Liquidity Risk and Mutual Fund Performance

Xi Dong Shu Feng Ronnie Sadka*

December 6, 2014

Abstract

The liquidity risk exposure of mutual funds represents their propensity for taking risk, but can also signify skill, if skillful managers' ability to outperform increases with market liquidity. Consistently, we document an annual liquidity-beta performance spread of 3.3% to 4% in the cross-section of mutual funds. Only a small portion of this spread is explained by risk premia. Instead, a large part is driven by the ability of high-liquidity-beta funds to outperform, either through holding underpriced assets or making informed trades, during periods of improved market liquidity. The findings highlight the multiple effects of liquidity risk on active asset management.

*Xi Dong is Assistant Professor of Finance at Baruch College, email: xi.dong@baruch.cuny.edu. Shu Feng is Assistant Professor of Finance at Clark University, email: sfeng@clarku.edu. Ronnie Sadka is Professor of Finance at Boston College, e-mail: sadka@bc.edu. We thank Mathijs van Dijk, Viral Acharya, Kent Daniel, Bernard Dumas, Xavier Gabaix, Hao Jiang, Robert Korajczyk, Alan Marcus, Gideon Ozik, Ľuboš Pástor, Lasse H. Pedersen, Joel Peress, Kalle Rinne, Erik Stafford, Ashish Tiwari, Hassan Tehranian, Russ Wermers, Hong Zhang, and seminar participants at the 1st Luxembourg Asset Management Summit, the 4th Financial Risks International Forum, the 5th Conference on Professional Asset Management, the American Economics Association Meetings 2012, INSEAD, and Inquire Europe Fall 2011 conference for valuable comments and discussions. We also thank David Hirsheleifer and Danling Jiang for providing their mispricing factor. Xi Dong thanks the research grant from INSEAD Alumni Fund (IAF).

1 Introduction

Liquidity risk has been the focus of recent literature, especially in light of the financial crisis. Prior works demonstrate the pricing of aggregate liquidity risk (beta) in the cross-section of stocks (e.g., Pástor and Stambaugh (2003) and Acharya and Pedersen (2005)). More recent works study the cross-sectional effects of liquidity risk exposure on treasury bonds (Li, Wang, Wu, and He (2009)) and corporate bonds (Lin, Wang, and Wu (2011)). This paper studies the implications of liquidity risk in the cross-section of mutual funds—an asset class with a combined $30 trillion under management globally (ICI 2014 Fact Book). As far as liquidity-risk-related performance is concerned, the sources of return of actively managed portfolios, such as mutual funds, versus those of passive portfolios of traditional assets, such as stocks and bonds, may substantially differ. While the return of both types of portfolios is driven by the amount of liquidity risk premium that each portfolio unconditionally/passively earns, the return of the former type of portfolio is additionally driven by the value generated from active management, which can vary with market liquidity conditions. Therefore, mutual funds provide a unique testing ground for an in-depth analysis of the effect of liquidity risk on the returns of assets that are actively managed.[1]

We advance two possible channels by which the liquidity beta of mutual funds predicts the cross-section of their future performance. One, perhaps natural, hypothesis is the

[1] Sadka (2010) demonstrates the impact of liquidity risk in the cross-section of hedge funds. However, limitations on fund holdings data prevent the study of the active management aspect in that setting.

unconditional liquidity risk premium of fund positions. That is, given the liquidity risk premium in the cross-section of traditional assets, a wide dispersion in the average liquidity risk of fund holdings in the cross-section of mutual funds will translate into a premium in the cross-section of expected mutual fund returns. The second channel is that informed trading varies with changes in market liquidity. As a result, the degree of market efficiency also varies with changes in market liquidity. If informed/skilled funds generate higher abnormal returns relative to uninformed funds during periods when market liquidity improves, the liquidity beta of their fund returns is likely to be higher than otherwise identical uninformed/unskilled funds. In this case, the liquidity beta captures the correlation between informed funds' ability to demonstrate skill (i.e., outperform) and changes in market liquidity.

Motivated by the above hypotheses, we examine the relation between the liquidity beta of active mutual funds and their future performance. Our analysis shows that high-liquidity-beta funds indeed outperform low-liquidity-beta funds by 3.3% (a Carhart four-factor alpha) annually in the equity fund universe, and 4% (an alpha adjusted by Carhart four factors and two fixed-income factors) annually in the entire fund universe, on average, over the period 1984−2010. The outperformance of high-liquidity-beta funds is robust to controlling for various risk and style factors, as well as to conditional performance models.

Using equity funds, for which detailed holding information is available, we find that the first hypothesis does not explain a substantial amount of this performance predictability. That is, only a small portion of the liquidity-beta performance spread is due to the difference in the liquidity-risk premium of funds' underlying equity holdings. Specifically, only about 22% to 25% of the outperformance (alpha) of high-liquidity-beta funds relative to low-liquidity-beta funds can be explained by exposures to equity liquidity-risk factors. The reason is that high- and low-liquidity-beta funds hold stocks whose liquidity beta is only slightly higher and lower than that of the average stock, respectively. Therefore, the cross-sectional dispersion in fund exposure to stocks with different liquidity risk is much smaller than the cross-sectional dispersion in liquidity risk in the stock universe. Such a relative small dispersion in stock liquidity beta is consistent with institutional features that restrict fund exposure to liquidity risk. However, it also implies a low cross-sectional risk premium, which cannot explain the large performance difference between high- and low-liquidity-beta funds.

In contrast, consistent with the second hypothesis, we find that high-liquidity-beta funds significantly outperform low-liquidity-beta funds by 2.5% per year or more, even after various ways of adjusting the fund exposure to the liquidity risk premium of stocks, i.e., a five-factor alpha (Carhart four factors plus a liquidity-risk factor). The high-liquidity-beta funds also deliver a significantly positive five-factor alpha. Inconsistent with a liquidity-risk-premium explanation, high-liquidity-beta funds outperform low-liquidity-beta funds in both up and down liquidity states. Moreover, consistent with the skill hypothesis, high-liquidity-beta funds generate a significantly positive five-factor alpha (after-fee) of 3.1% per year only during periods when aggregate liquidity improves, outperforming low-liquidity-beta funds by a five-factor alpha of 4.6% (t-value=3.40). This relative abnormal outperformance is positive but not statistically significant during periods when aggregate liquidity deteriorates. Therefore, most of the abnormal outperformance of high-liquidity-beta funds is due to their ability to generate alpha when market liquidity improves.

Several reasons suggest that informed/skilled funds are more likely to outperform uninformed funds during periods of improved market liquidity. First, informed funds are able to identify mispriced assets, and therefore they hold underpriced stocks and avoid overpriced stocks. Arbitrageurs trade against the mispricing at some point in time, generating abnormal returns in the mispriced stocks when prices converge to fundamentals. However, mispricing can persist for months (Lamont and Thaler, 2003; Lamont and Stein, 2004) due to limits faced by arbitrageurs such as price impacts and trading costs, redemptions, and margin constraints. These limits-to-arbitrage are more severe during market liquidity downturns such as liquidity crises (see, e.g., Merton (1987), Shleifer and Vishny (1997), Mitchell, Pedersen, and Pulvino (2007), Brunnermeier and Pedersen (2009), Ben-David, Franzoni and Moussawi (2012) and also see Gromb and Vayanos (2012) for a recent review).

Therefore, mispricing is more likely to be corrected during periods with positive market liquidity innovations, when it is easier to trade against mispricing (see, e.g., Sadka and Scherbina (2007)). Since underpriced stocks are included the informed/skilled funds' portfolios while overpriced stocks are in the market portfolio or in some other, uninformed funds' portfolios, informed/skilled funds are likely to realize positive abnormal returns or outperform other funds during periods of positive market liquidity innovations. In contrast, in market liquidity downturns, mispricing is corrected at a slower rate or can even exacerbate. If market frictions are of first-order importance (e.g., Mitchell, Pedersen, and Pulvino (2007)), the activity of informed funds that trade mispriced stocks will translate into a higher liquidity beta of fund returns, as the rate of price convergence to fundamentals is different in periods of up and down liquidity states (see Kondor (2009)).

Moreover, theory suggests that informed investors trade more aggressively the stocks for which they have private information when market liquidity improves than when it deteriorates. This is because during periods when noise trading (relative to informed trading) in the market increases, i.e., when market liquidity improves, informed traders can trade larger quantities of the assets for which they have private information without incurring additional price impacts or transactions costs (see, e.g., Kyle (1985)). They therefore earn more profits during such periods than other periods from their private signals that randomly arrive every period. A recent empirical example by Collin-Dufresne and Fos (2013) shows that informed traders indeed trade more aggressively when market liquidity improves. It follows again that informed/skilled funds are particularly able to outperform uninformed/unskilled funds, in states of the world for which market liquidity improves, even if prices converge to fundamentals at a constant rate in every period.

Studying fund holdings, we find that the stocks held by high-liquidity-beta funds deliver a significantly positive five-factor alpha (3.6% per year with a t-value of 2.93) during periods when market liquidity improves, and positive, yet mostly insignificant, returns when market liquid deteriorates. In contrast, the five-factor alpha of the stocks that low-liquidity-beta funds hold is insignificantly different from zero in either period. These results are consistent with the hypothesis that high-liquidity-beta fund managers are more skilled than their low-liquidity-beta counterparts, and that the former managers hold underpriced assets (and/or avoid overpriced assets) whose mispricing is particularly likely to be corrected in periods with positive liquidity innovations.

High-liquidity-beta funds trade stocks with significantly smaller size, higher idiosyncratic volatility, and lower analyst following than low-liquidity-beta funds. They also have significantly higher active share. These significant relations are almost entirely driven by the periods when market liquidity improves. Agarwal, Jiang, Tang, and Yang (2012) provide evidence that the stocks for which fund managers make private-information-based trades tend to have the aforementioned characteristics. Cremers and Petajisto (2009) show that funds with high active shares—a measure of the degree that a fund deviates its stock positions from its benchmark—are indeed informed insofar as the deviation from benchmarks leads to superior subsequent fund performance. Therefore, our results provide consistent evidence that high-liquidity-beta funds trade more aggressively the stocks for which they have private information during periods when market liquidity improves than when it deteriorates. The liquidity-beta performance effect is independent of the liquidity level of a fund, and it remains significant while controlling for various fund characteristics that might affect or predict fund performance, such as expenses and trading costs and different flow-related effects. We therefore conclude that it is unlikely that the performance predictability is due to other fund characteristics that may affect a fund's liquidity-risk exposure.

