0.52)		(3.40)**	(4.25)	(0.52)
VIX_{m-1}				0.021*				0.021**
				(1.93)				(1.97)
VIX_{m-2}				-0.013				-0.012
				(-0.98)				(-0.93)
VIX_{m-3}			-0.002	0.017			0.000	0.018
			(-0.21)	(0.81)			(-0.06)	(0.82)

Table 1.14: Summary Statistics of Fama French Factors

This table reports the correlations and covariances between the returns of the commonly used factors—excess market return (Mkt_Rf), size (SMB), value (HML) and momentum (UMD). I obtain these monthly factor returns from Professor Kent French's website. The data is from the year 1927 to 2004.

Panel A: Correlations Between Factors

	Mkt_Rf	SMB	HML	UMD
Mkt_Rf	1			
SMB	0.33	1		
HML	0.20	0.08	1	
UMD	-0.34	-0.17	-0.40	1

Panel B: Variance Covariance Matrix

	Mkt_Rf	SMB	HML	UMD
Mkt_Rf	0.0030			
SMB	0.0006	0.0011		
HML	0.0004	0.0001	0.0013	
UMD	-0.0009	-0.0003	-0.0007	0.0022

Panel C: Monthly Average Returns

Mkt_Rf	SMB	HML	UMD
0.0065	0.0023	0.0040	0.0075

Table 1.15: Stock Beta and Characteristics

This tables reports the Fama-Macbeth regression of stock betas on one-year lagged betas and stock characteristics. Betas are calculated using daily returns and the benchmark is the value weighted CRSP index. Each quarter, I run a cross sectional regression of stock betas on stock characteristics, such as book-to-market ratio, size, and momentum (prior year return). Then I calculate the quarterly average of the coefficients. Standard errors are adjusted using Newey-West method with up to six lags. T-statistics are in brackets.

	(1)	(2)	(3)	(4)
Beta (t-1)		0.251		0.239
		(4.90)		(5.26)
Book-to-Market Ratio			-0.118	-0.089
			(-4.37)	(-4.17)
Log (Size)	-0.021		-0.031	-0.040
	(-1.29)		(-1.80)	(-2.39)
Momentum			-0.006	-0.016
			(-0.26)	(-0.94)
Avg Adj. R^2	0.016	0.087	0.050	0.118

Chapter 2

Does investor sentiment affect mutual fund performance?

2.1 Introduction

Two important reasons have made mutual fund performance a lively topic of financial economics for decades. One is its implications for market efficiency, and the other is its implications for investors. Traditionally, no connection between mutual fund performance and investor sentiment has been established in the literature. This is reasonable based on conventional theories. First, according to the efficient market hypothesis (EMH), mutual fund managers on average can not outperform the market and their performance is not predictable, thus no factors other than idiosyncratic characteristics of fund managers are relevant to their risk adjusted performance[1]. Therefore, investor sentiment, a market-wide variable, can not provide any additional explanation for mutual fund performance; Second, since investor sentiment is not a long-established risk factor in the literature, traditional risk

[1] See, for example, Chevalier and Ellison (1999a).

factors in the mutual fund performance measures will capture the effect of investor sentiment if any. Thus, again, investor sentiment is irrelevant here. Last, investor sentiment may play a role in mutual fund performance in the sense that mutual fund managers can take advantage of small investor sentiment, but many constraints of mutual funds and limits of arbitrage (Shleifer and Vishny 1997) would prevent them from doing so.

However, newly established theories and documented empirical evidence suggest that investor sentiment may indeed have an impact on mutual fund performance. First, De Long, Shleifer, Summers, and Waldmann (1990a) show that noise traders earn higher average returns than sophisticated investors when noise traders' sentiment is high, and vice versa. This suggests that mutual fund performance be negatively correlated with investor sentiment, especially small investor sentiment. Second, recent empirical evidence shows that investor sentiment significantly affects stock prices along two dimensions. On the one hand, time-serially, investor sentiment has significant ability to predict future returns both weekly and in a long horizon (2-3 years) (Kaniel, Saar, and Titman (2004) and Brown and Cliff (2005)); On the other hand, cross-sectionally, stock returns vary with investor sentiment and exhibit different patterns in different sentiment (Baker and Wurgler 2003). Since fund managers trade on stocks, we would expect that investor sentiment may also affect mutual fund performance.

In this paper, I examine whether mutual fund performance varies with investor sentiment. Using a sentiment index developed in Baker and Wurgler (2003) to proxy for investor sentiment, my results show that mutual fund performance under conventional measures indeed strongly varies with investor sentiment. The variations documented here are along two dimensions. First of all, the universe of actively managed mutual funds performs better in low investor sentiment than in high investor sentiment, even after adjusting fund returns by various performance benchmarks. Secondly, there are also big variations in *relative* performance across size ranked mutual fund portfolios.

Specifically, the results in this paper show that almost all fund size quintiles subsequently outperform the market when sentiment is low while all of them underperform the market when sentiment is high. This also holds true after adjusting the fund returns by various performance benchmarks. Also, all the size quintiles perform better when sentiment is low than when sentiment is high. This means that fund performance is negatively related to investor sentiment. My results show that a one-standard deviation increase in sentiment at the beginning of this year yields about 4.3% decrease in this year's annual returns of the smallest fund quintiles and 0.72% decrease in this year's annual returns of the largest fund quintiles.

These results are consistent with the theoretical predictions of behavioral finance models. Suppose there are only two types of investors, small investors and institutional investors, in the stock market. Thus institutional investors' performance, measured by the excess returns of institutional investors to the market return, is proportional to the return difference between the two type of investors.[2] De Long, Shleifer, Summers, and Waldmann (1990a) show that the expect return difference between those two types of investors is proportional to small investor sentiment[3]. Basically they show that noise traders earn higher average returns than sophisticated investors when noise traders' sentiment is high, and vice versa. The intuition behind this is that noise traders will hold more risky assets when their sentiment is high thus earn higher returns and at the same time, sophisticated investors' performance is worse and vice versa. This is exactly what I show in the paper.

The sentiment proxy I use for the above results is derived from certain financial

[2]Suppose the density of the institutional investor is μ. The returns of institutional investors and small investors are r_I and r_S, respectively. Then the market return is $r_M = \mu r_I + (1-\mu) r_S$. Thus the performance of institutional investors relative to the market return is $r_I - r_M = (1-\mu)(r_I - r_S)$, which is proportional to the return difference of two types of investors.

[3]This is shown in the equation (17) in DSSW (1990) which is as follows, $E_t(\Delta R_{n-i}) = \rho_t - \frac{(1+r)^2(\rho_t)^2}{(2\gamma)\mu_t\sigma_p^2}$ where ρ_t measures small investors' sentiment at time t.

variables, many of which can be interpreted as small investor sentiment, but they are indirect sentiment measures. To clearly distinguish small investor sentiment from institutional sentiment and directly measure investor sentiment, I employ another two sentiment measures which are two surveys used in Brown and Cliff (2005). The first is a survey conducted by the American Association of Individual Investors (AAII). Since this survey is targeted toward individuals, it is interpreted as primarily a measure of individual investor sentiment. The other is from Investors Intelligence (II) who compiles another weekly bull-bear spread by categorizing approximately 150 market newsletters. Since many of the authors of these newsletters are current or retired market professionals, the Investors Intelligence data is interpreted as a proxy for institutional sentiment. Using these two measures, I further confirm the above results, and most importantly, mutual fund performance only varies with the AAII measure which captures small investor sentiment but not with the II measure which captures institutional sentiment. These results further support the theoretical predications in DSSW (1990).

However, there are some potential alternative explanations for these results. For example, it is possible that high sentiment erodes fund performance just because of high turnover and thus high trading costs in high sentiment. Or, high money flows into funds in high sentiment may dilute fund performance. To further validate that they are not driven by these factors, I test if the above pattern still holds after controlling for these factors. The results show that the negative relation between mutual fund performance and investor sentiment is robust. Therefore, it is confirmed again that the relation is purely because the different sentiment of institutional investors and small investors leads to their difference of risk attitudes and thus different performance during different periods.

In addition, Chen, Hong, Huang, and Kubik (2004) document that fund returns decline with lagged fund size, even after adjusting these returns by various performance benchmarks. My another results, in contrast, show that when conditioning on investor sentiment, the pattern of decreasing returns to scale in mutual funds is fully reversed when sentiment is high while the pattern persists and is more pronounced when sentiment is low. I confirm the statistical significance of these patterns with two regression approaches. One is a regression of long-short portfolio returns on investor sentiment ($SENTIMENT$), the market risk premium ($RMRF$), the Fama-French factors (SMB and HML), and a momentum factor (UMD). The long-short portfolio is formed as a long position in the fund size quintile 1 and a short position in the fund size quintile 5. The coefficient on investor sentiment turns out to be statistically significant and negative, which is consistent with the patterns of better performance of smaller funds in low sentiment and the reverse in high sentiment. The other directly looks at the impact of a fund's lagged assets under management on fund performance conditioned on the beginning period of investor sentiment, which is discussed in detail in Section 2.4. The results show that the effect of fund size on fund performance is inversely correlated with investor sentiment, which further confirms the existence of the above size patterns.

What drives the above size patterns? Baker and Wurgler (2003) documents that returns of smaller stocks tend to be higher when sentiment is low and lower when sentiment is high, which shows that cross-sectional size effect of Banz (1981) exists in low-sentiment conditions only. Thus a natural explanation of mutual funds exhibiting a similar pattern with common stocks may be that smaller funds tend to hold smaller stocks. I test this hypothesis by looking into mutual fund holdings. I join my data sample from the CRSP Mutual Fund database to the CDA/Spectrum Mutual Fund Holdings database using the MFLink database provided by WRDS. I obtain the size rank of each stock in each quarter by comparing its market values obtained from the CRSP stock database with the size breakpoints in the file provided by Kenneth French on his website. I then calculate the value weighted average size rank of all stocks in a fund's portfolio to get a fund's size rank. Then a size quintile's size rank is obtained by averaging all the fund's size ranks in the quintile. The results show that smaller funds hold significantly smaller stocks unconditionally or conditional on investor sentiment. Specifically, the difference of the average size rank of size quintile 1 and 5 is 1.6 when sentiment is low and 1.42 when sentiment is high. Both t-statistics are significant at the 1% level. I also run regressions of difference of fund returns directly on the size rank difference, controlling for other risk factors. The results support the hypothesis.

Since stocks are underpriced when investor sentiment is low and overpriced when sentiment is high, a natural question arises as to whether a fund manager is able to time investor sentiment. This question is important since if all the fund managers were able to time the investor sentiment, we would not observe the above patterns. I study the fund manager timing ability by checking if a fund's loading on the size factor (*SMB*) varies with investor sentiment. The results show that loadings of smaller funds on *SMB* are significantly negative but there is no statistical relationship between loadings of larger funds and investor sentiment. This suggests that smaller funds are better at sentiment timing than larger funds. However, we should not overstate the timing ability of small funds since the results may only reflect that it is more feasible for smaller funds to time the investor sentiment. As assets under management increase, position sizes also increase, thus it is harder and more expensive to time the investor sentiment by switching back and forth between small stocks and large stocks.

The rest of the paper is structured as follows. In Section 2.2, I further discuss the motivation for the investigation of whether mutual fund performance varies with investor sentiment and briefly introduce the related literature. In Section 2.3, I describe the data I used and variables of interest. In Section 2.4, I lay out my hypothesis and describe my empirical methodology. In Section 2.5, I report the results of empirical tests. Section 2.6

concludes this chapter.

2.2 Motivation

Actively managed equity mutual funds have trillions of dollars in assets[4] and keep attracting enormous attention from investors, the media, and researchers. Since the average returns of actively managed funds fail to outpace unmanaged indexes after expenses for years, many professional advisers suggest that investors would be better off in a low-cost passively managed index fund. However, active managers still dominate the mutual fund industry in spite of the recent growth in index funds. This naturally arises a puzzle about the existence of actively managed mutual funds, as pointed out by Gruber (1996).