In sum, this study contributes to understanding the liquidity risk of asset returns in the context of mutual funds. Following the widely studied effects of liquidity risk on traditional assets, such as stocks and bonds, this paper demonstrate that the liquidity-risk exposure of an active mutual fund is more complex than suggested by previous studies of traditional assets. Difference in asset liquidity beta is traditionally viewed as a measure of difference in liquidity risk. However, if market efficiency increases with market liquidity, informed fund managers are unlikely to create value at a constant rate through active management across up and down liquidity states. This performance dynamics is likely to translate into a higher liquidity beta for informed funds than uninformed funds. The difference in beta carries a minor covariance risk premia, but is economically important as it can differentiate between skilled/informed and uninformed fund managers.

The rest of this paper is organized as follows. Section 2 describes the data used for this study. Section 3 investigates the relation between the liquidity-risk exposure and the cross-section of individual-fund returns, while Section 4 considers the four different hypotheses for this relation. Section 5 studies the manner by which liquidity risk pertains to some stylized facts documented in the mutual-fund literature. Section 6 provides some additional results, and Section 7 concludes.

2 Data and Liquidity Risk Measures

Monthly mutual-fund return data are obtained from the CRSP survivor-bias-free database for the period 1983–2010. Only funds that report returns on a monthly basis and net of all fees are kept in the sample. Some fund families incubate many private funds and make historical performance available only for the funds that survive (Elton, Gruber, and Blake (2001) and Evans (2004)). In order to address the incubation bias in the data, we exclude the first 12-month fund performance. The removal of these young funds also alleviates a concern that these funds are more likely to be cross-subsidized by their respective fund families (Gaspar, Massa, and Matos (2006)). Since we focus on active mutual funds, consistent with prior studies, we exclude money-market, sector, emerging, global, and index funds.

The returns are based on U.S. dollars and are excess of the risk-free rate. The common-stock holding information for funds that hold equities is collected from the Thomson Reuters Mutual Fund Holdings Database. Mutual-fund families introduced different share classes in the 1990s. Since different share classes have the same holding composition, we manually aggregate all the observations pertaining to different share classes into one observation. For the qualitative attributes of funds (e.g., name, objectives), we retain the observation of the oldest fund. For the total-net-assets (TNA) under management, we sum the TNAs of the different share classes. Finally, for the other quantitative attributes of funds (e.g., returns, expenses, and loads), we compute the weighted average of the attributes of the individual share classes, where the weights are the lagged TNAs of the individual share classes.

Following the liquidity risk literature, systematic liquidity risk is measured by unexpected changes in market liquidity. Such changes are measured by various non-traded liquidity factors. The primary factor used here is based on the permanent-variable price-impact-based factor constructed in Sadka (2006). A permanent change in the stock price is dependent on the amount of uninformed trading relative to the amount of informed trading (see Kyle (1985); Admati and Pfleiderer (1988)). In contrast, a transitory price change corresponds to market making costs, such as the costs associated with inventory maintenance and order processing or search. Sadka shows that only the permanent-variable component of price impact is priced in the cross-section of momentum and post-earnings-announcement-drift portfolios. In addition, Sadka and Scherbina (2007) also show that the degree of stock mispricing is positively correlated with this component of price impact. We therefore focus on the permanent-variable component, henceforth simply referred to as the liquidity factor.

Table 1 reports the summary statistics of all active mutual funds (Panel A) and active domestic equity mutual funds (Panel B).[2] The sample includes 8,703 distinct

[2] For domestic equity funds, we first select funds with the following Lipper objectives: 'EI', 'EIEI', 'G', 'GI', 'LCCE', 'LCGE', 'LCVE', 'MC', 'MCCE', 'MCGE', 'MCVE', 'MLCE','MLGE', 'MLVE', 'SCCE', 'SCGE', 'SCVE'. If a fund does not have any of the above objectives, we select funds with the following Strategic Insights objectives: 'AGG', 'GMC', 'GRI', 'GRO', 'ING', 'SCG'. If a fund has neither the Lipper nor the SI objective, then we use the Wiesenberger Fund Type Code to select funds with the following objectives: 'G', 'G-I', 'AGG', 'GCI', 'GRI', 'GRO', 'LTG', 'MCG', 'SCG'. If none of these objectives are available and the fund has a CS policy or holds more than 80% of its value in common

active mutual funds and 3,716 active equity mutual funds. In early years, most active funds are equity funds. The number of active non-equity mutual funds steadily increase in recent years. Most of the characteristics of active equity funds are not too different from those of all active funds except the turnover ratio (93.07% for active equity and 165.72% for all active funds). The average liquidity beta is not far from zero for both all active funds (0.25) and active domestic equity funds (0.30).

3 Liquidity Risk and Fund Performance

This section investigates the ability of liquidity beta to predict performance in the cross-section of mutual funds. We form portfolios of individual mutual funds while allowing for time variation in liquidity loadings. Prior works suggest that a mutual fund's risk profile changes over annual or even shorter horizons (e.g., Brown, Harlow, and Starks (1996) and Chevalier and Ellison (1997, 1999)). Using stock data, Watanabe and Watanabe (2008) document that liquidity betas vary across high and low states while the high-liquidity-beta state is less than a year. Therefore, the liquidity beta of funds that buy and hold stocks may also significantly change for horizons longer than a year.

To account for the time variation in fund liquidity risk profile, we estimate liquidity by following previous studies that use a one-year rolling window to estimate time-varying beta or alpha.[3] The liquidity loading of a fund is calculated using a regression of the

shares, then the fund will be included. We also exclude funds that in the previous month manage less than $15 million.

[3]See, e.g., Chevalier and Ellison (1999), Nanda, Wang, and Zheng (2004), Lou (2012), and Kacper-

fund's monthly return on the market return and the liquidity factor over a one-year rolling window.[4] Quintile portfolios of mutual funds are formed every month (with equal number of funds in each portfolio) using the prior one-year rolling liquidity factor loadings. Funds are then kept in the portfolios for one month (the portfolio formation month). Portfolio formation begins from April 1984 and ends in December 2010.

3.1 All Active Funds

Berk and van Binsbergen (2013) point out the limitation of prior works in restricting attention exclusively on domestic equity funds and advocate examining mutual funds that do not only hold domestic stocks as these funds represent a large part of the total active mutual fund universe. Therefore, we start by examining the liquidity-beta sorted fund portfolios in the entire active mutual-fund universe that invest in domestic assets. The subset of US equity funds is analyzed in a section below.

Panel A of Table 2 reports the performance measures of liquidity-beta-sorted fund quintiles based on the net investor returns. To compute risk-adjusted returns, we use the following models: one-factor model of CAPM; the four-factor model of Carhart (1997), which includes MKT, SMB, and HML from the three-factor model of Fama and French

czyk, Nieuwerburgh, and Veldkamp (2013).

[4] In unreported results, we perform a sensitivity analysis of betas that are estimated using alternative horizons. Our main results remain similar for betas estimated using shorter (9-month) or longer (18-month or 24-month) windows, although the 24-month results are slightly weaker. We do not estimate betas using windows shorter than 9 months as the limited number of observations decrease the precision in estimating beta (and the literature does not offer daily liquidity risk factors).

(1993) and a momentum factor; the four-factor model of CPZ proposed by Cremers, Petajisto and Zitzewitz (2012), which includes the excess return on the S&P500 index, the returns on the Russell 2000 index minus the return on the S&P500 index, the Russell 3000 value index minus the return on the Russell 3000 growth index, and the Carhart's momentum factor; and the Ferson and Schadt (1996) conditional four-factor model based on the Carhart (1997) four-factor model.[5] The Carhart four-factor model is often used as a major benchmark model for domestic equity funds in prior work. However, since in this section we examine the entire mutual-fund universe, of which bond funds are a large portion, we also use a six-factor model by adding two bond factors to the Carhart four-factor model. The first factor (the term spread factor) is the difference between the monthly return on ten-year government bonds and the one-month risk-free rate. The second factor (the default spread factor) is the difference between the monthly returns on BBB-rated corporate bonds and ten-year Treasury notes.

The right half of the panel shows that the high liquidity-beta fund portfolio (Quintile 5) outperforms the low-liquidity-loading portfolio (Quintile 1) by a raw return of 0.33% per month, or 4% per year, with a t-value of 2.73. The magnitude and significance of such relative outperformance remains almost the same after adjusting for various

[5]The Carhart four factors are obtained from Kenneth French's website. To calculate Ferson-Schadt conditional performance alpha, we follow previous studies and include the following demeaned macroeconomic variables in month t-1: the dividend yield of the S&P 500 index, the term spread (the difference between the rates on a 10-year Treasury note and a three-month Treasury bill), the default spread (the difference between the rates on AAA and BAA bonds), and the three-month Treasury bill rate.

benchmarks. For example, the relative performance is 0.31% per month (t-value=2.52) using the Carhart+Fixed Income six-factor model. The significant performance difference suggests that high-liquidity-beta funds significantly outperform low-liquidity-beta funds in the subsequent month. The high liquidity-beta fund portfolio can also deliver a positive after-fee alpha of 1 to 2% per year. This positive alpha is significant based on some four-factor performance measures such as Ferson-Schadt and CPZ.

3.2 Measurement Errors and Back-testing

Mamaysky, Spiegel, and Zhang (2007) provide evidence that previous performance studies are subject to some estimation problems. In particular, since many sorting variables are measured with noise, the top and the bottom quintiles of a given trading strategy might not be populated by just the best and the worst funds, but also by funds that have the highest estimation errors. To alleviate this problem, they suggest using a back-testing technique in which the statistical sorting variable is required to exhibit some past predictive success for a particular fund before it is used to make predictions in the current period. Their paper shows that a strategy that uses back-testing to eliminate funds whose sorting variables likely derive primarily from estimation errors produces very significant out-of-sample risk-adjusted returns.