A large number of studies have tried to address this issue, including a conditional or unconditional framework based on factor models (for example, Carhart, Carpenter, Lynch, and Musto (2002) and Ferson and Harvey (1996)), characteristic-based models (Daniel, Grinblatt, Titman, and Wermers 1997) and most recently a Bayesian framework by Baks, Metrick, and Wachter (2001). We would argue, however, that an important aspect about fund performance has been overlooked up to now, both in traditional studies and in the more recent Bayesian analyses. The neglected information is the *time-varying* attitudes of investors on fund performance. The time-varying preference of investors has been well documented. Specifically, empirical research shows that investors' risk aversion is both state-dependent and counter-cyclical,[5] for which Routledge and Zin (2003) recently also pin down an axiomatic foundation using a model. By ignoring the time-varying property of investors' risk preferences, traditional studies all treat fund performance (conditional

[4]According to the Investment Company Institute's official survey of the mutual fund industry, the combined assets of the nation's mutual funds have accumulated to $7.628 trillion in 8,151 funds in March, 2004, 4,621 of which are stock funds that totally have net assets of $3.887 trillion under management.

[5]See, for example, Campbell and Cochrane (1999), Gordon and St-Amour (2000), Barberis and Huang (2001) and Barberis, Huang, and Santos (2001).

or unconditional alphas) of each period *equally*. However, if investors' risk aversion is state-dependent and count-cyclical, the more they are risk averse, the more they will value outperformance of funds to the market. That is, for investors, the same amount of outperformance in a bear market can not only cancel out the same amount of underperformance in a bull rampage but also add a positive value on top of that, thus they tend to put different wights on different period's performance. Therefore, traditional equal-weight methods would only be valid if mutual fund performance stay the same no matter what investors' risk aversion is.

The theoretical appeal to consider time-varying risk preference can be illustrated with the following highly stylized numerical example. Assume there are two states of the market as reflected in investors' risk attitudes; say, a "Fearful" state and a "Blithe" state. In a "Fearful" state, assume that a fund's performance, measured by a conditional alpha or characteristic-based measure (i.e., GT or CS measure in Daniel, Grinblatt, Titman, and Wermers (1997)), is 1%, and in a "Blithe" state, it is -1%. To measure the overall performance of the fund, traditional methods just make a simple average[6] of the performance in the two states, thus think of the performance to be zero. That is, the fund does not outperform the benchmarks in the view of an uninformed investor. However, if investors are more risk averse in a "Fearful" state than in a "Blithe" state, they will put more weights on the positive 1%,[7] thus they will prefer this fund to the benchmarks.

This can also be illustrated in a general equilibrium framework. Let's look at

[6]In a conditional factor model framework, the conditional alpha is $\alpha_{p0} + \alpha'_p Z_t$ (Christopherson, Ferson, and Glassman 1998), where Z_t is a vector of instrument variables. They assume that any abnormal performance of a fund p is captured by the fixed alpha coefficient, α_{p0}. If we de-mean the instrument variables (that is, let $E[Z_t] = 0$, or let $z_t = Z_t - E[Z_t]$ as Christopherson, Ferson, and Glassman (1998) adopt in their paper.), then α_{p0} is just a simple average of conditional alphas ($\alpha_{p0} + \alpha'_p Z_t$). In a characteristic-based framework, to calculate the overall performance, Daniel, Grinblatt, Titman, and Wermers (1997) just make a simple average of GT or CS measures of every period.

[7]This is not in the sense of the Positive Period Weighting Measure (PPWM) which is developed in Grinblatt and Titman (1989d) to address the timing-related perversities of traditional evaluation techniques based on factor models. In the PPWM framework, risk averse of investors is constant through time, and is assumed to be eight in a later empirical investigation (Grinblatt and Titman 1994).

Jensen's alpha first. Jensen's alpha measures the deviation from a benchmark which is supposed to correctly classify uninformed investors as zero performers. This benchmark has a linear form, which is the security market line. The reason it has a linear form is because the maximum sharp ratio of a portfolio in a constant risk aversion setting is constant and the sharp ratio attains its maximum when the portfolio is the market portfolio (Hansen and Jagannathan 1991). However, if the risk aversion is time varying, the bound for the sharp ratio of any portfolio is also time varying. For example, in a habit formation model, for example, in Campbell and Cochrane (1999), the coefficient of relative risk aversion is given by:

$$RRA_t = \frac{\gamma}{S_t}$$

where S_t is the state variable, or the surplus consumption ratio. Under this setting, Campbell and Cochrane (1999) demonstrate that the bound for sharp ratio is as follows:

$$max \frac{E_t(R^e_{i,t+1})}{\sigma_t(R^e_{i,t+1})} \approx \gamma\sigma_c[1+\lambda(s_t)]$$

where $s_t = ln(S_t)$, $R^e_{i,t+1}$ is the excess return of portfolio i at time $t+1$ and $\lambda(\cdot)$ is a decreasing function. Since the sharp ratio bound is time-varying, if we still use the benchmarks developed under a constant risk aversion setting, we may sometimes under- or over-estimate funds' performance.

This motivates us to study whether mutual fund performance measured by conventional methods varies with small investors' risk attitudes. As illustrate below, there is a pattern of better performance in low sentiment, which exactly provides the hedging when fund investors want the most. This results in a partial explanation of the puzzle addressed by Gruber (1996). I also investigate whether the cross sectional relative mutual fund performance varies with investor sentiment, which is a further examination of the question of whether mutual fund performance varies with investor sentiment.

I am not the first to investigate conditional mutual fund performance. Ferson and Khang (2002), Christopherson, Ferson, and Glassman (1998), Lynch, Wachter, and Boudry (2003), Kothari and Warner (2001), Becker, Ferson, Myers, and Schill (1999b), Ferson and Warther (1996) and Massa and Phalippou (2004) all study the conditional mutual fund performance. However, they all use aggregate economy information like business cycle, dividend yield and liquidity as conditional information. None of them conditions on investor sentiment.

The pattern of decreasing returns to scale has also been well documented in the literature. Agarwal, Daniel, and Naik (2003) and Goetzmann, Ingersoll, and Ross (2003) find decreasing returns to scale in hedge funds. Perold and Salomon (1991) and Chen, Hong, Huang, and Kubik (2004) report decreasing returns to scale in mutual funds. Kaplan and Schoar (2003) find decreasing returns to scale in the private equity industry. However, those investigations are all unconditional. None of them uses conditioning information as I do.

Becker, Ferson, Myers, and Schill (1999b), Rumsey (2000), Daniel, Grinblatt, Titman, and Wermers (1997), Wei (2003), Bollen and Busse (2001), Chacko and Das (1999) and Busse (1999) address the timing ability of mutual fund managers. They mostly talk about the volatility timing, characteristics timing, market timing and so on, but none of them aims at fund managers' investor sentiment timing ability or feasibility as this paper does.

Also, there is a lot of research on performance persistence. Carhart (1997), Carpenter and Lynch (1999) and ter Horst and Verbeek (2000) check the persistence of mutual fund performance. Bers and Madura (2000) study closed-end fund performance persistence. Agarwal and Naik (2000) investigate persistence in the performance of hedge funds using a multi-period framework. Since fund size and investor sentiment have an impact on fund performance and none of those papers consider these factors, it is worth redoing the research on performance persistence under a framework using size and investor sentiment as conditioning information.

2.3 Data

2.3.1 Mutual Fund Data

My data on mutual funds come from three sources. The first one is from the Center for Research in Security Prices (CRSP) Mutual fund Database, which spans the years of 1962 to 2002. The second is from CDA/Spectrum Mutual Funds Holdings data at Wharton Research Data Services (WRDS) which has a data range from 1978 to 2002. The last is from WRDS' MFlink database which provides a way to link the former two databases.[8] To be consistent with Chen, Hong, Huang, and Kubik (2004), we get the fund returns and styles from the CRSP mutual fund data. We restrict our analysis to diversified U.S. equity mutual funds by excluding from our sample bond, international and specialized sector funds.[9] We also clean the data by eliminating redundant observations due to the different share classes of some funds.

Table 2.1 reports summary statistics for our sample. In Panel A, I report means and standard deviations of the variables of interest for each fund size quintiles and for all funds.

[8]This database mainly provide the correspondence of the fund identifier numbers of one database (CRSP Mutual Fund data base) to the other (CDA/Spectrum database).

[9]More specifically, like Chen, Hong, Huang, and Kubik (2004), we select mutual funds in the CRSP Mutual Fund database that have reported one of the following investment objectives at *any* point in their lives. We first select mutual funds with Investment Company Data, Inc. (ICDI) mutual fund objective of 'aggressive growth', 'growth and income', or 'long-term growth' (code: 'AG','GI','LG'). We then add in mutual funds with Strategic Insight mutual fund objective of 'aggressive growth', 'flexible', 'growth and income', 'growth', 'income-growth', or 'small company growth' (code: 'AGG', 'GRI', 'GRO','ING', 'SCG','FLX','GMC'). Finally, we select mutual funds with Wiesenberger mutual fund objective code of 'G', 'G-I', 'G-I-S','G-S','GCI','I-G', 'I-S-G', 'MCG', 'SCG'.

I utilize 7840 distinct funds and a total 43,651 fund years in our analysis. In each month, our sample includes on average about 1048 funds. The total sample is then divided into five quintiles according to funds' end-of-last-year TNA. There are on average around 218 funds in each size quintile.

I calculate the net money inflows following many prior studies (e.g. Zheng (1999)) as follows:

$$Flow_{i,t} = TNA_{i,t} - TNA_{i,t-1}(1 + R_{i,t}) - Merger_{i,t} \tag{2.1}$$

In words, the new money flow in dollar term is defined as the dollar change in total net assets (TNA) minus the appreciation in the fund assets and the increase in total assets due to merger. I assume that new money is invested at the end of each year. Then I aggregate the money flow of all funds in each size quintile and divide it by the total assets under management in the quintile to get the flow in percentages in the quintile, which is denoted as VWFLOW.

In addition, the database reports a host of other fund characteristics that we utilize in our analysis. AGE is the number of years since the organization of the fund. The average age of all funds is about 13.65 years. Smaller funds are younger on average. The average age of quintile 1 (small funds) is 6.8 while the average age of quintile 5 (large funds) is 23.47 years. TOTLOAD is the total front-end, deferred and rear-end charges as a percentage of new investments. EXPRATIO is the total annual management fees and expenses divided by year-end TNA. TURNOVER is fund turnover, defined as the minimum of aggregate purchases and sales of securities divided by the average TNA over the calendar year. The summary statistics show that small funds are on average more active than larger funds.

Panel B reports monthly average fund returns of each fund size quintile and monthly average market returns unconditional or conditional on investor sentiment. There are some interesting patterns in this panel. I will elaborate on this panel in more detail in Section 2.5.

In addition to the CRSP Mutual Fund Database, I also utilize the CDA/Spectrum Mutual Fund Holdings Database to analyze the composition of fund stock holdings of each fund size quintile. To link these two database, I use the MFLINK database provided by WRDS. I will provide a more detailed discussion of this in Section 2.5.

2.3.2 Investor Sentiment Data

I first use the investor sentiment index developed by Baker and Wurgler (2003) to measure investor sentiment, then use two direct sentiment measures, AAII measure and II measure which are described below.

Indirect Measure: investor sentiment index

Basically the investor sentiment index is calculated using the following formula.

$$\begin{aligned} SENTIMENT_t &= -0.358CEFD_t + 0.402TURN_{t-1} + 0.414NIPO_t \\ &\quad +0.464RIPO_{t-1} + 0.371S_t - 0.431P_{t-1}^{D-ND} \end{aligned} \tag{2.2}$$

This formula is derived as the first principal component of the correlation matrix of six proxies for investor sentiment. The six proxies are the average closed-end fund discount ($CEFD$), NYSE share turnover ($TURN$), the monthly average number of IPOs ($NIPO$), the monthly average first-day returns on IPOs ($RIPO$), the equity share in new issues (S), and the dividend premium (P^{D-ND}). The sentiment proxies are measured annually from 1962 through 2001. To isolate the sentiment component of the proxies from business cycle components, each proxy is orthogonalized with respect to several macroeconomic variables. Specially, as elaborated in Baker and Wurgler (2003), each of the raw proxies is regressed on growth in the industrial production index (Federal Reserve Statistical Release G.17), growth in consumer durables, nondurables and services (all from BEA National Income

Accounts Table 2.10), and a dummy variable for NBER recessions. The residuals from these regressions form a cleaned proxy that is independent of major business cycle effects.

A dummy variable *SENT* is obtained from the sentiment index. When the sentiment index is positive, which means that investor sentiment is high, the dummy variable is equal to 1. And the dummy variable is equal to 0 when investor sentiment is low, i.e., the sentiment index is negative.

I also use the individual proxy, like the average closed-end fund discount, to measure investor sentiment. All the major conclusions remain unchanged . For brevity, I do not include these results in this paper.

Direct Sentiment Measures

I also use two surveys used in Brown and Cliff (2005) to directly measure the sentiment of market participants. The first is from Investors Intelligence (II). It basically analyzes proximately 150 market newsletters every week and each newsletter is marked as bullish, bearish and neutral based on the expectation of future market movements. Since most of the newsletters are written by current or retired market professionals, the II measure is interpreted as a proxy for institutional sentiment.

The other direct measure I use in this study is from the survey conducted by the American Association of Individual Investors (AAII). The association polls a random sample of its members each week, beginning in July 1987. Each participant is asked where they think the stock market will head in six months: up, down, or the same. AAII then labels these responses as bullish, bearish, or neutral, respectively. Since this survey is targeted toward individuals, we interpret it as primarily a measure of individual investor sentiment.

The II data are from 1962 to 2001 and the AAII data are from 1987 to 2001. I get the whole II data and partial AAII data (1987-1999) from Brown and Cliff (2005) and I hand-collect the remaining data from Barron's.

2.3.3 Other Data

I obtain the NYSE size breakpoints from Kenneth R. French's website, and I get all the stock information from the Center for Research in Security Prices (CRSP).

2.4 Methodology

The theme of empirical tests in this paper is to see how fund performance varies with investor sentiment and varies with lagged fund size conditional on investor sentiment.

The basic empirical framework is based on the following commonly used conditional model:

$$E[R_{it}] = a + b_1' \, x_{i,t-1} + b_2' \, T_{t-1} \, x_{i,t-1} \tag{2.3}$$

where i indexes funds, t is time, x is a vector of fund or security characteristics, and T is a time series conditioning variable that proxies for investor sentiment.

Five fund size portfolios are formed with an equal number of funds in each portfolio in each month. I tabulate the subsequent conditional and unconditional performance in each quintile, and run predictive regressions specified below. Either way, the basic strategy is to use sentiment proxies as conditioning variables and then check whether the performance difference between different size portfolios depends on the conditioning variable.

First, I report mutual fund performance measured by different benchmarks. Then, I run two predictive regressions to check the robustness of the relationship between fund size and fund performance conditional on investor sentiment. Also, I check whether fund managers have the ability to time investor sentiment.

2.4.1 Fund Performance Benchmarks

In this paper, considering the heterogeneity in fund styles, I measure fund performance using various benchmarks. I first adjust the fund returns by the Capital Asset Pricing Model (CAPM) of Sharpe (1964) as stated in Equation 2.4. I then consider returns adjusted using the Fama and French (1993) three factor model and this model augmented with the momentum factor of Jegadeesh and Titman (1993), which has been shown to have incremental explanatory power for the observed cross-sectional variation in fund performance (Carhart 1997).

$$R_{i,t} = \alpha_i + \beta_i \, RMRF_t + \varepsilon_{i,t} \qquad t = 1,...,T \tag{2.4}$$

The Fama French three factor model is as follows.

$$R_{i,t} = \alpha_i + \beta_i \, RMRF_t + s_i \, SMB_t + h_i \, HML_t + \varepsilon_{i,t} \quad t = 1,...,T \tag{2.5}$$

The Carhart four factor model is as follows.

$$R_{i,t} = \alpha_i + \beta_i \, RMRF_t + s_i \, SMB_t + h_i \, HML_t + m_i \, UMD_t + \varepsilon_{i,t} \quad t = 1,...,T \tag{2.6}$$

2.4.2 DGTW Measures

DGTW (1997) decompose the overall fund returns into several components based on the characteristics of stocks in their portfolio. I investigate two components of DGTW measures here: a 'Characteristic Selectivity' measure CS and a 'Characteristic Timing' measure CT. CS is a measure of stock selection ability and uses as a benchmark the return of portfolio of stocks that is matched to each of the fund's holdings every quarter along the dimensions of size, book-to-market ratio, and momentum:

$$CS_t = \sum_{j=1}^{N} \tilde{\omega}_{j,t-1} \left[\tilde{R}_{j,t} - \tilde{R}_t^{b_{j,t-1}} \right]$$

where $\omega_{j,t-1}$ is the portfolio weight on stock j at the end of quarter $t-1$, $\tilde{R}_{j,t}$ is the quarter t buy-and-hold return of stock j, and $\tilde{R}_t^{b_{j,t-1}}$ is the quarter t buy-and-hold return of the characteristic-based benchmark portfolio that is matched to stock j at the end of quarter $t-1$. CT is a measure of style timing ability. It is defined as follows.

$$CT_t = \sum_{j=1}^{N} \left[\tilde{\omega}_{j,t-1} \tilde{R}_t^{b_{j,t-1}} - \tilde{\omega}_{j,t-5} \tilde{R}_t^{b_{j,t-5}} \right]$$

where the terms are defined similarly as in CS measure.

I run the following regressions to further check the relationship between fund performance and investor sentiment:

$$DGTW\_Measure_{i,t} = \alpha_i + d_i \cdot Sentiment_{i,t-1} \quad i = 1, \ldots, 5$$

2.4.3 Predictive Regression Specification

To carry out a robustness check on the relationship of fund size and fund performance conditioned on investor sentiment, I run two additional regressions. The first is a regression of long-short portfolio returns on investor sentiment ($SENTIMENT$), the market risk premium ($RMRF$), the Fama-French factors (SMB and HML), and a momentum factor (UMD), which is stated as follows.

$$R_{quintile\,1,t} - R_{quintile\,5,t} = c + dSENTIMENT_{t-1} + \beta\, RMRF_t + s\, SMB_t + h\, HML_t + m\, UMD_t + \varepsilon_t \quad (2.7)$$

The long-short portfolio is formed as a long position in the fund size quintile 1 and a short position in the fund size quintile 5.

The second is a three-stage regression. In the first stage, we adjust the fund returns using various performance benchmarks including CAPM, Fama-French three factor model and Carhart four factor model. In the second stage, we compute coefficients (ϕ_t) from monthly regressions of adjusted fund returns on funds' lagged log size ($LOGTNA$) and fund characteristics (X) which include funds' turnover ($TURN$), expenses ($EXPERATIO$), 12b1 fees ($x2b1$), funds' age (AGE), total loads including front-end, deferred and rear-end loads ($TOTLOAD$), last year annual net inflows ($FLOWR$), and previous year returns ($LAGARET$). I run the following regressions every month. It is based on the regression framework proposed by Fama and MacBeth (1973).

$$ADJRET_{i,t} = \mu + \phi_t \, LOGTNA_{i,t-1} + \gamma_t \, X_{i,t-1} + \varepsilon_{i,t} \quad i = 1, ..., N \tag{2.8}$$

In the third stage, we regress the monthly coefficients ϕ_t on investor sentiment.

$$\hat{\phi}_t = c + d \, SENTIMENT_{t-1} + \varepsilon_t \tag{2.9}$$

If the hypothesis that fund performance is positively correlated with fund size when sentiment is high while the relationship is negative when sentiment is low, we should expect the coefficient d to be significantly negative.

Also, to check the variations of fund performance over investor sentiment, I run regressions of size quintile portfolio excess returns on the market risk premium ($RMRF$), the Fama-French factors (SMB and HML), the momentum factor (UMD) and investor sentiment ($SENTMENT$) as follows:

$$FUNDRET_{i,t} = c_i + \beta_i \, RMRF_t + s_i \, SMB_t + h_i \, HML_t + m_i \, UMD_t + d_i \, SENTIMENT_{t-1} + \varepsilon_{i,t} \tag{2.10}$$

If fund performance varies with investor sentiment, we should expect the coefficient d on sentiment to be significantly negative.

To address the concern with estimate biases in predictive regressions of small samples addressed by Stambaugh (1999), I also report the bootstrap p-values.

2.4.4 Sentiment Timing

To investigate the sentiment timing ability of fund managers, I run regressions of size quintile portfolio returns on the market risk premium ($RMRF$), the Fama-French factors (SMB and HML), the momentum factor (UMD) and the size factor (SMB) interacted with investor sentiment ($SENTMENT$).

$$FUNDRET_{i,t} = c_i + \beta_i \, RMRF_t + (s_i + d_i \, SENTIMENT_{t-1}) SMB_t + h_i \, HML_t + m_i \, UMD_t + \varepsilon_{i,t} \tag{2.11}$$

If fund managers do have the ability to time investor sentiment, we should expect the coefficient d_i on the interacted term to be significantly negative.

2.5 Results

2.5.1 Aggregate pattern: time varying fund performance

Panel B in Table 2.1 reports the monthly average fund returns of each fund size quintile and monthly average market returns. The market return is the value weighted average of all stocks in the CRSP stock database. Unconditionally, all fund size quintiles except for the smallest quintile underperform the market, which is consistent with Gruber (1996). When conditioned on investor sentiment, the monthly average market return is 1.03% when the sentiment is low while it is 0.94% when the sentiment is high. All the size quintiles underperform the market but almost all the quintiles except for the largest quintiles outperform the market. This means that mutual funds generally do well when beginning-of-period investor sentiment is low but perform poorly when beginning-of-period investor sentiment is high.

This pattern is robust after the fund returns are adjusted using various performance benchmarks. Table 2.2 reports Jensen measures (Alphas) and the loadings of the five TNA-sorted fund portfolios on the market risk premium (*RMRF*, the difference of the value weighted average returns of all stocks in the CRSP stock database and the returns of the one month T-bill). Jensen's alpha is a risk-adjusted performance measure that is the average return on a portfolio over and above that predicted by the CAPM, given the portfolio's beta and the average market return and was first mentioned in Jensen (1968). In the table, we can see that unconditionally only the three smallest quintile 1 to 3 beat the market. All the alphas are negative when investor sentiment is high, which means all the size portfolios underperform the market. When the sentiment is low, all the alphas are positive. These results still show that mutual funds perform better when sentiment is low than when sentiment is high. Fama and French (1993) fine-tuned CAPM and developed a three factor model which proves to better describe the common risk factors. Table 2.3 reports the loadings of the five TNA-sorted fund portfolios on the market risk premium (*RMRF*, the difference of the value weighted average returns of all stocks in the CRSP stock database and the return of the one month T-bill), the size factor (*SMB*) and the value factor (*HML*). The pattern here is similar to previous results. To further adjust the fund returns, Table 2.4 reports the loadings using the Carhart four factor model (Carhart 1997). Although the results show that fewer size portfolios outperform the market when sentiment is low, the pattern of better performance in low sentiment than in high sentiment does not change.

To check the robustness of the pattern, I add the investor sentiment into the Carhart four factor model. If fund performance which is measured by risk adjusted returns do vary with investor sentiment, then we expect the coefficient on investor sentiment to be statistically significant. Since the above results show that funds perform better in low sentiment than in high sentiment, the sign of the coefficient should be negative. Table 2.5 Panel A reports the regression results, and the coefficients on investor sentiment are indeed statistically significant and negative. I also equally divide the whole sample into two sub-samples and run this regression during each period. The results are shown in Table 2.5 Panel B. As we can see, the results are mostly robust except for the smallest fund quintile in the first half sample and the largest fund quintile in the second half sample, which have correct signs but insignificant t-statistics.

This interesting pattern has never been addressed in the literature. Using dividend yield to track the business cycle, Lynch, Wachter, and Boudry (2003) find that conditional mutual fund performance moves with the business cycle, with all fund types except growth performing better in downturns than in peaks. The converse holds for growth funds, which do better in peaks than in downturns. Their findings, however, are quite different from mine although they also report time varying property of mutual fund performance. My conditioning variable–investor sentiment has been cleaned such that it is independent of business cycles. In addition, Lynch, Wachter, and Boudry (2003) did not report the fund performance in each size quintile as I do here. They also did not compare the performance of the whole fund universe with the market. Moreover, my focus here is different and broader as we will see in the following sections.

Our results are consistent with the behavioral finance models and show that the method of treating different period's fund performance equally is not valid.