Since our liquidity beta is a statistical measure, which is highly likely subject to a similar criticism of estimation errors and noise, we mitigate these concerns using the back-testing method. Specifically, we eliminate funds for which the liquidity beta has a different sign from the excess fund return in two non-overlapping time periods. In a first step, we sort all funds into quintiles according to their liquidity beta computed using returns between $t-12$ and $t-1$ prior to the portfolio formation month t. The sorting yields exactly the same quintile portfolios as those described in the left half of Panel A of Table 2. We then require that the fund excess return relative to the market at month $t-1$ has the same sign as the lagged liquidity beta computed using returns between $t-13$ and $t-2$. Thus, we keep only funds for which there is a concordance between the lagged liquidity beta and the lagged excess return. In this way, the liquidity beta of a fund is required to exhibit some predictive success in the recent periods before it can be used to predict the returns during the portfolio formation month t. That is, the sign of the liquidity beta computed using returns between $t-13$ and $t-2$ at least can predict the sign of the fund's excess return at month $t-1$, i.e., the month just before the portfolio formation month t.

The results, reported in the right half of Panel A, indicate that this method leads to a substantial increase in the performance difference between the top and bottom quintiles, which is consistent with prior studies that use the back-testing method (e.g., Kacperczyk, Sialm, and Zheng (2008); Dong and Massa (2014)). For example, the performance difference for the Carhart+Fixed Income model increases from 0.31% (t-value=2.52) before using back-testing to 0.72% (t-value=4.19) per month. We can also better identify the funds that can deliver positive alphas. Now the high-liquidity beta fund quintile delivers significantly positive alphas across all measures. For example, the high liquidity-beta fund quintile generates a positive Carhart+Fixed Income alpha of 0.35% per month (t-value=3.36).

3.3 Active Equity Funds

We now restrict our analysis to the funds that only hold domestic equity to ease comparison with prior mutual-fund studies and also for setting up the ground for examining the channels that lead to such a liquidity-beta effect in later sections.

Table 2, Panel B, reports the after-fee portfolio returns of domestic equity fund quintiles. To increase power, we follow a similar methodology used in Pástor and Stambaugh (2003) in constructing the liquidity-beta-sorted stock portfolios. Specifically, we use all the funds (i.e., those used for Table 2, Panel A) in the ranking procedure to create the quintile portfolios because the inclusion of non-domestic-equity funds increases the dispersion of the postranking liquidity betas of the sorted portfolios as well as the dispersion of their returns,[6] in line with the purpose of the sorting procedure (simple sorting methods yield similar results albeit slightly weaker statistical significance).

Panels A and B of Figure 1 plot returns and alphas of liquidity-loading quintiles (in bars) along with the respective t-statistics (in symbols), where the alphas are returns adjusted by the Carhart four-factor model. The figure shows that the high-liquidity-loading portfolio has the highest average next-month return, while the low-liquidity-

[6]The equity-fund portfolios remain highly diversified with roughly 300 funds in each quintile per month.

loading portfolio has the lowest average next-month return. The rest of the portfolio returns as well as alphas generally increase with the liquidity loading. The figure also includes the high-minus-low liquidity-risk portfolio, whose Carhart four-factor alpha is 0.27% per month or 3.3% annually with a t-statistic of 2.45. These results are also reported in Panel B of Table 2.

The right part of Panel B in Table 2 also includes the results using the back-testing method. The performance difference for the Carhart model increases to 0.61% (t-value=4.17) per month. The high-liquidity-beta fund quintile generates a positive Carhart alpha of 0.29% per month (t-value=2.99). Overall, the back-tested and non-back-tested results based on equity funds are similar to those based on all active funds. That is, the liquidity-risk exposure of a fund provides valuable information to investors for predicting its future performance.

4 Explanations

In this section, we investigate the main hypotheses that can lead to the relation between fund liquidity-risk exposure and future performance. Since mutual funds are only required to report their domestic equity holdings and the performance attribution models for domestic equity funds are well established in the literature, we focus our investigation on the universe of domestic equity funds.

4.1 Hypothesis 1: Liquidity-risk premium

4.1.1 Do High-Liquidity-Beta Funds hold High-Liquidity-Beta Stocks?

We first examine the extent to which the difference in liquidity-risk premium between fund stock holdings can explain the performance difference between high and low liquidity-beta funds. Panel A of Figure 2 plots the density of the liquidity beta of the stocks that funds hold (dotted line) as well as that of the liquidity beta of the stocks in the NYSE, AMEX, and NASDAQ common stock universe during the same sample period (solid line), while stocks with price below five dollars are removed as most institutions can not invest in such stocks. The figure shows that the cross-sectional dispersion of liquidity beta across fund stock holdings is far narrower than the cross-sectional dispersion of liquidity beta across the entire stock universe.

Panel B of Figure 2 provides further information. On the left-hand side, funds are sorted into quintile portfolios according to their fund liquidity beta. On the right-hand side, all the stocks in the stock universe are also sorted into quintile portfolios according to their stock liquidity beta, which is calculated in the same manner as the fund's liquidity beta. The arrow that links a fund quintile to a stock quintile indicates the average rank of the fund-quintile stock holdings in the stock universe. The box in the middle of the figure provides the exact value of the average quintile rank. For example, for Quintile 5 of funds, the liquidity betas of the stocks that this fund quintile hold have a quintile ranking of 3.3 in the stock universe, thus an arrow linking Quintile 5 of funds to Quintile

3 of stocks. The liquidity-beta rank of the stock holdings of each fund is computed as the value-weighted average rank of the individual stock liquidity betas in the stock universe. The rank of the fund-quintile stock holdings is then computed as the equal-weighted average of the liquidity-beta rank of the stock holdings of each fund in the fund quintile portfolio.

The figure shows that the liquidity betas of mutual fund stock holdings are not ranked very differently from each other in the stock universe. They are located between Quintile 2.5 and Quintile 3.3 of liquidity beta in the stock universe on average. The results suggest that mutual funds tend to overweight stocks with average liquidity beta (the average beta is close to zero) in the stock universe. High liquidity-beta funds' stock portfolio returns are not highly driven by the returns of the stocks with very high liquidity risk. Their stock holdings only have slightly higher average liquidity-beta ranking than the stock holdings of low liquidity-beta funds.

The figures provide the intuition as to why the liquidity-risk premium can only play a small role in explaining the performance difference between high and low liquidity-beta funds. A narrow dispersion in liquidity beta of stocks can only generate a small difference in liquidity risk premium. For example, the premium difference between Quintile 2 and Quintile 3 of stocks is very small with a Carhart alpha of 0.06% per month, which is only 22% of the Carhart alpha of the return spread between high and low liquidity-beta funds.

Consider two investors: if they choose to passively invest in stocks directly, one holds the stock portfolio of Quintile 3 of liquidity beta, while the other holds the stock portfolio of Quintile 2 of liquidity beta. The monthly Carhart alpha spread between the two investors is roughly 0.06% per month. If these two investors instead choose to hold active mutual-funds, that is, one holds Quintile 5 of funds, and the other would hold Quintile 3 of funds, their performance difference is about four times higher (a Carhart alpha of 0.27% per month), even though the liquidity-beta differences between the two investors in these two cases are almost identical.

The small cross-sectional dispersion in the liquidity beta of fund holdings is consistent with several institutional features of mutual funds. First, mutual funds are subject to the "mark-to-market" discipline and are required to allow for redemptions and inflows on a daily basis. Holding high-liquidity-beta stocks hampers a fund's ability to accommodate investors' flows if flows have a common component that commoves with systematic liquidity conditions. Second, unlike size and value, they are not required to differentiate their investment style based on liquidity risk. They also face restrictions in the form of position limits, leverage constraints, choice of assets, and investment styles.

Therefore, the analysis in this section suggests that the cross-sectional dispersion in the liquidity beta of fund holdings is quite small in comparison to that of the stock universe. Such a narrow dispersion implies that investors should only expect a small difference in stock liquidity-risk premium, which should not generate a large performance difference between high and low liquidity-beta funds.

4.1.2 Factor Model

Fund holdings are reported at the quarterly frequency, which do not account for fund managers' activity within the quarter. For example, round-trip transactions within the quarter and fund trading costs can both affect a fund's actual return, which could differ from the return inferred from the fund quarterly reported holdings. Therefore, for the purpose of evaluating the liquidity beta of fund true performance, a fund's actual net monthly return is a more appropriate variable as it also reflects the impact of all the trades and positions during the quarter. In unreported results, we verify that the liquidity beta based on mutual fund actual returns are not statistically different from the liquidity beta estimated from fund reported holdings on average.

Nevertheless, in this section, we formally use factor models to explain funds' actual net return. This quantifies the fraction of the high-minus-low liquidity-beta actual fund return (rather than returns based on disclosed holdings) difference that can be explained by its exposure to the liquidity-risk premium in equities. In Table 3, we try to explain the high-minus-low liquidity-beta fund portfolio performance spread by regressing the spread on a five-factor model, that is a four-factor model along with a traded liquidity risk factor. For robustness, we use three different four-factor models. These are the Carhart model, the Ferson-Schadt conditional model, and the CPZ model. To interpret the intercept of the five-factor regression as alpha, one needs to use a traded liquidity-risk factor. We use three different traded liquidity risk factors "Amihud", "PS", and "SadkaPV". They are based on the commonly used liquidity measures from Amihud (2002), Pástor and

Stambaugh (2003), and Sadka (2006).[7] To be conservative, we use the five-factor model to explain the performance spread without back-testing as the performance spread with back-testing is even stronger and therefore even less explained by the five-factor model.

The results, reported in Panel A of Table 3, show that the alpha of the performance spread only drops by a small magnitude after adjusting its exposure to the liquidity-risk premium of equities using various benchmark models as well as different liquidity factors. The largest drop is from the 0.27% Carhart alpha in Panel B of Table 2 to the 0.20% five-factor Carhart+SadkaPV alpha, which implies that 25% of the performance difference can be explained by the exposure to the liquidity-risk premium of equities.