2.5.2 Aggregate pattern: further robustness check

The sentiment proxy I use for the above results is derived from certain financial variables, many of which can be interpreted as small investor sentiment, but they are indirect sentiment measures. To clearly distinguish small investor sentiment from institutional sentiment and directly measure investor sentiment, I employ another two sentiment measures which are two surveys used in Brown and Cliff (2005). The first is a survey conducted by the American Association of Individual Investors (AAII). Since this survey is targeted toward individuals, it is interpreted as primarily a measure of individual investor sentiment. The other is from Investors Intelligence (II) who compiles another weekly bull-bear spread by categorizing approximately 150 market newsletters. Since many of the authors of these newsletters are current or retired market professionals, the Investors Intelligence data is interpreted as a proxy for institutional sentiment. Using these two measures, I further confirm the above results, and most importantly, mutual fund performance only varies with the AAII measure which captures small investor sentiment but not with the II measure which captures institutional sentiment. These results are shown in Table 2.7, which further support the theoretical predications in DSSW (1990).

However, there are some potential alternative explanations for these results. For example, it is possible that high sentiment erodes fund performance just because of high turnover and thus high trading costs in high sentiment. Or, high money flows into funds in high sentiment may dilute fund performance. To further validate that they are not driven by these factors, I test if the above pattern still holds after controlling for these factors. The results show that the negative relation between mutual fund performance and investor sentiment is robust. Therefore, it is confirmed again that the relation is purely because the different sentiment of institutional investors and small investors leads to their difference of risk attitudes and thus different performance during different periods. For brevity, I do not include these results in the paper.

As a final check, I use the measures developed in DGTW (1997) to check the relationship between fund performance and investor sentiment. As we can see in Table 2.6, sentiment indeed affects fund managers' stock picking ability. *CS* measures are negatively related to investor sentiment, but *CT* measure seems not related to investor sentiment. This is consistent with DSSW(1990). When the sentiment is low, fund managers can take advantage of the low sentiment and buy the most undervalued stocks, thus exhibiting bigger stock picking ability, but when sentiment is high, since fund managers have short-sale constraints, they can not take advantage of small investor sentiment, thus we can not find strong stock picking ability from their holdings.

2.5.3 Size pattern: relationship between fund size and performance

The previous subsection reports the time varying property of mutual fund performance as a whole. In this subsection, we will look into the pattern of performance across fund size quintiles.

I mainly investigate the relationship between fund size and performance. Unconditionally, Chen, Hong, Huang, and Kubik (2004) document that fund returns decline with lagged fund size, even after adjusting these returns by various performance benchmarks. Table 2.1, 2.2, 2.3 and 2.4 report similar results under the unconditional situation.

Conditionally, however, the pattern of decreasing returns to scale in mutual funds is fully reversed when sentiment is high while the pattern persists and is more pronounced when sentiment is low. In Table 2.1, when sentiment is low, the raw return of the smallest funds is 1.04% per month on average while that of the largest funds is 1.01% per month.

When sentiment is high, the pattern fully reverses, larger funds perform better. After adjusting returns in Table 2.2, 2.3 and 2.4, similar results are shown.

2.5.4 Size pattern: robustness check

Table 2.8 checks the robustness of the relationship between fund size and performance mentioned above. Panel A reports regression of long-short portfolio returns on investor sentiment ($SENTIMENT$), the market risk premium ($RMRF$), the Fama-French factors (SMB and HML), and a momentum factor (UMD), which is specified in the Equation 2.7. The long-short portfolio is formed as a long position in the fund size quintile 1 and a short position in the fund size quintile 5. The coefficient on investor sentiment is -0.003 and statistically significant at 1% level. This means the return difference of smallest fund quintile and largest fund quintile is negatively correlated with investor sentiment. This shows that fund performance is positively correlated with fund size when sentiment is high and the reverse when sentiment is low.

Panel B reports the results of a three-stage regression. In the first stage, we adjust the fund returns using various performance benchmarks including CAPM, Fama-French three factor model and Carhart four factor model. In the second stage, we compute coefficients (ϕ_t) from monthly regressions of adjusted fund returns on funds' lagged log size ($LOGTNA$) and fund characteristics (X) which include funds' turnover ($TURN$), expenses ($EXPERATIO$), 12b1 fees ($x2b1$), funds' age (AGE), total loads including front-end, deferred and rear-end loads ($TOTLOAD$), last year annual net inflows ($FLOWR$), and previous year returns ($LAGARET$). The regressions are specified in Equation 2.8. In the third stage, we regress the monthly coefficients ϕ_t on investor sentiment as in Equation 2.9. Since this is in the form of predictive regressions, there may be biases in the t-statistics (Stambaugh 1999). I bootstrap the sample, run $2,500$ regressions and obtain the p values.

The panel shows that the coefficients on sentiment are statistically significant and negative no matter which model is used to adjust fund returns.

The above results prove that the relationship of fund performance and fund size conditioned on sentiment is robust.

2.5.5 Size pattern: explanation

What accounts for the conditioning effects of scale on fund performance? Baker and Wurgler (2003) document that common stocks have a similar pattern to that of mutual funds described here. That is, returns of smaller stocks tend to be higher when sentiment is low and lower when sentiment is high, which shows that the cross-sectional size effect of Banz (1981) exists in low-sentiment conditions only. Thus a natural explanation for mutual funds exhibiting a similar pattern with common stocks may be that smaller funds hold smaller stocks.

Table 2.10 tests this hypothesis. First I link my data sample from the CRSP Mutual Fund database to the CDA/Spectrum Mutual Fund Holdings database using the MFLink database provided by WRDS. Panel A reports the summary statistics of variables of interest. Compared with Table 2.1, the statistics show that the merge does not alter the features of the original sample. Panel B reports quarterly average size rank of mutual fund holdings of each quintile. I obtain the size rank of each stock in each quarter by comparing the market values obtained from the CRSP stock database with the size breakpoints in the file provided by Kenneth French on his website. I then calculate the value weighted average size rank of all stocks in a fund's portfolio to get a fund's size rank. Then a size quintile's size rank is obtained by averaging all the fund's size ranks in the quintile. Panel B shows that smaller funds hold significantly smaller stocks unconditionally or conditional on investor sentiment. Specifically, the difference of the average size rank of size quintile 1 and 5 is 1.6

when sentiment is low and 1.42 when sentiment is high. Both t-statistics are significant at 1% level.

Can the difference in size rank explain the spread of fund returns in different size quintiles? Table 2.11 formally tests this hypothesis. The table reports regressions of returns of a long-short portfolio on the market risk premium (*RMRF*), the Fama-French factors (*SMB* and *HML*), the momentum factor (*UMD*) and the size rank difference of the two portfolios.

$$R_{quintile\ 1,t} - R_{quintile\ 5,t} = c + d\ RANKDF_{t-1} + \beta\ RMRF + s\ SMB_t + h\ HML_t + m\ UMD_t + \varepsilon_t \tag{2.12}$$

The long-short portfolio is formed as a long position in the fund size quintile 1 and a short position in the fund size quintile 5. The regressions are run both unconditional and conditional on investor sentiment. The coefficients on the rank difference are statistically significant both unconditional and conditional on low sentiment as expected. The coefficient is not significant when sentiment is high. This may be because the rank difference may not be a good proxy to describe the actual size difference in their holdings since the ranks are closer together when sentiment is high according to Panel B in Table 2.10.

2.5.6 Sentiment timing

Since stocks are underpriced when investor sentiment is low and overpriced when sentiment is high, a natural question arises as to whether a fund manager is able to time investor sentiment. This question is important since if all the fund managers can time the investor sentiment, we will not observe the above patterns. I study the fund manager timing ability by checking if a fund's loading on the size factor (*SMB*) varies with investor sentiment. Table 2.9 reports regressions of size quintile portfolio returns on the market risk premium (*RMRF*), the Fama-French factors (*SMB* and *HML*), the momentum factor (*UMD*) and the size factor (*SMB*) interacted with investor sentiment ($SENTMENT$). The coefficients on the interacted item are -0.09 for size quintile 1 (smallest fund quintile) and -0.06 for quintile 2. The coefficients are statistically significant. However the coefficients of larger funds are not significant. The results show that loadings of smaller funds on *SMB* are significantly negative but there is no statistical relationship between loadings of larger funds and investor sentiment. This suggests that smaller funds are better at sentiment timing than larger funds. However, we should not overstate the timing ability of small funds since the results may only reflect that it is more feasible for smaller funds to time the investor sentiment. As assets under management increase, position sizes also increase, thus it is harder and more expensive to time the investor sentiment by switching back and forth between small stocks and large stocks.

2.6 Conclusion

To the best of my knowledge, I am the first to explicitly address the performance of actively managed mutual funds conditioned on investor sentiment. Almost all fund size quintiles subsequently outperform the market when sentiment is high while all of them underperform the market when sentiment is low. This also holds true after adjusting the fund returns by various performance benchmarks. I further show that the source of variations come from small investor sentiment. These results are consistent with the behavioral finance models and show that the conventional method of treating mutual fund performance in different periods equally is *not* valid. This finding can thus partially validate the existence of actively managed mutual funds which underperform the market overall (Gruber 1996). Additionally, when conditioned on investor sentiment, the pattern of decreasing returns to scale in mutual funds, recently documented in Chen, Hong, Huang, and Kubik (2004), is fully reversed when sentiment is high while the pattern persists and is more pronounced when sentiment is low. Further results suggest that smaller funds on average hold smaller stocks, which is shown to drive the above patterns. I also document that smaller funds have more sentiment timing ability or feasibility than larger funds. These findings have many important implications including the persistence of fund performance which may not exist under conventional performance measures (Carhart 1997).

Table 2.1: Summary statistics

This table reports summary statistics of the funds in our sample. The total sample is divided into five quintiles according to funds' end-of-last-year TNA. The number of funds is the number of actively managed mutual funds that meet our selection criteria in each month. AGE is the number years since the organization of the fund. TNA is the total net assets under management in millions of dollars. TOTLOAD is the total front-end, deferred and rear-end charges as a percentage of new investments. EXPRATIO is the total annual management fees and expenses divided by year-end TNA. TURNOVER is fund turnover, defined as the minimum of aggregate purchases and sales of securities divided the average TNA over the calendar year. VWFLOW is the percentage of new net fund inflow into the fund quintile over the past year. It is calculated by dividing the total net inflow into a quintile by the total assets under management in the quintile. FUNDRET is the monthly fund return. Panel A reports the time-series averages of monthly cross-sectional averages and monthly cross-sectional standard deviations (shown in brackets) of fund characteristics. Panel B reports Monthly average fund returns of each fund size quintile and monthly average market returns unconditionally or conditional on investor sentiment.

Panel A: Time-series average of cross-sectional averages and standard deviations

	Mutual Fund Size Quintile					All
	1	2	3	4	5	Funds
Number of Funds	217.90	218.60	218.30	218.50	218.00	1048
AGE	6.80	9.33	12.59	15.56	23.47	13.65
(years)	(3.39)	(3.71)	(4.19)	(4.33)	(4.42)	(3.83)
TNA	6.60	19.52	53.11	124.68	1096.21	252.58
($ million)	(4.23)	(10.00)	(23.09)	(65.25)	(792.22)	(199.55)
TOTLOAD	3.06	3.95	4.02	4.05	4.90	4.00
(%)	(1.53)	(1.64)	(1.50)	(1.41)	(1.86)	(1.53)
EXPRATIO	1.68	1.27	1.09	0.96	0.78	1.15
(% per year)	(0.47)	(0.24)	(0.21)	(0.22)	(0.19)	(0.22)
TURNOVER	91.93	84.17	80.82	75.27	60.62	76.25
(% per year)	(21.23)	(21.29)	(13.27)	(15.65)	(17.37)	(15.58)
VWFLOW	130.45	32.90	15.35	5.92	0.78	2.57
(% per year)	(151.99)	(31.19)	(16.56)	(11.25)	(8.00)	(8.69)

Panel B: Monthly average fund returns of each fund size quintile and monthly average market returns

Sentiment	Market	Fund Quintile					Difference
		1	2	3	4	5	1-5
Unconditional	0.95%	0.98%	0.95%	0.94%	0.92%	0.85%	0.13%
							(2.88)
Low	1.03%	1.40%	1.27%	1.20%	1.16%	1.01%	0.39%
							(3.88)
High	0.94%	0.71%	0.76%	0.78%	0.77%	0.79%	-0.09%
							(-1.26)
Low-High		0.69%	0.51%	0.42%	0.40%	0.21%	
		(6.78)	(5.78)	(5.60)	(4.56)	(3.54)	

Table 2.2: Performance measures and loadings calculated using the CAPM

This table reports the loadings of the five TNA-sorted fund portfolios on the market risk premium (*RMRF*, the difference of the value weighted average returns of all stocks in the CRSP stock database and the returns of the one month T-bill). The regression specification is as follows.

$$R_{i,t} = \alpha_i + \beta_i \, RMRF_t + \varepsilon_{i,t} \qquad t = 1, ..., T$$

where $R_{i,t}$ is the excess return of each fund size portfolio i at month t. I do the above regressions for each size portfolio unconditionally first and then divide the whole sample into two sub-samples according to beginning-of-year sentiment. Then I do the above regressions in each sub-sample for each size portfolio.

			Sentiment			
	Unconditional		Low		High	
Quintile	Alpha	Beta	Alpha	Beta	Alpha	Beta
1 (small)	0.109%	0.93	0.412%	0.93	-0.210%	0.93
2	0.052%	0.96	0.261%	0.97	-0.169%	0.96
3	0.024%	0.97	0.198%	0.96	-0.155%	0.97
4	-0.007%	0.97	0.157%	0.96	-0.172%	0.98
5 (large)	-0.065%	0.96	0.003%	0.96	-0.136%	0.96

Table 2.3: Performance measures and loadings calculated using Fama-French three factor model

This table reports the loadings of the five TNA-sorted fund portfolios on the market risk premium ($RMRF$, the difference of the value weighted average returns of all stocks in the CRSP stock database and the return of the one month T-bill), the size factor (SMB) and the value factor (HML). The regression specification is as follows.

$$R_{i,t} = \alpha_i + \beta_i\, RMRF_t + s_i\, SMB_t + h_i\, HML_t + \varepsilon_{i,t} \quad t = 1, \dots, T$$

where $R_{i,t}$ is the excess return of each fund size portfolio i at month t. I do the above regressions for each size portfolio unconditionally first and then divide the whole sample into two sub-samples according to beginning-of-year sentiment. Then I do the above regressions in each sub-sample for each size portfolio.

Sentiment	Quintile	Alpha (%)	RMRF	SMB	HML
Unconditional	1 (small)	0.026	0.883	0.329	0.089
	2	0.021	0.908	0.267	0.009
	3	0.013	0.912	0.227	-0.019
	4	-0.002	0.921	0.191	-0.040
	5 (large)	-0.048	0.927	0.088	-0.045
Low	1 (small)	0.220	0.855	0.405	0.036
	2	0.146	0.894	0.331	-0.063
	3	0.120	0.890	0.278	-0.092
	4	0.113	0.902	0.217	-0.107
	5 (large)	0.006	0.929	0.081	-0.082
High	1 (small)	-0.199	0.898	0.276	0.091
	2	-0.128	0.917	0.234	0.027
	3	-0.111	0.930	0.207	0.013
	4	-0.126	0.939	0.190	0.001
	5 (large)	-0.101	0.930	0.104	-0.016

Table 2.4: Performance measures and loadings calculated using Carhart four factor model

This table reports the loadings of the five TNA-sorted fund portfolios on the market risk premium ($RMRF$, the difference of the value weighted average returns of all stocks in the CRSP stock database and the return of the one month T-bill), the size factor (SMB), the value factor (HML) and the momentum factor (UMD). The regression specification is as follows.

$$R_{i,t} = \alpha_i + \beta_i \, RMRF_t + s_i \, SMB_t + h_i \, HML_t + m_i \, UMD_t + \varepsilon_{i,t} \quad t = 1, ..., T$$

where $R_{i,t}$ is the excess return of each fund size portfolio i in month t. I do the above regressions for each size portfolio unconditionally first and then divide the whole sample into two sub-samples according to beginning-of-year sentiment. Then I do the above regressions in each sub-sample for each size portfolio.

Sentiment	Quintile	Alpha (%)	RMRF	SMB	HML	UMD
Unconditional	1 (small)	0.050	0.881	0.329	0.083	-0.023
	2	-0.010	0.911	0.268	0.017	0.030
	3	-0.025	0.915	0.228	-0.009	0.037
	4	-0.041	0.924	0.192	-0.030	0.037
	5 (large)	-0.071	0.928	0.089	-0.039	0.022
Low	1 (small)	0.145	0.858	0.403	0.059	0.074
	2	-0.001	0.900	0.326	-0.018	0.147
	3	-0.043	0.896	0.272	-0.043	0.162
	4	0.002	0.906	0.213	-0.074	0.110
	5 (large)	-0.088	0.933	0.077	-0.053	0.093
High	1 (small)	-0.137	0.891	0.272	0.073	-0.060
	2	-0.113	0.916	0.232	0.023	-0.014
	3	-0.103	0.929	0.206	0.010	-0.008
	4	-0.137	0.941	0.191	0.005	0.011
	5 (large)	-0.097	0.930	0.103	-0.017	-0.004

Table 2.5: Time varying mutual fund performance with investor sentiment

This table reports the loadings of the five TNA-sorted fund portfolios on the market risk premium (*RMRF*, the difference of the value weighted average returns of all stocks in the CRSP stock database and the return of the one month T-bill), the size factor (*SMB*), the value factor (*HML*), the momentum factor (*UMD*) and investor sentiment. The regression specification is as follows.

$$R_{i,t} = \alpha_i + \beta_i\, RMRF_t + s_i\, SMB_t + h_i\, HML_t + m_i\, UMD_t + d_i\, SENTIMENT_{t-1} + \varepsilon_{i,t} \quad t = 1,...,T$$

where $R_{i,t}$ is the excess return of each fund size portfolio i in month t. The t-statistics (shown in brackets) are adjusted for heteroscedasticity and autocorrelation using Newey-West variance covariance matrix (Newey and West 1987).

Panel A: Full Sample (1962-2002)

Quintile	RMRF	SMB	HML	UMD	SENTIMENT
1	0.88	0.32	0.09	-0.03	$-0.36\%^{***}$
	(27.85)	(7.69)	(2.36)	(-0.79)	(-3.14)
2	0.91	0.26	0.02	0.03	$-0.19\%^{***}$
	(56.50)	(8.50)	(0.72)	(1.34)	(-3.16)
3	0.91	0.22	-0.01	0.04	$-0.13\%^{***}$
	(58.87)	(7.82)	(-0.29)	(1.82)	(-2.73)
4	0.92	0.19	-0.03	0.04	$-0.13\%^{***}$
	(69.88)	(7.99)	(-1.18)	(2.06)	(-3.29)
5	0.93	0.09	-0.04	0.02	$-0.06\%^{*}$
	(86.51)	(5.55)	(-2.08)	(1.58)	(-1.82)

Panel B: Two Sub-samples (Only the coefficients on sentiment are reported)

	Fund Quintiles				
	1	2	3	4	5
1962-1987	-0.06%	$-0.14\%^{***}$	$-0.08\%^{*}$	$-0.15\%^{***}$	$-0.13\%^{***}$
	(-1.05)	(-3.04)	(-1.66)	(-2.87)	(-2.60)
1988-2002	$-0.36\%^{**}$	$-0.14\%^{**}$	$-0.10\%^{**}$	$-0.09\%^{**}$	-0.04%
	(-2.05)	(-1.99)	(-2.15)	(-2.05)	(-1.02)

*** Statistically significant at 1% level.
** Statistically significant at 5% level.
* Statistically significant at 10% level.

Table 2.6: Time varying performance: DGTW measures

This table reports the relation between fund performance under DGTW measures (DGTW, 1997) and investor sentiment. I investigate two components of DGTW measures here: a 'Characteristic Selectivity' measure CS and a 'Characteristic Timing' measure CT. CS is a measure of stock selection ability and uses as a benchmark the return of portfolio of stocks that is matched to each of the fund's holdings every quarter along the dimensions of size, book-to-market ratio, and momentum:

$$CS_t = \sum_{j=1}^{N} \tilde{\omega}_{j,t-1} \left[\tilde{R}_{j,t} - \tilde{R}_t^{b_{j,t-1}} \right]$$

where $\omega_{j,t-1}$ is the portfolio weight on stock j at the end of quarter $t-1$, $\tilde{R}_{j,t}$ is the quarter t buy-and-hold return of stock j, and $\tilde{R}_t^{b_{j,t-1}}$ is the quarter t buy-and-hold return of the characteristic-based benchmark portfolio that is matched to stock j at the end of quarter $t-1$. CT is a measure of style timing ability. It is defined as follows.

$$CT_t = \sum_{j=1}^{N} \left[\tilde{\omega}_{j,t-1} \tilde{R}_t^{b_{j,t-1}} - \tilde{\omega}_{j,t-5} \tilde{R}_t^{b_{j,t-5}} \right]$$

where the terms are defined similarly as in CS measure.
This table reports the coefficients (d_i) of the following regressions:

$$DGTW\_Measure_{i,t} = \alpha_i + d_i \cdot Sentiment_{i,t-1} \quad i = 1, \ldots, 5$$

	Fund Quintile				
	1 (Small)	2	3	4	5 (Large)
CS	−0.19%**	−0.16%*	−0.09%*	−0.13%*	−0.19%*
	(−1.96)	(−1.65)	(−1.88)	(−1.68)	(−1.75)
CT	−0.15%	−0.05%	−0.05%	−0.07%	−0.01%
	(−0.35)	(−0.12)	(−0.23)	(−0.20)	(−0.02)

** Statistically significant at 5% level.
* Statistically significant at 10% level.

Table 2.7: Time varying performance under two new sentiment measures

This table reports the regressions of the excess returns of five TNA-sorted fund portfolios on the market risk premium ($RMRF$, the difference of the value weighted average returns of all stocks in the CRSP stock database and the return of the one month T-bill), the size factor (SMB), the value factor (HML), the momentum factor (UMD) and investor sentiment. The investor sentiment measures used here are Investors Intelligence (II) measure and American Association of Individual Investors (AAII) measure, where the former proxies for institutional investor sentiment and the latter for small investor sentiment. The regression specification is as follows.

$$R_{i,t} = \alpha_i + \beta_i\, RMRF_t + s_i\, SMB_t + h_i\, HML_t + m_i\, UMD_t + d_i\, SENTIMENT_{t-1} + \varepsilon_{i,t} \quad t = 1, ..., T$$

where $R_{i,t}$ is the excess return of each fund size portfolio i in month t. To save space, only the coefficients d_i on $SENTIMENT$ are reported for each fund size quintile and each sentiment measure. The t-statistics (shown in brackets) are adjusted for heteroscedasticity and autocorrelation using Newey-West variance covariance matrix (Newey and West 1987).

Sentiment	Fund Quintiles				
Measure	1 (small)	2	3	4	5 (large)
II	0.76%	0.52%	0.51%	0.15%	0.05%
	(0.71)	(0.54)	(0.57)	(0.16)	(0.06)
AAII	$-0.76\%^{**}$	$-0.92\%^{***}$	$-0.72\%^{**}$	$-0.79\%^{*}$	$-0.80\%^{**}$
	(-2.09)	(-2.89)	(-2.11)	(-1.91)	(-2.33)

*** Statistically significant at 1% level.
** Statistically significant at 5% level.
* Statistically significant at 10% level.

Table 2.8: Time series regressions: portfolios

This table reports a robustness check of the relationship of fund size and fund performance conditioned on investor sentiment. Panel A reports regression of long-short portfolio returns on investor sentiment ($SENTIMENT$), the market risk premium ($RMRF$), the Fama-French factors (SMB and HML), and a momentum factor (UMD).

$$R_{quintile\,1,t} - R_{quintile\,5,t} = c + dSENTIMENT_{t-1} + \beta\, RMRF + s\, SMB_t + h\, HML_t + m\, UMD_t + \varepsilon_t$$

The long-short portfolio is formed as a long position in the fund size quintile 1 and a short position in the fund size quintile 5. The Newey-West t-statistics (Newey and West 1987) are reported.