To alleviate concerns that the high-minus-low liquidity-beta performance spread is driven by cost differences across funds, Panel B of Table 3 reports fund gross performance before fees. The gross fund performance provides a cleaner picture of the value in terms of

[7] The traded Pástor-Stambaugh factor is obtained from Ľuboš Pástor's website. The traded Amihud liquidity factor is constructed as the high-minus-low liquidity-beta quintile return spread of equities, where liquidity beta is calculated through a regression of prior one-year returns on the market factor and the nontraded Amihud liquidity factor. The nontraded Amihud liquidity factor is the innovations computed in the same way as in Acharya and Pedersen (2005). The traded Sadka liquidity factor is constructed as the high-minus-low liquidity-beta quintile return spread of equities, where liquidity beta is calculated through a regression of prior one-year returns on the market factor and the nontraded Sadka permanent variable liquidity factor. The one-year rolling window corresponds to the one-year rolling window used to calculate fund liquidity beta. In unreported results, we also study alternative ways of constructing the liquidity factor including increasing the length of rolling window to longer horizons such as 60 months or using a five-factor model in the rolling regression. These alternatives are in fact less powerful in explaining the high-minus-low liquidity-beta return spread of funds than the factors used in the tables.

alpha created by fund managers. The results convey the same message as those in Panel A. Moreover, the results indicate that after adding back fees and expenses, the five-factor models perform well in explaining the returns of funds with lower liquidity betas such as Quintile 1 and 2 of funds. These funds have zero alphas, thus neither underperforming nor outperforming the benchmark stock portfolios. The five-factor models only fail to completely explain the returns of the funds with higher liquidity betas including Quintile 4 and Quintile 5. For example, Quintile 5 generates a significantly positive annual alpha of 2% to 3% under all the performance measures. Therefore, the reason for the gross performance difference between high and low liquidity-beta funds is not that low liquidity-beta funds can not match the benchmark performance, but rather that high-liquidity-beta funds are able to outperform the benchmarks.

Overall, the results in Table 3 confirm the conclusion from the previous section. That is, only a small portion of the relative outperformance of high liquidity-beta funds can be explained by the exposure to the liquidity-risk premium of equities. The before-fee performance analysis further supports that the driver of the performance difference is the ability of high liquidity-beta funds to generate positive alpha.

4.2 Hypothesis 2: Investment Skill

Consistent with the hypothesis that funds with higher fund liquidity beta are also more likely to be funds with better skill to generate alpha, our previous analysis indicates that high-liquidity-beta funds significantly outperform low-liquidity-beta funds even after adjusting the fund exposure to the liquidity risk premium of stocks and that they deliver significantly positive alpha. This section therefore examines the second hypothesis, that is, a skilled fund is also more likely to have a higher liquidity beta than an otherwise identical fund.

4.2.1 Market Liquidity and Abnormal Performance

As discussed in the introduction, several reasons suggest that informed/skilled fund managers may outperform particularly when market liquidity conditions improves. This section demonstrates the performances of high- and low-liquidity-beta funds in periods with positive and negative market liquidity innovations.

We focus on market liquidity conditions measured by unexpected changes rather than levels for three reasons. First, similar to trading volume (e.g., Lo and Wang (2000)), the level of market liquidity is nonstationary. It is highly persistent and displays a significant time trend. Therefore, using liquidity level for our tests would mimic the inclusion of a time dummy variable, comparing the first and second halves of the sample period.[8] Second, in an efficient market, prices should react to unexpected (not expected) changes in market conditions in the same period, as anticipated changes are already reflected in prices. Similarly, in Kyle (1985), the liquidity shock that shifts informed traders' trading

[8] Such a time trend is generally observed for various liquidity level measures such as the Amihud liquidity measure and the Sadka liquidity measure. This paper's main conclusion remains unchanged if we measure market conditions using a detrended market liquidity level series, which is computed by removing the prior 12-month moving average from each monthly observation.

quantity and profits is unanticipated.

Table 4 reports the net returns and alphas of liquidity-beta-sorted fund quintiles during these two subperiods. Unexpected changes in market liquidity are measured by the non-traded Sadka liquidity factor, which has a mean of zero. This factor focuses on capturing the changes in the noise to informed trading ratio in the market and is therefore particularly relevant for investigating our second hypothesis which focuses on informed trading. The previous section also shows that five-factor models that use Amihud and Pástor-Stambaugh traded liquidity factors explain less of the high-minus-low liquidity-beta fund performance spread than the Sadka traded factor. Therefore, the five-factor alphas we report henceforth will only focus on the Sadka traded liquidity factor.

The results show that high-liquidity-beta funds outperform low-liquidity-beta funds both in periods with positive market liquidity innovations and in periods with negative market liquidity innovations. But the outperformance is only significant in periods with positive innovations. For example, the Carhart+Liquidity five-factor alpha of the high-minus-low liquidity-beta fund return spread is 0.37% per month or 4.6% per year with a t-value of 3.40 during months with positive innovations, while it is only 0.07% per month with a t-value of 0.55 during months with negative innovations.

In addition, during months with positive innovations, high-liquidity-beta funds significantly outperform various benchmarks. For example the Carhart+Liquidity five-factor alpha of high-liquidity-beta funds is 0.26% per month with a t-value of 2.80 and the CPZ+Liquidity five-factor alpha is 0.32% per month with a t-value of 3.56. In contrast, the low liquidity-beta funds do not perform significantly differently from the benchmarks.

Overall, the results suggest that the relative outperformance of high-liquidity-beta funds is positive in both subperiods, but predominantly driven by the ability of high-liquidity-beta funds to deliver significantly positive alpha relative to various benchmarks upon improvement in market liquidity.

The results also provide further evidence inconsistent with the liquidity-risk-premium hypothesis. Table 4 indicates that the 4-factor- or 5-factor-adjusted performance spread between high- and low-liquidity-beta funds is positive in both up liquidity states and down liquidity states. To clearly qualify for a risk-premium explanation, high-liquidity-beta funds would need to significantly underperform low-liquidity-beta funds in down liquidity states. It is then reasonable to expect such risk of significant underperformance to be compensated. If instead high-liquidity-beta funds do not significantly underperform low-liquidity-beta funds in either up or down states of the world, it is harder to argue for the risk explanation. To illustrate this point using a simple example, suppose that Fund A delivers a 4% return on average in up liquidity states and a 2% return on average in down liquidity states. Further assume that Fund B on average delivers 2% return in either liquidity states. A liquidity-risk-averse investor has little reason to require additional compensation for holding Fund A relative to Fund B based on their aversion to liquidity risk.

A. Asymmetric Abnormal Performance and Liquidity Beta This subsection formally explains the reason that the performance asymmetry documented in the above section can lead to a positive relation between a fund's liquidity beta and its ability to generate alpha. Consider the following specification of two funds. One is a skilled fund and the other an unskilled fund. The two are otherwise identical except for their abnormal performance (alpha) in different periods. The expected return of the skilled fund $E(R_S)$ in periods with positive liquidity innovations is driven by the fund's alpha, its liquidity risk premium ($\beta^+ \cdot RP^+_{Liq}$), and its other risk premiums (RP^+).

$$E(R_S) = \alpha + \beta^+ \cdot RP^+_{Liq} + RP^+. \tag{1}$$

The unskilled fund does not generate alpha. Therefore, the expected return of the unskilled fund $E(R_U)$ in periods with positive liquidity innovations is driven by the fund's liquidity risk premium and its other risk premiums, which are the same as the skilled fund, i.e., $\beta^+ \cdot RP^+_{Liq}$ and RP^+.

$$E(R_U) = \beta^+ \cdot RP^+_{Liq} + RP^+. \tag{2}$$

In periods with negative liquidity innovations, the expected returns of the two funds are the same as each other as described below

$$E(R_S) = E(R_U) = \beta^- \cdot RP^-_{Liq} + RP^-, \tag{3}$$

where β^- and β^+ are not restricted to be necessarily equal to each other.[9]

A fund's overall liquidity risk exposure (i.e., its liquidity beta) is the covariation between the fund returns and market liquidity innovations over a certain period. During the period, the months of positive or negative liquidity innovations randomly arrive, on average.[10] If skilled funds tend to generate positive alphas relative to unskilled funds in months with positive liquidity innovations, but generate zero alpha relative to the unskilled fund in months with negative liquidity innovations, then they are more likely to have a higher liquidity beta over the period than unskilled funds, everything else equal, due to the additional covariation of the skilled fund's abnormal performance with market liquidity.

Overall the analysis in this section suggests that skilled funds are more likely to be high-liquidity-beta funds as long as skilled funds are likely to create more value from

[9] To match more closely with the data described by Table 4, we can also specify the expected returns of these two types of funds in the two subperiods as follows:

$$E(R_S) = \alpha - c^+ + \beta^+ \cdot RP^+_{Liq} + RP^+, \tag{4}$$

$$E(R_U) = -c^+ + \beta^+ \cdot RP^+_{Liq} + RP^+, \tag{5}$$

$$E(R_S) = E(R_U) = -c^- + \beta^- \cdot RP^-_{Liq} + RP^-, \tag{6}$$

where c^+ and c^- are positive constants. Such specification does not change the conclusion.

[10] Liquidity risk measures, by construction, remove the serial correlation in changes in liquidity (See, e.g., Pástor and Stambaugh (2003), Acharya and Pedersen (2005), and Sadka (2006)).

their private signals when market liquidity improves than when it deteriorates.

B. Market Timing and Up Liquidity Beta Our second hypothesis is independent of whether the skilled fund does well in timing their exposure to the liquidity risk factor. A successful factor-timing fund would exhibit a high beta w.r.t. the systematic risk factor when the factor realization is positive and a low beta when the factor realization is negative. Therefore, the average beta of the fund over a period with both positive and negative factor realization subperiods is neither necessarily higher nor lower than a fund that maintains a constant beta throughout the period, i.e., a fund without a factor-timing ability.

A skilled fund manager can simply hold underpriced assets without advance knowledge of when market liquidity will improve. As long as the mispricing is corrected more in periods when liquidity improves than in periods when it deteriorates, the fund will generate more alpha during periods of improved liquidity. In unreported results, we confirm that high-liquidity-beta funds do not have significantly better ability in timing the liquidity factor than low-liquidity-beta funds.

Similarly, our hypothesis does not require the monthly performance of the skilled fund to be more sensitive to market liquidity changes than that of the unskilled fund during the months with positive liquidity innovations. In other words, the liquidity beta conditional on positive innovation periods (i.e., β^+) can be similar for the skilled fund and for the unskilled fund, as is demonstrated in Equations (1) and (2). In unreported results, we confirm that sorting on a conditional fund liquidity beta (i.e., β^+) does not provide incremental information to the simple, symmetric liquidity beta we use for our main tests.