Panel B reports the results of a three-stage regression. In the first stage, we adjusted the fund returns using various performance benchmarks including CAPM, Fama-French three factor model and Carhart four factor model. In the second stage, we compute coefficients (ϕ_t) from monthly regressions of adjusted fund returns on funds' lagged log size ($LOGTNA$) and fund characteristics (X) which include funds' turnover ($TURN$), expenses ($EXPERATIO$), 12b1 fees ($x2b1$), funds' age (AGE), total loads including front-end, deferred and rear-end loads ($TOTLOAD$), last year annual net inflows ($FLOWR$), and previous year returns ($LAGARET$).

$$ADJRET_{i,t} = \mu + \phi_t\, LOGTNA_{i,t-1} + \gamma_t\, X_{i,t-1} + \varepsilon_{i,t} \quad i = 1,...,N$$

In the third stage, we regress the monthly coefficients ϕ_t on investor sentiment.

$$\hat{\phi}_t = c + d\, SENTIMENT_{t-1} + \varepsilon_t$$

The first row is the estimates from regressions where adjusted fund returns come from different models. The second row is the Newey-West t-statistics for the estimates which are adjusted for autocorrelations and heteroscedasticity. The last row reports the bootstrap p values.

Panel A: Time series regression for a long-short portfolio

	Estimate	T-stat
Sentiment(lagged)	-0.003^{***}	-2.78
RMRF	-0.048	-1.61
SMB	0.231	5.95
HML	0.125	3.64
UMD	-0.047	-1.54

Panel B: Three-stage regression

	Model Used to Adjust the Returns		
	CAPM	Three Factor	Four Factor
Estimate	$-0.04\%^{***}$	$-0.03\%^{***}$	$-0.03\%^{***}$
t-stat	(-3.15)	(-2.37)	(-2.37)
p value	[0.00]	[0.01]	[0.01]

*** Statistically significant at 1% level.

Table 2.9: Sentiment timing test

This table reports regressions of size quintile portfolio returns on the market risk premium ($RMRF$), the Fama-French factors (SMB and HML), the momentum factor (UMD) and the size factor (SMB) interacted with investor sentiment ($SENTMENT$).

$$FUNDRET_{i,t} = c_i + \beta_i\, RMRF_t + (s_i + d_i\, SENTIMENT_{t-1})SMB_t + h_i\, HML_t + m_i\, UMD_t + \varepsilon_{i,t}$$

T-statistics are in parentheses and heteroscedasticity robust.

Quintile	RMRF	SMB	HML	UMD	LAG(SENT)*SMB
1 (small)	0.87	0.34	0.05	-0.03	-0.09^*
	(26.02)	(8.42)	(1.16)	(-1.05)	(-1.90)
2	0.91	0.27	0.00	0.02	-0.06^*
	(54.97)	(9.37)	(-0.15)	(1.01)	(-1.82)
3	0.91	0.23	-0.02	0.03	-0.03
	(59.22)	(8.16)	(-0.78)	(1.58)	(-0.88)
4	0.92	0.19	-0.03	0.04	-0.01
	(70.01)	(7.80)	(-1.44)	(1.90)	(-0.31)
5 (large)	0.93	0.09	-0.03	0.02	0.02
	(87.32)	(5.32)	(-1.93)	(1.63)	(0.99)

* Statistically significant at 10% level

Table 2.10: Summary statistics of the merged database

This table reports the summary statistics of the merged table. I link my data sample from the CRSP Mutual Fund database to the CDA/Spectrum Mutual Fund Holdings database using the MFLink database provided by WRDS. Panel A reports the summary statistics of variables of interest. The standard deviations are reported in parentheses. Panel B reports quarterly average size rank of mutual fund holdings of each quintile. I obtain the size rank of each stock in each quarter by comparing the market values obtained from the CRSP stock database with the size breakpoints in the file provided by Kenneth French on his website. I then calculate the value weighted average size rank of all stocks in a fund's portfolio to get a fund's size rank. Then a size quintile's size rank is obtained by averaging all the fund's size ranks in the quintile. The t-statistics are reported in parentheses.

Panel A: Summary statistics

	Mutual Fund Size Quintile				
	1	2	3	4	5
Number of Funds	171.35	193.75	200.00	204.68	211.70
AGE	6.99	9.64	13.59	16.73	24.63
(years)	(3.83)	(3.84)	(4.66)	(4.47)	(4.46)
TNA	7.03	19.88	51.14	133.39	1011.75
($ million)	(5.46)	(13.00)	(29.62)	(76.21)	(867.37)
TOTLOAD	3.04	4.06	4.23	4.35	5.00
(%)	(1.37)	(1.67)	(1.56)	(1.52)	(1.85)
EXPRATIO	1.64	1.27	1.10	0.97	0.78
(% per year)	(0.44)	(0.25)	(0.21)	(0.21)	(0.20)
TURNOVER	93.88	83.21	81.26	75.13	60.19
(% per year)	(34.18)	(20.06)	(13.17)	(15.75)	(18.56)
VWFLOW	143.24	33.42	17.38	7.06	0.63
(% per year)	(164.51)	(31.62)	(20.33)	(11.29)	(8.00)

Panel B: Quarterly average size rank of mutual fund holdings of each quintile

		Sentiment	
Quintile	Unconditional	Low	High
1 (small)	13.34	13.20	13.40
2	13.29	13.35	13.27
3	13.61	13.58	13.62
4	13.77	13.75	13.77
5 (large)	14.81	14.80	14.82
diff (5-1)	1.48***	1.60***	1.42***
	(13.98)	(16.28)	(9.61)

*** Statistically significant at 1% level.

Table 2.11: Time series regressions

This table reports regressions of returns of a long-short portfolio on the market risk premium (*RMRF*), the Fama-French factors (*SMB* and *HML*), the momentum factor (*UMD*) and the size rank difference of the two portfolios.

$$R_{quintile\ 1,t} - R_{quintile\ 5,t} = c + d\ RANKDF_{t-1} + \beta\ RMRF + s\ SMB_t + h\ HML_t + m\ UMD_t + \varepsilon_t$$

The long-short portfolio is formed as a long position in the fund size quintile 1 and a short position in the fund size quintile 5. The regressions are run both unconditionally and conditional on investor sentiment. The Newey-West t-statistics are reported in parentheses.

Sentiment	RMRF	SMB	HML	UMD	RANK DIFF
Unconditional	-0.054	0.086	0.051	-0.010	0.120%**
	(-4.41)	(6.87)	(3.70)	(-1.22)	(2.41)
Low	-0.065	0.101	-0.007	0.006	0.114%***
	(-7.61)	(6.09)	(-0.47)	(0.44)	(2.76)
High	-0.049	0.088	0.065	-0.010	0.099%
	(-3.04)	(5.89)	(3.58)	(-1.13)	(0.88)

*** Statistically significant at 1% level.
** Statistically significant at 5% level.

Chapter 3

Robustness Check and Extensions

3.1 Paper I: Does Investor Sentiment Affect Mutual Fund Performance?

3.1.1 Test of Significance in Difference

In the original paper, I have calculated the funds' alphas which are the intercepts from the regression of fund returns on several factor portfolios including Fama-French three factors plus the momentum factor. The alphas show how well a fund has performed in a risk adjusted manner. My results show that overall, small funds outperform large funds, but conditioned on the sentiment, small funds tend not to outperform large funds when sentiment is high while they still tend to outperform large funds when sentiment is low.

Here, I test if the difference in alphas is significantly correlated with sentiment, and report them in Table 3.6. As shown in the table, when I add the lagged sentiment into the 4-factor model, the coefficients on sentiment is significantly negative. This means, the differnce in performance between small funds and large funds does vary significantly with investor sentiment. I use the same method in Chen, Hong, Huang, and Kubik (2004) to remove outliers and use Newey-West method to correct the autocorrelations when calculating the standard errors.

3.1.2 Flow and Sentiment

Greene and Hodges (2002) show that fund flows have some dilution impact on certain fund categories (mostly U.S.-based international funds). Also, Indro (2004) reports that the net aggregate fund flows somehow correlate with investor sentiment in a short horizon (weekly). Therefore, if in our sample, the fund flows and our definition of investor sentiment have a positive relation, the patterns of fund performance may be caused by the dilution effect of flows.

In order to test whether this is true or not, I check the relation between fund flows and investor sentiment in my sample in Table 3.7, but I don't find a significant relation between flow and investor sentiment in our horizon (annual) no matter whether it is at the aggregate level or at size quintile level.

Specifically, flow is measured using net money inflows both in actual dollar amount and as a percentage of TNA. For each fund i at month t, I calculate the net money inflows following many prior studies (e.g. Zheng (1999)) as follows:

$$Flow_{i,t} = TNA_{i,t} - TNA_{i,t-1}(1 + R_{i,t}) - Merger_{i,t} \tag{3.1}$$

where $R_(i,t)$ is the fund's return in month t. $Merger_{i,t}$ is the flow due to merger and acquisition. Percent flows are dollar flows divided by last period's TNA ($TNA_{i,t-1}$).

As shown in Panel A, we can see that correlations between the total inflow into all mutual funds and sentiment are small. If we use percent flow, the correlation is 28%, while it is 24% for dollar flow. P-values are not significant. In Panel B, I regress the percent flow on sentiment. The coefficients are not statistically significant either on the contemporaneous term or the lagged term of sentiment. In Panel C, all funds are divided into five quintiles according to their size (TNA). The correlation between flows into each fund size quintile and the correlation between flows into each quintile and sentiment is reported. As we see in the table, sentiment is more significantly correlated with flows into large funds than into small funds. P-value for the small funds (quintile 1) is 15% but for the large funds, it is 6%. However, sentiment is not significantly correlated with the difference in flows into small and large funds. The correlation is -23%, but the p-value is 20%.

In summary, the correlation between fund flows and sentiment is not significant at the aggregate level, and sentiment is also not highly correlated with flows into smaller funds (quintile 1-3). Moreover, the difference in flows into small and large funds is not correlated with sentiment. Therefore, it is hard to believe that the pattern of fund performance in the paper is driven by the relation between flows and sentiment.

3.1.3 Size Effect

Baker and Wurgler (2006) find that when investor sentiment is low, subsequent returns of small stocks tend to be high and on the other hand when sentiment is high, small stocks have low returns. If small funds tend to hold small stocks, we may observe the second pattern in the paper. This section is trying to investigate whether if this is a size effect. Size effect has two aspects. One is that overall, a fund holds more on one size quintile of stocks, say, small stocks. This is the unconditional pattern. The other is that funds may try to migrate money from one size quintile to another conditioned on investor sentiment. I'll investigate both in this section.

First of all, as shown in Panel A in Table 3.9, small funds generally hold stocks tilting toward small stocks compared to large funds, although majority (51%) of their holdings are large stocks. This is also true if conditioned on sentiment as shown in Panel B. There is slight difference in weights on each size quintile when investor sentiment changes, but the pattern that small funds hold more small stocks still holds.

Also, I check if their weights on each size quintile of stocks vary with investor sentiment. Table 3.10 reports regressions of fund weights on size quintile of stocks on investor sentiment. As shown in Panel A, we do not find any evidence that their weights change with sentiment at the aggregate level. Panel B reports the Regression of the weights of each fund quintile on each size quintile of stocks on last year's sentiment. As we see in the table, small fund tend to load more large stocks when sentiment is high but large funds tend to load more small stocks when sentiment is high. However, most t-stats are not significant.

In summary, the second pattern in the paper may be driven by the fact that small funds tend to hold small stocks and small funds are better at timing the sentiment.

3.1.4 Predictability of Size Concentration

To further investigate whether the pattern is a size effect or not, I test if the size concentration of funds can predict factor returns. I run the regression of factor returns on the weight difference of funds in size quintiles.

Table 3.11 reports the predictability of weight difference of mutual funds on size to factor returns. Stocks are divided into five quintiles according to their market value (size). Funds are also divided into five quintiles according to their TNA. Weight difference is defined as the difference in weights on certain stock size quintile between small funds (fund quintile 1) and large funds (fund quintile 5). Factors include market excess return, size (SMB), value (HML), momentum (UMD). Factor returns are quarterly returns. Quarters are defined in three ways, including calendar quarter, extended quarter and short quarter. Extended quarter is from 45 days after last quarter end to 45 days after next quarter beginning. Short quarter is from 45 days after last quarter end to next quarter beginning.

As shown in the table, the weight difference in small stocks can predict return on size and value factors but not market return and momentum return. This is interesting and needs further investigation.

3.2 Paper II: Beta Choice of Institutional Investors

3.2.1 Beta Choice in Each Fund Category

The paper documents that overall institutional investors tend to choose higher betas than their benchmarks. It's interesting to see how funds in each category choose their betas. For mutual funds, there are four fund categories including Aggressive Growth, Growth, Growth & Income and Balanced, corresponding to the code 2,3,4 and 7 in the mutual fund holdings database. As shown in Table 3.2, funds in the Aggressive Growth and Growth category tend to choose higher beta but funds in the Growth & Income and Balanced category tend to choose lower beta. Therefore, the results are mainly driven by the funds in the first two categories.