The specification in the previous section reflects the notion that fund managers' returns can be affected by variables other than market liquidity alone. It is also generally not easy for mutual-fund managers to uncover alpha opportunities every month. For example, in a month with a very positive market liquidity innovation, the skilled manager may not identify any mispricing opportunity to begin with and will not be able to outperform, even if the correction of mispriced stocks in the market itself is correlated with changes in market liquidity. Therefore, the specification allows a degree of freedom for the fund performance not to be too dependent on the speed of price convergence of traditional assets to fundamentals in every month. It is based on the realistic expectation that skilled funds outperform more on average in periods when market liquidity improves, but the arrival and magnitude of such abnormal performance can be random in these subperiods.

4.2.2 Stock Holdings

If arbitrage activities (not only by informed mutual funds but all kinds of other informed traders) remain at a constant level, mispricing will be corrected at a constant rate. Therefore, an investor who longs underpriced assets and/or shorts overpriced assets is likely to earn an abnormal return of similar magnitude in each period, holding everything else equal. However, the previous literature discussed in the introduction show that mispricing may persist or is even less likely to be corrected in periods of adverse liquidity shocks. Sadka and Scherbina (2007) show that a positive liquidity shock increases arbitrage trading activity and forces prices to converge to fundamentals faster than in other periods. The intuition is that positive shocks to market liquidity reduce the costs of arbitrage, which induces more arbitrage trading and accelerates the convergence of prices to fundamentals. When mispricing is corrected, the price of underpriced stocks increases, realizing a positive alpha, while the price of overpriced stocks declines, realizing a negative alpha. Therefore, a skilled manager, who can hold underpriced stocks and avoid overpriced stocks, is likely to particularly outperform during periods with positive market liquidity innovations, leading to a positive alpha in these periods. This section examines the contribution of this channel to the asymmetry of the relative outperformance in Table 5.

In Table 5, Panel A, the sample period is divided into months with positive and negative liquidity innovations. We report the average monthly stock holding returns of liquidity-beta-sorted fund quintiles over the two subsample periods separately. The stock holding return of a fund is the return of a strategy that buys the stocks that are in the fund's most recent quarterly disclosed stock holdings (weighted by the value of each stock holding) and holds them until the next time the fund discloses its holdings. The return is exactly the performance of the fund's stock portfolio if the fund holds the disclosed stock holdings throughout the quarter before the next disclosure date and is fully invested.

The results show that the stocks held by high-liquidity-beta funds significantly outperforms the stocks held by low-liquidity-beta funds with a five-factor alpha of 0.23 per month (t-value=2.46) during periods with positive liquidity innovations. The outperformance is driven by the positive alpha (a five-factor alpha of 0.29% per month) of the stocks held by high-liquidity-beta funds. In contrast, the performance of the stocks held by low-liquidity-beta funds does not significantly differ from the benchmarks during both subperiods. During periods with negative liquidity innovations, the relative outperformance of the stocks held by high-liquidity-beta funds is still positive but not statistically significant (e.g., a five-factor alpha of 0.10% per month with a t-value of 0.93).

Table 5, Panel B, reports the average monthly stock holding returns of liquidity-beta-sorted fund quintiles over the full sample period. The results show that the stock holding return of high-liquidity-beta funds significantly outperforms that of low-liquidity-beta funds by a five-factor alpha of 0.14% per month.

Overall, the results provide consistent evidence that high-liquidity-beta funds are more skilled than low-liquidity-beta funds and that they hold underpriced stocks and avoid overpriced stocks, whose mispricing is likely to be corrected in periods with positive liquidity innovations.

It is worth noting that the mispricing of some stocks may exacerbate rather than just persist when liquidity deteriorates, as arbitrageurs experiencing withdrawals during liquidity crises may be forced to liquidate their mispriced securities, causing prices to further deviate from fundamentals (e.g., Long-Term Capital Management (LTCM)). In this case, the price of underpriced stocks may be further pressured down, realizing negative returns, while the price of overpriced stocks may be further pressured up, realizing positive returns during such periods. A skilled fund trading mispriced assets thus realizes more positive abnormal returns following positive liquidity shocks but incurs more losses than uninformed funds following negative liquidity shocks. This case suggests that the skilled fund is still likely to have a higher liquidity beta than other funds, everything else equal, due to the positive relation between deterioration in mispricing and deterioration in market liquidity. Along this line, Kondor (2009) provides a theoretical result that the returns of an informed arbitrageur unavoidably has a feature of higher liquidity beta than an otherwise identical investor. Therefore, our main conclusion that informed funds are more likely high-liquidity-beta funds is consistent with theory in this case.

In addition, the above case would imply that the traded liquidity factor return may partially capture the return of the informed funds' mispricing-based strategy, because both are positively related to changes in market liquidity. However, it is unclear whether an informed fund is truly "informed" or "skilled" if the entire performance it can deliver is completely explained by the unconditional liquidity-risk premium of traditional assets that an otherwise identical average/marginal investor of these assets can passively earn. We therefore elect to focus more on the funds that can deliver better five-factor alpha. Our message is that a higher liquidity beta captures the characteristic that differs between an informed/skilled fund and other funds, but "being informed/skilled" means that the fund should have the ability to deliver better risk-adjusted performance than other funds. In this sense, our focus on the five-factor alpha measures of the relative outperformance of high-liquidity-beta funds in Tables 2-5 is a conservative presentation of the performance difference between informed and uninformed managers, relative to the four-factor alpha measures.

4.2.3 Stock Trading

Another channel by which skilled/informed funds can outperform particularly in periods with positive market liquidity innovations is trading more aggressively the stocks for which they have private information during such periods than other periods. This is the optimal manner to capitalize on their private signals (e.g., Kyle (1985)) that randomly arrive each period. That is, an exogenous positive liquidity change induces informed traders to increase their trading quantities, which increases the expected profits from their private signals. In this section, our market liquidity shock is a proxy for the exogenous liquidity shock to individual mutual-fund managers. Comparing to individual stock liquidity, market liquidity can hardly be endogenously determined by any individual trader of an individual stock. A market liquidity shock is therefore a close proxy to the notion of an exogenous shock.

We examine whether this channel contributes to the asymmetry of the relative outperformance in Table 6. We perform Fama-MacBeth regressions of fund liquidity beta on fund characteristics. The control variables include expense ratio, turnover ratio, fund flow, TNA, family TNA, fund age, a load dummy, and the average illiquidity of fund stock holdings, where the illiquidity measure used is the Amihud illiquidity measure. The t-values are calculated based on Newy-West standard errors with a lag length of 12 months.

The primary characteristic variables of interest are active share and the value-weighted averages of idiosyncratic volatility, stock size, and the number of analyst following of the stocks of which the fund changes (increase or decrease) their holdings during the quarter (denoted 'Trading IVOL', 'Trading Stock Size', and 'Trading Analyst Following' in the table). The characteristics of these stocks are used to proxy for the characteristics of the stocks that the fund trades during the quarter. Agarwal, Jiang, Tang, and Yang (2012) provide evidence that the stocks for which institutional investors make informed trades are disproportionately stocks with smaller size, higher idiosyncratic volatility, and lower analyst following. Intuitively, these stocks have higher information asymmetry and therefore offer informed investors a better chance to gain an informational advantage over the market. If high-liquidity-beta funds are informed traders, the stocks they trade should be disproportionately such stocks, especially during periods when market liquidity improves.

Active share measures the degrees by which a fund deviates its stock positions from its benchmark. Cremers and Petajisto (2009) show that funds with high active shares are indeed informed insofar as the deviation from benchmarks leads to superior subsequent fund performance. By the same logic, if high-liquidity-beta funds make aggressive informed trades during periods when market liquidity improves, then they should particularly make informed deviations from their benchmarks, i.e., higher active share, during such periods.

Table 6 presents the results. All the variables in the regression are standardized to a mean of 0 and standard deviation of 1. The first vertical panel presents the relation between fund liquidity beta and fund characteristics over the entire sample period. The results show that the stocks that high-liquidity-beta funds trade are indeed disproportionately stocks with significantly smaller size, higher idiosyncratic volatility, and lower analyst following. The active share of these funds is also higher. Such a relationship is not caused by high-liquidity-beta funds holding more illiquid stocks. In fact, the results show that fund liquidity beta is not significantly related to the illiquidity of fund stock holdings. This confirms that the relationship between fund future performance and fund liquidity beta is not due to the difference in the illiquidity of fund holdings, which is consistent with the findings in earlier studies.[11]

In the next two vertical panels, the sample period is divided into the months where the aggregate (calendar) quarterly liquidity innovations are positive, and the months where the aggregate quarterly liquidity innovations are negative.[12] We perform Fama-MacBeth (1973) regressions for the two subsample periods separately. The results show that the

[11]For example, Massa and Phalippou (2005) document that the illiquidity of fund holdings is independent of fund future performance (unconditionally).

[12]We use aggregate quarterly innovations instead of monthly innovations because changes in mutual-fund holdings are only available at quarterly frequency.

significant relation between fund liquidity beta and idiosyncratic volatility, size, analyst following, and active share of fund holdings is almost entirely driven by the periods when market liquidity improves. For example, a one-standard-deviation increase in the idiosyncractic volatility of stocks that funds trade during such periods results in a 0.29 standard deviation increase in fund liquidity beta. The active share of their positions is also significantly higher than that of low-liquidity-beta funds during such periods only.

Overall, the results provide consistent evidence that high-liquidity-beta funds trade more aggressively high-information-asymmetry stocks during periods when market liquidity improves.

5 Additional Analysis

In this section, we perform additional analysis to examine the significance and robustness of our findings.

5.1 Multivariate Regression

To control for the effect of different fund characteristics on fund performance, we run Fama-MacBeth regressions of fund performance on multiple lagged explanatory variables (Table 7). The performance measure we focus on is the five-factor alpha (Carhart four factors plus liquidity). The list of explanatory variables includes liquidity beta, expense ratio, turnover ratio, flow, load dummy, fund TNA, fund family TNA, fund age, flow volatility, systematic flow risk, and funding liquidity risk. All the variables in the regression are standardized to a mean of 0 and standard deviation of 1. The t-values are calculated based on Newy-West standard errors with a lag length of 12 months.

These regressions address several concerns. First, fund-flow-related concerns. Fund flows are related to fund performance (e.g., Zheng (1999), Sapp and Tiwari (2004), Alexander, Cici, and Gibson (2007)). Fund flow volatility may also impose liquidity costs to fund managers, which hurt their performance. Additionally, a fund's market liquidity beta can be affected by the systematic component of fund flows if fund flows are positively correlated with market liquidity shocks. We therefore construct a systematic flow risk measure.[13] To address all of the above flow-related concerns, we include all three flow-related controls: flow, flow volatility, and systematic flow risk.

Second, funding liquidity risk. Since market liquidity and funding liquidity are closely related (e.g., Brunnermeier and Pedersen (2009)), we examine whether our main results are driven by a fund's funding liquidity beta instead of its market liquidity beta. We therefore include a control for funding liquidity risk. It is calculated as the regression coefficient of a fund's monthly return on aggregate funding liquidity shock over the prior 12 months. The aggregate funding liquidity shock is measured as the residual from an

[13] We first compute fund-specific flow shocks as the residuals of an AR(3) model for fund flow. Systematic flow shocks are the aggregate flow shocks to the fund industry (the residuals from an AR(3) model for aggregate fund flow). Then, a fund's systematic flow risk is measured by the beta of individual fund flow shocks with respect to the aggregate fund flow shocks over the same rolling period as the corresponding fund liquidity beta.

AR(2) model of the TED spread.

Third, cost-related concerns. Fund performance difference could be driven by fund expenses and fees. It could also be correlated with managers' trading frequency (i.e., turnover). Fourth, relatedly, fund size is related to fund performance as funds with different capital under management incur different liquidity-based costs (e.g., Chen, Hong, Huang, and Kubik's (2004)). Finally, business expansions and recessions. The relative importance of timing and stock picking skills for skilled funds during expansions and recessions could be different (Kacperczyk, Nieuwerburgh, and Veldkamp (2013)). We therefore report the subperiod results for Liq Up, Liq Down, Recession, Expansion, and for the Liq Up and Liq Down months within Recession and Expansion, respectively.

Overall, the results show that the positive relation between lagged liquidity beta and next-month abnormal performance remain economically and statistically significant after controlling for the above concerns regarding flows and costs. A one-standard-deviation increase in the liquidity beta increases the future fund return by roughly 9 basis points per month.

In addition, consistent with results in earlier sections, the relation is only significant during Liq Up periods. Kacperczyk, Nieuwerburgh, and Veldkamp (2013) argue that expansions and recessions drive the relative importance of timing and stock picking skills for skilled funds. Market timing is more important in recessions while individual stocking picking is more important in expansions. Based on this, they identify a type of skilled funds that can consistently outperform because these funds time the market well in recessions while pick stock well in expansions at the same time. The subperiod results suggest that the type of funds in their study and the high-liquidity-beta funds are different types of funds. First, the liquidity-beta-performance relation is only significant during expansions, suggesting that the high-liquidity-beta funds do not have the market timing skills to outperform over the entire recession period. Second, the percentage of months with positive liquidity shocks during either expansions or recessions are not far from 50%, suggesting that positive and negative liquidity changes are almost equally likely to happen in expansions and recessions.[14] Our results indicate that high-liquidity-beta funds significantly outperform during the Liq Up subperiods of both recessions and expansions, but do not significantly outperform during the Liq Down subperiods of both recessions and expansions. Therefore, the more important difference is that the ability of the high-liquidity-beta funds to outperform is related to market liquidity rather than the business cycle.

5.2 Difficult-to-measure Flow and Cost Effects

Fund flows and trading costs may affect fund performance in ways that are difficult to measure. For example, different funds might handle capital inflows differently. Some fund mangers may choose to invest the new capital in their risky holdings immediately, while others may choose to hold onto the cash for some time (and vice versa for capital

[14] Raw market liquidity level is even less correlated with the business cycle due to the long-term trend in market liquidity.

outflows). Such decisions are likely to be correlated with market liquidity and would significantly impact fund returns. Therefore, high-liquidity-beta funds may react to flows in a particular way, which may increase both their liquidity beta and performance. However, skilled fund managers should make optimal decisions on the timing of trades based on the joint information they have about their funds' assets and capital flows. If a fund's decision leads to an inferior performance relative to another fund with the same flow and asset information, then we view such a fund as one that lacks fund managerial skill in making optimal investment decisions in the first place.

In addition, trading costs can not be fully captured by variables such as fund turnover, fund size, and expense ratio. Such costs may induce performance differences across funds, a common concern among existing studies that identify skilled funds based on fund characteristics. However, such difficult-to-measure costs can only induce negative returns relative to benchmarks. Table 4 shows that the relative outperformance of high-liquidity-beta funds is largely driven by their significant positive abnormal performance during Liq Up periods. The positive abnormal performance is also observed for tests based on gross fund return in Table 3, Panel B, as well as for results over the full sample period in Table 2 and Panel A of Table 3, especially after back-testing. Taken together, the results do not support the hypothesis that high-liquidity-beta funds outperform simply because of low difficult-to-measure trading costs.

5.3 Performance Persistence

If a fund manager has the skill to generate alpha, we would expect persistence in its performance. To show this, we track the high-minus-low performance spread over holding periods of 1, 3, 6, 9, and 12 months after portfolio formation in Figure 4.[15] The figure reveals that high-liquidity-beta fund managers, on average continue to relatively outperform for holding periods up to 12 months after portfolio formation. The performance spread becomes statistically insignificant thereafter. These results indicate that the relative outperformance of high-liquidity-beta funds is fairly persistent.

5.4 Passive Portfolios

We also evaluate the power of the standard factor models we use to explain non-actively managed portfolios by using the Fama-French 100 size and book-to-market value-weighted portfolios from Kenneth French's website as test assets. We treat each of these portfolio as a fund and estimate the rolling liquidity betas for these hypothetical funds. Table 8 reports the liquidity-beta-sorted quintiles of these "funds."

The results show that the high-minus-low liquidity-beta return spread is not significant especially after the five-factor model is used. All of the liquidity-beta quintile

[15] We follow the portfolio construction approach of Jegadeesh and Titman (1993) to compute the average monthly returns for strategies with different holding horizons. Specifically, the average returns of multiple portfolios with the same holding horizon are calculated. For example, the January return of a three-month holding period return is an average of the January returns of three portfolios that are constructed in October, November, and December of the previous year.

portfolios do not generate positive five-factor alpha, thereby providing no evidence that the five-factor model induces positive alphas. This is in stark contrast to the positive alphas of high liquidity-beta funds in Panel B of Table 3 (since size and book-to-market portfolios do not involve significant costs and expenses, the results based on before-fee fund returns in Panel B of Table 3 are a comparable benchmark).

Additionally, it is known that among the 100 size and book-to-market portfolios, some extreme small and high book-to-market portfolios may deliver positive Fama-French three-factor alphas. Such an effects is unlikely to impact our main results for two reasons. First, we only group funds into five portfolios in our main tests. Any effect of extremely risky stocks are likely to be diluted. For example, in Table 8, we do not observe any positive Fama-French three-factor alpha for the quintile portfolios, which are built upon the 100 size and book-to-market portfolios, because each of these quintile portfolios is an average of 20 size and book-to-market portfolios. Second, as shown in an earlier section, both high- and low-liquidity-beta mutual funds do not hold stocks with extremely high and low liquidity betas, respectively. Their holdings are concentrated in stocks of average liquidity beta (close to zero). We further verify that they also tend to hold large stocks and avoid extreme value stocks. Therefore, the effect of any extreme risky stock is likely to be very small.

Overall, the analysis suggests the factor models we use completely explain the high-minus-low liquidity-beta return spread for passive portfolios.[16]

[16]This conclusion does not change if we use index funds. But the index-fund results are subject to the concern that there are too few index funds in the earlier part of the sample period, tracking relatively

5.5 Mispricing-Arbitrage Portfolios

The second hypothesis is based on the idea that informed traders trade more aggressively, and mispricing is corrected faster, when market liquidity improves. In this section, we provide additional evidence that mispricing is corrected more when liquidity improves than when it deteriorates. To do so, we obtain the mispricing factor in Hirshleifer and Jiang (2010). The factor is a portfolio that explores certain types of potential mispricing suggested by the existing literature. It longs underpriced stocks and shorts overpriced stocks in anticipation of a future price correction, similar to the activity of skilled funds discussed in an earlier section. We find that the average returns to such mispricing-arbitrage portfolio is 50% higher during periods when market liquidity improves than when market liquidity deteriorates. This result provides further evidence consistent with the view that market frictions such as liquidity are of first order importance (e.g., Mitchell, Pedersen, and Pulvino (2007)). It supports our conclusion that the asymmetry of mispricing correction between Liq Up and Liq Down periods is large and its effect on the profits of arbitragers is economically important.

5.6 Severe Negative States

One concern regarding the main results in Table 3 is that high-liquidity-beta funds perform extremely poorly in some severe negative states of the world, which would explain why investors demand a high liquidity-risk premium; but once we lump these severe

similar indices. We therefore focus on results based on size and book-to-market portfolios.

negative states with other mild negative states, we may no longer detect such poor performance.

Figure 4 provides another way to examine the variation of the relative risk-adjusted outperformance of high-liquidity-beta funds across different market liquidity conditions. The sample period is divided into three subperiods: months for which the liquidity innovation is one standard deviation below its mean, months for which it is one standard deviation above its mean, and the remaining months. This division allows us to focus more on the extreme market liquidity changes.

The figure plots the Carhart+Liquidity five-factor alpha of the high-minus-low liquidity-beta fund return spread during these three subperiods. The figure confirms that as market liquidity improves, the relative outperformance of high-liquidity-beta funds becomes increasingly positive. However, during the worst market liquidity states, i.e., months for which market liquidity innovation is one standard deviation below its mean, the high-liquidity-beta funds still perform marginally better than the low-liquidity-beta funds.

In unreported tests, we also check the high-minus-low liquidity-beta fund return when market liquidity innovation is two standard divisions below its mean. This criterion effectively reduces the number of months to 7% of the total length of the sample period. Statistical significance becomes less relevant because of the small number of observations. Therefore, given the small number of these liquidity crisis months, the alpha of high-liquidity-beta funds during these months would need to be substantially lower than that of low-liquidity-beta funds to support a risk compensation explanation. However, in contrast, our results show that the five-factor alpha of the high-minus-low liquidity-beta return spread in fact remains positive.