Table 3.1 reports the number of mutual funds in each fund category during each year from 1980 to 2004 in our sample. We can see that funds in the Growth & Income and Balanced category account for about 70%.

3.2.2 Beta Choice Conditioned on Trailing 12-month Return

The different tendency for funds in different category to choose betas may be due to their different choices in different market environment.

Table 3.3 reports the average Beta Choice (BC) measure of mutual funds conditioned on last year's market return. When past 12 months' market return (return on VW

CRSP index return) is positive, it's denoted as an UP period; otherwise, it is denoted as a DOWN period. "Average BC" is the quarterly average of the average BC measures across funds (firms). "Average BC" is multiplied by 100 in the table.

As shown in the table, funds in the Aggressive Growth and Growth category always tend to choose higher betas no matter how the market was for the past twelve months. However, they tend to choose even higher betas when the market was up in the past year. To the contrary, funds in the Growth & Income and Balanced category always tend to choose lower betas no matter how the market was for the past twelve months, and there is no difference in magnitude between up and down markets either.

3.2.3 Causality of the Change of Beta and the Change of Institutional Ownership

Overall, as we see in the paper that institutional investors tend to choose higher beta than their benchmarks. It is possible that the trading of institutional investors causes the increase of beta of stocks. Then institutional investors would end up with higher beta stocks.

To investigate whether the trading of institutional investors have any impact on a stock's beta, I run Fama-Macbeth regressions between the change of the beta of a stock and its change of institutional ownership. From the regressions, I do not find evidence that the trading of institutional investors can change the beta of a stock.

Specifically, the change of beta for a stock is defined as the percentage change of the beta from last quarter. And the change of ownership is defined as the difference of institutional ownership this quarter and last quarter for the stock. The regressions are controlled for stocks' one quarter lagged market value (size). As shown in Table 3.4, the coefficient on the lagged change of institutional ownership is actually negative and the t-statistic is not significant.

3.2.4 Risk Shifting?

If a mutual fund chooses a bigger beta than its benchmark beta, it may be the case that the fund wants to take more risks when they didn't perform well recently. Table 3.5 investigates this possibility. As shown in the table, distressed funds indeed tend to choose higher betas, which is consistent with the risk shifting story.

Specifically, all funds are divided into ten groups according to last year's money inflows. The biggest inflow group is decile 10 and the smallest one is decile 1. Distressed funds are defined as funds in decile 1 to 4, and hot funds are defined as funds in decile 7-10. Other funds are denoted as medium funds. Then I run the Fama-French regressions of the beta choice of each group on the lagged percent inflows. That is, every quarter, I run a cross sectional regression of a fund's beta choice on its lagged flow in each group, and then I take an average of the coefficients for all the quarters. As shown in the Table 3.5, the coefficient on all funds as a group is positive but not significant. However, the distressed group has a significant negative coefficient. The t-stat is -3.03. The average percent flow into distressed funds is negative. So this means that distressed funds who are most concerned about their performance tend to take more risks, which echoes the risk shifting story. The coefficients on another two groups are not significant, which makes this story more plausible.

Table 3.1: Number of Mutual Funds in Each Fund Category

This table reports the number of mutual funds in each fund category during each year from 1980 to 2004 in our sample. The fund categories are Aggressive Growth, Growth, Growth & Income and Balanced, corresponding to the code 2,3,4 and 7 in the mutual fund holdings database.

Year	**Aggressive Growth**	**Growth**	**Growth & Income**	**Balanced**	**Percentage of funds in first 2 categories**
1980	96	211	107	31	0.69
1981	96	224	110	31	0.69
1982	89	221	122	41	0.66
1983	84	219	126	47	0.64
1984	114	240	140	43	0.66
1985	109	251	140	69	0.63
1986	116	308	161	66	0.65
1987	123	352	171	76	0.66
1988	142	376	176	79	0.67
1989	157	396	187	102	0.66
1990	162	425	203	113	0.65
1991	195	473	228	131	0.65
1992	205	542	249	137	0.66
1993	229	901	330	173	0.69
1994	238	1307	379	219	0.72
1995	233	1535	581	283	0.67
1996	202	1533	557	273	0.68
1997	206	1901	574	287	0.71
1998	198	1860	550	263	0.72
1999	184	1798	506	244	0.73
2000	176	1710	484	225	0.73
2001	176	1611	456	214	0.73
2002	173	1553	439	206	0.73
2003	164	1458	414	192	0.73
2004	161	1364	390	177	0.73
Average	161.12	910.76	311.2	148.88	0.68

Table 3.2: Average Beta Choice Measures of Mutual Funds in Each Category

This table reports the average Beta Choice (BC) measure of mutual funds. Negative quarters is the number of quarters that have negative average BC measures across funds (firms). Positive Quarters is the number of quarters that have non-negative average BC measures across funds (firms). The numbers in square brackets are the number of quarters that is statistically significant. "Average BC" is the quarterly average of the average BC measures across funds (firms). "Average BC" is multiplied by 100 in the table. T-statistics are in brackets. I measure the Beta Choice (BC) of a portfolio during quarter t as follows.

$$BC_t = \sum_{j=1}^{N} \omega_{j,t} \left[\tilde{\beta}_{j,t} - \tilde{\beta}_t^{b_{j,t}}\right]$$

where $\omega_{j,t}$ is the portfolio weight for stock j at the beginning of period t, and $\tilde{\beta}_{j,t}$ is the estimated beta for stock j at time t, and $\tilde{\beta}_t^{b_{j,t}}$ is the group average of betas within the group which stock j belongs to at time t. Panel A reports average Beta Choice Measures based on betas derived from daily returns, and Panel B reports average Beta Choice Measures based on betas derived from monthly returns.

		Daily Beta		**Monthly Beta**	
Fund Category	**Statistics**	**VW CRSP Beta**	**S&P 500 Beta**	**VW CRSP Beta**	**S&P 500 Beta**
Aggressive Growth	Total Quarters	100	100	100	100
	Positive Qtrs	98	98	99	99
	Average BC	18.62	16.56	17.64	16.07
		(21.12)	(19.66)	(27.88)	(23.39)
Growth	Positive Qtrs	98	99	99	97
	Average BC	6.94	6.44	6.36	5.94
		(19.04)	(18.80)	(22.06)	(19.81)
Growth & Income	Positive Qtrs	23	25	2	2
	Average BC	-2.01	-1.81	-3.30	-2.96
		(-7.15)	(-6.59)	(-16.49)	(-16.37)
Balanced	Positive Qtrs	34	30	28	26
	Average BC	-1.60	-1.79	-3.15	-3.24
		(-3.95)	(-5.07)	(-6.43)	(-6.69)

Table 3.3: Average Beta Choice Measures of Mutual Funds in Each Category Conditioned on Last Year's Market Return

This table reports the average Beta Choice (BC) measure of mutual funds conditioned on last year's market return. When past 12 months' market return (return on VW CRSP index return) is positive, it's denoted as an UP period; otherwise, it is denoted as a DOWN period. "Average BC" is the quarterly average of the average BC measures across funds (firms). "Average BC" is multiplied by 100 in the table. T-statistics are in brackets. I measure the Beta Choice (BC) of a portfolio during quarter t as follows.

$$BC_t = \sum_{j=1}^{N} \omega_{j,t} \left[\tilde{\beta}_{j,t} - \tilde{\beta}_t^{b_{j,t}}\right]$$

where $\omega_{j,t}$ is the portfolio weight for stock j at the beginning of period t, and $\tilde{\beta}_{j,t}$ is the estimated beta for stock j at time t, and $\tilde{\beta}_t^{b_{j,t}}$ is the group average of betas within the group which stock j belongs to at time t.
The difference between up periods and down periods is also calculated. T-statistics are corrected for hertero-geneity and auto-correlation and shown in parenthesis.

	Last year's Market Return		
Fund Category	**Down**	**Up**	**Difference**
Aggressive Growth	0.127	0.169	-0.041
	(10.00)	(21.86)	(-2.78)
Growth	0.050	0.062	-0.011
	(11.05)	(17.52)	(-2.00)
Growth & Income	-0.027	-0.030	0.003
	(-5.80)	(-15.45)	(0.68)
Balanced	-0.034	-0.032	-0.002
	(-5.83)	(-5.49)	(-0.21)

Table 3.4: The Causality of the Change of Beta and the Change of Institutional Ownership

This table reports a Fama-Macbeth style regression between the change of the beta of a stock and its change of institutional ownership. The change of beta for a stock is defined as the percentage change of the beta from last quarter. And the change of ownership is defined as the difference of institutional ownership this quarter and last quarter for the stock. T-statistics are corrected for herterogeneity and auto-correlation and shown in parenthesis. The regressions are controlled for stocks' one quarter lagged market value (size).

Dependent Variable	**% change of beta (t-1)**	**Change of Institutional Ownership (t-1)**	**Size(t-1)**
Percent Change of Beta (t)	-0.6650	-0.3101	-0.0913
	(-0.86)	(-0.75)	(-0.72)
Change of Institutional Ownership (t)	0.0004	-0.0668	0.0010
	(1.74)	(-6.71)	(6.63)

Table 3.5: A Fund's Beta Choice and Its Net Money Flow

This table reports regressions of a fund's beta choice on its past year's net money inflow. All funds are divided into ten groups according to last year's money inflows. The biggest inflow group is decile 10 and the smallest one is decile 1. Distressed funds are defined as funds in decile 1 to 4, and hot funds are defined as funds in decile 7-10. Other funds are denoted as medium funds. The Fama-French approach is used for the regressions. Every quarter, we run a cross sectional regression of a fund's beta choice on its lagged flow in each category, and then take an average of the coefficients for all the quarters. Newey-West adjusted t-statistics are in parenthesis. An average R-squared is included.

Fund Flow	**Intercept**	**Percent Flow**	**R-Squared**
Distressed (Decile 1-4)	0.065	-0.081	0.008
	(13.49)	(-3.03)	
Medium (Decile 5-6)	0.064	-0.112	0.006
	(10.42)	(-0.45)	
Hot (Decile 7-10)	0.070	0.010	0.009
	(17.08)	(1.17)	
All Funds	0.069	0.008	0.006
	(17.56)	(0.84)	

Table 3.6: The Significance of the Relation between Difference in Alphas and Sentiment

This table tests if the difference in alphas is highly correlated with investor sentiment. It reports the regression of monthly return difference between small and large funds on factors including sentiment. Carhart 4-factor are used. That is, market excess return, size (SMB), value (HML) and momentum (UMD) factors are used. T-stats are in parenthesis.

SENTIMENT	**MKT-RF**	**SMB**	**HML**	**UMD**
-0.0030	-0.0484	0.2310	0.1247	-0.0467
(-3.02)	(-1.93)	(7.12)	(3.30)	(-1.83)

Table 3.7: Flow and Sentiment

This table reports relation between mutual fund flows and investor sentiment, including correlations between flow and sentiment and whether sentiment leads flows. Flow is measured using net money inflows both in actual dollar amount and as a percentage of TNA. For each fund i at month t, I calculate the net money inflows following many prior studies (e.g. Zheng (1999)) as follows:

$$Flow_{i,t} = TNA_{i,t} - TNA_{i,t-1}(1 + R_{i,t}) - Merger_{i,t} \tag{3.2}$$

where $R_(i,t)$ is the fund's return in month t. $Merger_{i,t}$ is the flow due to merger and acquisition. Percent flows are dollar flows divided by last period's TNA ($TNA_{i,t-1}$). Panel A report the correlations between the total inflow into all mutual funds and sentiment. Panel B reports the regression of percent flow on sentiment. Newey West adjusted t-stats are in parentheses. In Panel C, all funds are divided into five quintiles according to their size (TNA). The correlation between flows into each fund size quintile and the correlation between flows into each quintile and sentiment is reported. P-values are in parentheses.