Overall, the results suggest that in severe negative liquidity states, the alpha of high-liquidity-beta funds is far from poor relative to that of low-liquidity-beta funds. This evidence is inconsistent with a rational, risk compensation explanation for the outperformance of high-liquidity-beta funds.

5.7 Other factors

The hypotheses of this paper center on the argument that market liquidity and market efficiency (e.g., informed trading and correction of mispricing) are highly related, and that the impact of such a relation on fund liquidity-risk exposure is important. This argument does not equally affect the factors in the widely accepted standard model for evaluating equity mutual-fund performance, i.e. the Carhart four-factor model. For example, there are both underpriced and overpriced stocks in the market portfolio, in the small stock portfolio, or the value portfolio. In unreported results, we perform a similar test to that in Table 2 for each of the Carhart four factors. We find that none of the fund betas w.r.t. each of the four factors can positively predict future fund performance. The results confirm the unique role of liquidity beta in the cross-section of mutual funds.

5.8 Other Predictors of Manager Skill

In this subsection, we examine whether a fund's liquidity beta has incremental performance prediction over and above other documented performance predictors. Table 9 reports the Fama-MacBeth regression results controlling for the active share measure of Cremers and Petajisto (2009), the return gap measure of Kacperczyk, Sialm, and Zheng (2008), and the R^2 measure of Amihud and Goyenko (2013). The results show that while these other measures indeed predict fund performance in the direction consistent with their original studies, the positive relation between liquidity beta and fund alpha remains statistically and economically significant.

6 Conclusion

This paper highlights the importance of understanding the liquidity-risk exposure of mutual funds. On the one hand, fund managers can choose to run a high liquidity-risk-taking fund by holding high-liquidity-beta assets, which naturally increases the correlation of fund returns with changes in market liquidity. On the other hand, informed fund managers' ability to generate alpha is not constant across up and down market liquidity states, which also induces a higher correlation of their performance with changes in market liquidity.

We find evidence consistent with both hypotheses, while the skill hypothesis plays a much bigger role than the risk-premium hypothesis. Specifically, funds with a high liquidity-risk exposure indeed earn significantly high future returns during 1984–2010. However, the cross-sectional difference in liquidity beta of fund portfolios is much smaller than that of traditional assets, e.g., stocks. This narrow dispersion introduces a minor difference in stock liquidity-risk premium across funds, which only explains a small portion of the performance difference between high- and low-liquidity-beta funds. In contrast, inconsistent with a liquidity-risk-compensation explanation, high-liquidity-beta funds outperform low-liquidity-beta funds in both up and down liquidity states. But consistent with the skill hypothesis, high-liquidity-beta funds generate significantly more positive alpha in periods when market liquidity improves than when it deteriorates. The stocks they hold deliver positive alpha mainly in periods when market liquidity improves. They also trade more aggressively the stocks for which they have private information during such periods.

The results therefore demonstrate that the ability of skilled fund managers to generate alpha from mispricing is not independent of market liquidity conditions. This finding leads to economically meaningful cross-sectional differences in fund liquidity-risk exposures.

References

Acharya, Viral V., and Lasse H. Pedersen, 2005, Asset pricing with liquidity risk, *Journal of Financial Economics* 77, 375–410.

Admati, Anat R., Pfleiderer, Paul, 1988, Theory of intraday patterns: volume and price variability, *Review of Financial Studies* 1, 3–40.

Agarwal, Vikas, Wei Jiang, Yuehua Tang, and Baozhong Yang, 2012, Uncovering hedge fund skill from the portfolio holdings they hide, *Journal of Finance*, Forthcoming.

Alexander, Gordon J., Gjergji Cici, and Scott Gibson, 2007, Does motivation matter when assessing trade performance? An analysis of mutual funds. *Review of Financial Studies* 20,125-150.

Amihud, Yakov, 2002, Illiquidity and stock returns: Cross-section and time-series effects, *Journal of Financial Markets* 5, 31–56.

Amihud, Yakov, and Ruslan Goyenko, 2013, Mutual fund's R2 as predictor of performance, *Review of Financial Studies*, hhs182.

Ben-David, Itzhak, Francesco Franzoni, and Rabih Moussawi, 2012, The behavior of hedge funds during liquidity crises, *Review of Financial Studies* 25, 1–54.

Berk, Jonathan, and Jules van Binsbergen, 2013, Measuring managerial skill in the mutual fund industry, NBER Working Paper 18184, Stanford University.

Brown, Keith C., Van Harlow, and Laura T. Starks, 1996, Of tournaments and temptations: An analysis of managerial incentives in the mutual fund industry, *Journal of*

Finance 51, 85–110.

Brunnermeier, Markus and Lasse Pederson, 2009, Market liquidity and funding liquidity, *Review of Financial Studies* 22, 2201–2238.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.

Chen, Joseph, Harrison Hong, Ming Huang, and Jeffrey D. Kubik, 2004, Does fund size erode mutual fund performance? The role of liquidity and organization, *American Economic Review* 94, 1276–302.

Chevalier, Judith, and Glenn Ellison, 1997, Risk taking by mutual funds as a response to incentives, *Journal of Political Economy* 105, 1167–200.

Chevalier, Judith, and Glenn Ellison, 1999, Are some mutual fund managers better than others? Cross-sectional patterns in behavior and performance, *Journal of Finance* 54, 875–899.

Collin-Dufresne, Pierre and Vyacheslav Fos, 2013, Do prices reveal the presence of informed trading?, NBER Working Paper No. 18452

Cremers, Martin K.J., and Antti Petajisto, 2009, How active is your fund manager? A new measure that predicts performance, *Review of Financial Studies* 22, 3329–3365.

Cremers, Martijin K.J., Antti Petajisto, and Eric Zitzewitz, 2012, Should benchmark Indices have alpha? Revisiting performance evaluation, *Critical Finance Review* 2, 1–48

Dong, Xi, and Massimo Massa, 2014, Excess autocorrelation and mutual fund performance, Working Paper, INSEAD.

Elton, Edwin J., Martin J. Gruber, and Christopher R. Blake, 2001, A first look at the accuracy of the CRSP mutual fund database and a comparison of the CRSP and Morningstar mutual fund databases, *Journal of Finance* 56, 2415–2430.

Evans, Richard B., 2004, Does alpha really matter? Evidence from mutual fund incubation, termination, and manager change, Working Paper, University of Pennsylvania.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the return on bonds and stocks, *Journal of Financial Economics* 33, 3–53.

Ferson, Wayne E., and Rudi W. Schadt, 1996, Measuring fund strategy and performance in changing economic conditions, *Journal of Finance* 51, 425–462.

Gaspar, Jose M., Massimo Massa, and Pedro Matos, 2006, Favoritism in mutual fund families? Evidence on strategic cross-fund subsidization, *Journal of Finance* 61, 73–104.

Gromb, Denis, and Dimitri Vayanos, 2010, Limits of arbitrage, *Annual Review of Financial Economics* 2, 251–275.

Hirshleifer, David and Danling Jiang, 2010, A financing-based misvaluation factor and the cross section of expected returns, *Review of Financial Studies* 23, 3401-36.

Jegadeesh, Narasimhan and Sheridan Titman, 1993, Returns to buying winners and selling losers: implications for stock market efficiency, *Journal of Finance* 48, 65-91.

Kacperczyk, Marcin, Clemens Sialm, and Lu Zheng, 2008, Unobserved actions of mutual funds, *Review of Financial Studies* 21, 2379–2416.

Kacperczyk, Marcin, Stijn Van Nieuwerburgh, and Laura Veldkamp, 2013, Time-varying fund manager skill, *Journal of Finance*, forthcoming.

Kondor, Péter, 2009, Risk in dynamic arbitrage: the price effects of convergence trading, *Journal of Finance* 64(2), 631-655.

Kyle, Albert S., 1985, Continuous auctions and insider trading, *Econometrica* 53, 1315–1336.

Li, Hai Tao, Junbo Wang, Chunchi Wu, and Yan He, 2009, Are liquidity and information risks priced in the Treasury bond market? *Journal of Finance* 64, 467–503.

Lin, Hai, Junbo Wang, and Chunchi Wu, 2011, Liquidity risk and expected corporate bond returns, *Journal of Financial Economics* 99, 628–650.

Lo, Andrew, and Jiang Wang, 2000, Trading volume: definitions, data analysis, and implications of portfolio theory, *Review of Financial Studies* 13, 257-300.

Lou, Dong, 2012, A flow-based explanation for return predictability, *Review of Financial Studies* 25(12), 3457-3489.

Mamaysky, Harry, Matthew Spiegel, and Hong Zhang, 2007, Improved forecasting of mutual fund alphas and betas, *Review of Finance* 11, 359–400.

Massa, Massimo and Ludovic Phalippou, 2005, Mutual fund and the market for liquidity, Unpublished Working Paper, INSEAD and Oxford.

Merton, Robert C., 1987, A simple model of capital market equilibrium with incomplete information, *Journal of Finance* 42(3), 483-510.

Mitchell, Mark, Lasse Heje Pedersen, and Todd Pulvino, 2007, Slow Moving Capital, *American Economic Review* 97, 215-220.

Nanda, Vikram, Jay Wang, and Lu Zheng, 2004, Family values and the star phenomenon: strategies of mutual fund families, *Review of Financial Studies* 17(3), 667-698.

Pástor, Ľuboš, and Robert F. Stambaugh, 2003, Liquidity risk and expected stock returns, *Journal of Political Economy* 111, 642–685.

Sadka, Ronnie, 2006, Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk, *Journal of Financial Economics* 80, 309–349.

Sadka, Ronnie, and Anna Scherbina, 2007, Analyst disagreement, mispricing, and liquidity, *Journal of Finance* 62, 2367–2403.

Sadka, Ronnie, 2010, Liquidity risk and the cross-section of hedge-fund returns, *Journal of Financial Economics* 98, 54–71.

Sapp, Travis, and Ashish Tiwari, 2004, Does stock return momentum explain the "smart money" effect? *Journal of Finance* 59, 2605–2622.