Panel A: Correlation Between Flow and Sentiment

	Dollar Flow	**Percent Flow**	**Sentiment**
Total Flow	1.00		
Percent Flow	0.91	1.00	
Sentiment	0.28	0.24	1.00
p-value	(0.12)	(0.18)	

Panel B: Dependent Variable: Percent Flow to the whole mutual fund industry

Intercept	**Sentiment(0)**	**Sentiment(-1)**	R^2
0.0007	0.0053	0.0034	0.13
(0.20)	(1.05)	(0.76)	

Panel C: Correlation Between Flow and Sentiment in Each Fund Category

	Fund Quintiles					
Fund Quintiles	**Small**	**2**	**3**	**4**	**Large**	**Small-Large**
Small	1.00					
2	0.62	1.00				
3	0.86	0.74	1.00			
4	0.86	0.75	0.87	1.00		
Large	0.85	0.77	0.91	0.94	1.00	
Sentiment	0.26	0.19	0.20	0.38	0.34	-0.23
p-value	(0.15)	(0.30)	(0.27)	(0.03)	(0.06)	(0.20)

Table 3.8: Relation Between Sentiment and Difference in Flow into small funds and big funds

This table reports regressions of difference in percentage change of flows to small funds and large funds on sentiment. All the funds are divided into 5 quintiles according to last year's TNA. The difference in flows is calculated as the aggregate flow into small funds (quintile 1) in percentage of last year's total TNA minus the flow into large funds. Panel A reports the regression results. Panel B reports the regressions of the change in flows on two sentiment dummy variables, one of which is the High_Sent which equals 1 when sentiment is above zero, and the other is the Low_Sent which equals 1 when sentiment is below zero. The one lag of High_Sent is also used. Note that we can't use the lag of High_Sent and Low_Sent at the same time. The dependent variable is the difference of percentage flow. Newey-West corrected t-statistics are in parenthesis.

Panel A: Regression of the difference in percentage change of flows to small funds and large funds on sentiment

Intercept	**Sentiment(0)**	**Sentiment(-1)**	R^2
-0.012	-0.005	-0.022	
(-0.93)	(-0.24)	(-1.25)	0.1

Panel B: Dependent Variable: Percent Flow to the whole mutual fund industry

	HIGH_SENT(0)	**LOW_SENT(0)**	**HIGH_SENT(-1)**	R^2
Small Funds	0.004	-0.002	0.000	0.04
	(0.64)	(-0.39)	(0.02)	
Large Funds	0.007	-0.001	0.023	0.06
	(0.22)	(-0.03)	(0.66)	
Small-Large	-0.003	-0.001	-0.023	0.07
	(-0.10)	(-0.06)	(-0.78)	

Table 3.9: Funds' Weights in Each Size Quintile of Stocks

This table reports funds' weights in each size quintile of stocks. First, I Combine all the funds in each fund quintile together as an aggregate portfolio, and then calculate the weight of each fund quintile on each size quintile of stocks as shown in Panel A. Then, I calculate the weights conditioned on last year's sentiment as in Panel B. T-statistics are in parenthesis.

Panel A: Unconditional Weights on Stocks in Different Size Category

	Fund Size Quintile				
Stock Size Quintile	**Small**	**2**	**3**	**4**	**Large**
Small	0.075	0.068	0.054	0.042	0.016
2	0.100	0.100	0.096	0.089	0.037
3	0.127	0.131	0.134	0.132	0.077
4	0.184	0.182	0.186	0.193	0.173
Large	0.514	0.518	0.530	0.544	0.698

Panel B: Funds' Weights on Stocks in Different Size Category Conditioned on Sentiment

		Fund Size Quintile				
Sentiment	**Stock Size Quintile**	**Small**	**2**	**3**	**4**	**Large**
Low	**Small**	0.073	0.066	0.047	0.041	0.014
	2	0.106	0.104	0.099	0.089	0.038
	3	0.131	0.132	0.130	0.129	0.080
	4	0.182	0.184	0.184	0.197	0.181
	Large	0.508	0.514	0.540	0.544	0.686
High	**Small**	0.075	0.068	0.056	0.043	0.016
	2	0.096	0.097	0.094	0.088	0.036
	3	0.124	0.129	0.135	0.132	0.073
	4	0.184	0.180	0.186	0.190	0.165
	Large	0.521	0.526	0.529	0.548	0.710

Table 3.10: Regression of funds' size weights on sentiment

This table reports regressions of fund weights on size quintile of stocks on investor sentiment. First, funds are sorted into 5 quintiles at each quarter end according to their size. And then stocks are sorted into 5 size quintiles too. Panel A reports the percentage of money invested in each size quintiles of stocks on last year's sentiment. The dependent variable is the percentage of money of all the mutual funds as a whole invested in each size quintiles of stocks, that is, the weight on each size quintile. The regression is as follows.

$$\text{Fund Weight on Size Quintile } i(t) = \text{Intercept} + a_i \cdot \text{Sentiment}(t-1),\ i = 1,2,...,5$$

Panel B reports the Regression of the weights of each fund quintile on each size quintile of stocks on last year's sentiment.

$$\text{Weight of Fund Quintile } j \text{on Size Quintile } i(t) = \text{Intercept} + a_{ij} \cdot \text{Sentiment}(t-1), \quad i,j = 1,2,...,5$$

Only the coefficients on sentiment a_{ij} are reported. Newey-West corrected t-statistics are in parenthesis.

Panel A: The percentage of money invested in each size quintiles of stocks on last year's sentiment

Size Quintiles	**Intercept**	**Sentiment**
Small	0.019	0.59
	(7.32)	(1.85)
2	0.045	0.59
	(11.24)	(1.13)
3	0.083	0.35
	(14.05)	(0.45)
4	0.172	-0.19
	(21.18)	(-0.18)
Large	0.681	-1.33
	(34.21)	(-0.51)

Panel B: Funds' weights on wtocks in different size category conditioned on sentiment

	Fund Size Quintile				
Stock Size Quintile	**Small**	**2**	**3**	**4**	**Large**
Small	-0.36	0.18	1.02	0.49	0.29
	(-0.99)	(0.66)	(4.21)	(2.17)	(2.10)
2	-0.71	-0.24	0.24	0.79	0.27
	(-2.92)	(-0.90)	(0.95)	(2.98)	(1.32)
3	-0.38	-0.18	0.39	0.66	0.14
	(-1.71)	(-0.95)	(1.63)	(2.61)	(0.38)
4	0.36	-0.09	0.13	-0.34	-0.12
	(2.03)	(-0.48)	(0.74)	(-1.74)	(-0.22)
Large	1.09	0.34	-1.78	-1.60	-0.57
	(1.43)	(0.43)	(-2.47)	(-2.06)	(-0.47)

Table 3.11: Predictive Regression of Weight Difference of Mutual Funds on Size

This table reports the predictability of weight difference of mutual funds on size to factor returns. Stocks are divided into five quintiles according to their market value (size). Funds are also divided into five quintiles according to their TNA. Weight difference is defined as the difference in weights on certain stock size quintile between small funds (fund quintile 1) and large funds (fund quintile 5). Factors include market excess return, size (SMB), value (HML), momentum (UMD). Factor returns are quarterly returns. Quarters are defined in three ways, including calendar quarter, extended quarter and short quarter. Extended quarter is from 45 days after last quarter end to 45 days after next quarter beginning. Short quarter is from 45 days after last quarter end to next quarter beginning. Time series regressions are run as follows.

$$\text{Factor Return}_t = \text{Intercept} + a \cdot \text{Weight Difference}_{t-1}$$

Newey-West adjusted t-statistics are in parentheses.

Panel A: Dependent Variable: Market Return minus Risk-free Return

	Calendar Quarter			**Extended Quarter**			**Short Quarter**		
Stock Size quintile	**Intercept**	**Weight Difference**	R^2	**Intercept**	**Weight Difference**	R^2	**Intercept**	**Weight Difference**	R^2
Small	-0.016	-0.625	0.021	-0.018	-0.640	0.027	-0.018	-0.640	0.027
	(-0.58)	(-1.42)		(-0.75)	(-1.61)		(-0.75)	(-1.61)	
2	0.008	-0.199	0.001	-0.025	-0.712	0.016	-0.025	-0.712	0.016
	(0.21)	(-0.31)		(-0.69)	(-1.23)		(-0.69)	(-1.23)	
3	0.033	0.244	0.003	0.025	0.117	0.001	0.025	0.117	0.001
	(1.39)	(0.56)		(1.15)	(0.29)		(1.15)	(0.29)	
4	0.023	0.135	0.003	0.021	0.116	0.003	0.021	0.116	0.003
	(2.37)	(0.55)		(2.37)	(0.52)		(2.37)	(0.52)	
Large	0.020	0.002	0.000	0.011	0.045	0.001	0.011	0.045	0.001
	(0.76)	(0.02)		(0.44)	(0.36)		(0.44)	(0.36)	

Panel B: Dependent Variable: Size Factor Portfolio (SMB)

	Calendar Quarter			**Extended Quarter**			**Short Quarter**		
Stock Size quintile	**Intercept**	**Weight Difference**	R^2	**Intercept**	**Weight Difference**	R^2	**Intercept**	**Weight Difference**	R^2
Small	0.039	0.652	0.067	0.027	0.447	0.028	0.027	0.447	0.028
	(2.54)	(2.60)		(1.60)	(1.65)		(1.60)	(1.65)	
2	0.043	0.681	0.035	0.028	0.445	0.013	0.028	0.445	0.013
	(1.86)	(1.85)		(1.13)	(1.13)		(1.13)	(1.13)	
3	0.006	0.095	0.001	0.003	0.046	0.000	0.003	0.046	0.000
	(0.44)	(0.37)		(0.20)	(0.17)		(0.20)	(0.17)	
4	-0.001	-0.155	0.012	-0.001	-0.090	0.004	-0.001	-0.090	0.004
	(-0.19)	(-1.09)		(-0.12)	(-0.60)		(-0.12)	(-0.60)	
Large	0.011	-0.053	0.005	0.008	-0.038	0.002	0.008	-0.038	0.002
	(0.71)	(-0.67)		(0.47)	(-0.46)		(0.47)	(-0.46)	

Panel C: Dependent Variable: Value Factor Portfolio (HML)

	Calendar Quarter			Extended Quarter			Short Quarter		
Stock Size quintile	**Intercept**	**Weight Difference**	R^2	**Intercept**	**Weight Difference**	R^2	**Intercept**	**Weight Difference**	R^2
Small	0.060	0.796	0.062	0.054	0.708	0.059	0.054	0.708	0.059
	(3.02)	(2.48)		(2.99)	(2.43)		(2.99)	(2.43)	
2	0.098	1.370	0.088	0.088	1.229	0.086	0.088	1.229	0.086
	(3.39)	(3.01)		(3.37)	(2.97)		(3.37)	(2.97)	
3	0.031	0.355	0.013	0.037	0.486	0.029	0.037	0.486	0.029
	(1.77)	(1.10)		(2.33)	(1.67)		(2.33)	(1.67)	
4	0.013	0.015	0.000	0.013	0.034	0.000	0.013	0.034	0.000
	(1.88)	(0.08)		(1.99)	(0.20)		(1.99)	(0.20)	
Large	0.046	-0.175	0.032	0.046	-0.179	0.040	0.046	-0.179	0.040
	(2.33)	(-1.76)		(2.58)	(-1.99)		(2.58)	(-1.99)	

Panel D: Dependent Variable: Momentum Factor Portfolio (UMD)

	Calendar Quarter			Extended Quarter			Short Quarter		
Stock Size quintile	**Intercept**	**Weight Difference**	R^2	**Intercept**	**Weight Difference**	R^2	**Intercept**	**Weight Difference**	R^2
Small	0.031	0.069	0.000	0.027	0.002	0.000	0.027	0.002	0.000
	(1.34)	(0.18)		(1.19)	(0.01)		(1.19)	(0.01)	
2	-0.020	-0.768	0.021	-0.012	-0.630	0.015	-0.012	-0.630	0.015
	(-0.60)	(-1.43)		(-0.37)	(-1.20)		(-0.37)	(-1.20)	
3	0.010	-0.344	0.009	0.014	-0.260	0.006	0.014	-0.260	0.006
	(0.48)	(-0.93)		(0.69)	(-0.73)		(0.69)	(-0.73)	
4	0.024	-0.203	0.010	0.023	-0.252	0.017	0.023	-0.252	0.017
	(2.96)	(-0.98)		(2.93)	(-1.26)		(2.93)	(-1.26)	
Large	0.004	0.124	0.012	0.002	0.131	0.015	0.002	0.131	0.015
	(0.18)	(1.08)		(0.11)	(1.18)		(0.11)	(1.18)	

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