Shleifer, Andrei, and Robert W. Vishny, 1997, The limits of arbitrage, *Journal of Finance* 52.1, 35-55.

Watanabe, Akiko, and Masahiro Watanabe, 2008, Time-varying liquidity risk and the cross-section of stock returns, *Review of Financial Studies* 21, 2449–2486.

Zheng, Lu, 1999, Is Money smart? A study of mutual fund investors' fund selection ability, *Journal of Finance* 54, 901–933.

Table 1

Summary Statistics

This table summarizes the characteristics of all active mutual funds (Panel A) and active equity mutual funds (Panel B) in our sample over the period between April 1983 and December 2010.

	Mean	Median	Std. Dev.
Panel A. All Active Funds			
Expense Ratio (%)	1.19	1.15	0.55
Turnover Ratio (%)	165.72	63.00	15,427.53
Flow (%)	69.09	-7.70	390.09
Flow Volatility (%)	433.08	256.17	488.38
Load Dummy	0.56	1.00	0.50
TNA (Millions)	1,031.59	165.00	4,681.50
Family TNA(Millions)	38,208.19	3,243.02	115,138.22
Liquidity Beta	0.25	0.09	2.44
Investor Return (%)	0.69	0.91	5.17
Total Number of Funds	8,703		
Panel B. Active Equity Funds			
Expense Ratio (%)	1.19	1.16	0.57
Turnover Ratio (%)	93.07	63.00	165.60
Flow (%)	63.23	-11.63	386.01
Flow Volatility (%)	355.34	199.06	445.59
Load Dummy	0.58	1.00	0.49
TNA (Millions)	1,050.44	170.43	4,531.69
Family TNA(Millions)	44,961.35	3,841.80	128,877.48
Liquidity Beta	0.30	0.11	2.40
Investor Return (%)	0.70	0.96	5.22
Total Number of Funds	3,716		

Table 2

Liquidity Beta Sorted Portfolios

Each month mutual funds are sorted into equal-weighted quintile portfolios according to historical liquidity beta. The liquidity beta is calculated using a regression of monthly portfolio returns on the market portfolio and the liquidity factor, using the 12 months prior to portfolio formation. Portfolio returns begin from April 1984, using funds with at least 11 months of returns during the prior year. The table reports the average monthly excess return (in percent) of the quintile portfolios, as well as of the high-minus-low portfolio. Panel A reports the results for all active mutual funds. Panel B reports the results for active equity mutual funds. For risk-adjusted returns, we use the one-factor model of CAPM, the four-factor model of Carhart (1997), which includes MKT, SMB, and HML from the three-factor model of Fama and French (1993) and a momentum factor, the four-factor model of CPZ proposed by Cremers, Petajisto and Zitzewitz (2010), the Ferson and Schadt (1996) conditional four-factor model, and the Carhart+Fixed Income six-factor model (for Panel A), where two bond factors are used to capture term premium and default-risk premium. For each panel, we report results with and without back-testing. The back-testing method is similar to the back-testing/filtering methodology described in Mamaysky, Spiegel, and Zhang (2007b). Specifically, for any fund to be included in any quintile at month t, the fund excess return relative to the market at month t-1 needs to have the same sign as the lagged liquidity beta computed using returns between t-13 and t-2. T-statistics are reported in parentheses. The sample includes the CRSP mutual-fund universe for the period April 1983 to December 2010.

	Liq Beta Sorted Portfolios											
	Without Back-testing						With Back-testing					
	1	2	3	4	5	5-1	1	2	3	4	5	5-1
Panel A. All Active Fund	[low]				[high]		[low]				[high]	
Return	0.23	0.17	0.14	0.28	0.56	0.33	0.17	0.14	0.25	0.46	0.78	0.61
	(1.12)	(1.62)	(1.52)	(2.08)	(2.60)	(2.73)	(0.70)	(0.92)	(1.96)	(2.99)	(3.48)	(3.63)
CAPM	-0.22	-0.05	-0.03	0.01	0.10	0.32	-0.35	-0.16	0.02	0.16	0.33	0.68
	(-2.89)	(-1.07)	(-0.56)	(0.15)	(1.16)	(2.68)	(-3.34)	(-2.00)	(0.27)	(1.90)	(2.95)	(4.08)
Carhart	-0.23	-0.07	-0.06	-0.02	0.12	0.34	-0.36	-0.19	0.04	0.17	0.35	0.71
	(-3.17)	(-1.47)	(-1.20)	(-0.25)	(1.35)	(2.79)	(-3.55)	(-2.37)	(0.47)	(2.12)	(3.29)	(4.21)
Carhart+Fixed Income	-0.22	-0.07	-0.07	-0.02	0.09	0.31	-0.38	-0.20	0.04	0.18	0.35	0.72
	(-3.11)	(-1.54)	(-1.38)	(-0.37)	(1.04)	(2.52)	(-3.63)	(-2.50)	(0.45)	(2.17)	(3.36)	(4.19)
Ferson-Schadt	-0.21	-0.05	0.02	0.05	0.16	0.37	-0.35	-0.17	0.12	0.20	0.37	0.72
	(-2.96)	(-1.04)	(0.60)	(0.88)	(1.94)	(3.06)	(-3.39)	(-2.20)	(1.57)	(2.60)	(3.49)	(4.22)
CPZ	-0.18	-0.05	-0.01	0.03	0.16	0.34	-0.32	-0.17	0.09	0.21	0.39	0.71
	(-2.44)	(-1.06)	(-0.21)	(0.39)	(1.88)	(2.82)	(-3.12)	(-2.12)	(1.10)	(2.66)	(3.94)	(4.28)
Panel B. Active Equity Fund												
Return	0.39	0.41	0.42	0.48	0.63	0.25	0.30	0.38	0.45	0.57	0.81	0.51
	(1.57)	(2.05)	(2.17)	(2.27)	(2.60)	(2.31)	(1.12)	(1.75)	(2.21)	(2.69)	(3.35)	(3.55)
CAPM	-0.16	-0.04	-0.02	0.00	0.10	0.26	-0.28	-0.11	0.00	0.10	0.30	0.59
	(-2.21)	(-1.08)	(-0.46)	(0.01)	(1.18)	(2.44)	(-3.13)	(-1.88)	(-0.06)	(1.69)	(2.91)	(4.12)
Carhart	-0.19	-0.09	-0.06	-0.02	0.08	0.27	-0.31	-0.14	-0.02	0.09	0.29	0.61
	(-3.01)	(-2.30)	(-1.52)	(-0.49)	(0.98)	(2.45)	(-3.69)	(-2.63)	(-0.42)	(1.66)	(2.99)	(4.17)
Ferson-Schadt	-0.17	-0.05	-0.01	0.02	0.14	0.31	-0.30	-0.11	0.01	0.12	0.33	0.62
	(-2.74)	(-1.42)	(-0.29)	(0.55)	(1.79)	(2.83)	(-3.48)	(-2.14)	(0.10)	(2.32)	(3.33)	(4.24)
CPZ	-0.13	-0.04	-0.02	0.02	0.14	0.27	-0.26	-0.10	0.02	0.13	0.35	0.61
	(-1.96)	(-1.07)	(-0.45)	(0.40)	(1.77)	(2.49)	(-2.99)	(-1.81)	(0.36)	(2.48)	(3.64)	(4.24)

Table 3

Performance Evaluation Using Traded Liquidity Factors

Each month mutual funds are sorted into equal-weighted quintile portfolios according to historical liquidity beta. The liquidity beta is calculated using a regression of monthly portfolio returns on the market portfolio and the liquidity factor, using the 12 months prior to portfolio formation. Portfolio returns begin from April 1984, using funds with at least 11 months of returns during the prior year. The table reports the average monthly excess return (in percent) of the quintile portfolios, as well as of the high-minus-low portfolio. Panel A reports the results for net fund return. Panel B reports the results for gross fund return. For liquidity-risk-adjusted alpha, we use a five-factor model, where the five factors are one liquidity-risk factor (Amihud, PS, or SadkaPV) plus four factors from the four-factor model of Carhart (1997), the four-factor model of CPZ proposed by Cremers, Petajisto and Zitzewitz (2010), or the Ferson and Schadt (1996) conditional four-factor model. For each panel, we also results with and without back-testing. The back-testing method is similar to the back-testing/filtering methodology described in Mamaysky, Spiegel, and Zhang (2007b). Specifically, for any fund to be included in any quintile at month t, the fund excess return relative to the market at month t-1 needs to have the same sign as the lagged liquidity beta computed using returns between t-13 and t-2. T-statistics are reported in parentheses. The sample includes the CRSP active equity mutual funds for the period April 1983 to December 2010.

Panel A. Net Fund Return

	Liq Beta Sorted Portfolios											
	Without Back-testing						With Back-testing					
	1	2	3	4	5	5-1	1	2	3	4	5	5-1
Liquidity Risk Adjusted Alpha	[low]				[high]		[low]				[high]	
Carhart+Amihud	-0.17	-0.08	-0.05	-0.01	0.11	0.29	-0.30	-0.13	-0.01	0.09	0.32	0.62
	(-2.78)	(-2.14)	(-1.38)	(-0.21)	(1.40)	(2.61)	(-3.51)	(-2.46)	(-0.17)	(1.71)	(3.25)	(4.22)
Carhart+PS	-0.20	-0.09	-0.07	-0.05	0.06	0.26	-0.34	-0.16	-0.03	0.07	0.29	0.63
	(-3.17)	(-2.27)	(-1.79)	(-1.16)	(0.67)	(2.29)	(-4.01)	(-2.90)	(-0.60)	(1.36)	(2.90)	(4.28)
Carhart+SadkaPV	-0.16	-0.09	-0.07	-0.04	0.04	0.20	-0.29	-0.14	-0.03	0.07	0.26	0.55
	(-2.83)	(-2.26)	(-1.82)	(-1.01)	(0.53)	(2.31)	(-3.56)	(-2.62)	(-0.57)	(1.43)	(2.83)	(4.13)
Ferson-Schadt+Amihud	-0.16	-0.04	0.00	0.03	0.17	0.33	-0.28	-0.10	0.02	0.12	0.35	0.64
	(-2.57)	(-1.23)	(-0.10)	(0.79)	(2.14)	(2.97)	(-3.32)	(-1.94)	(0.29)	(2.34)	(3.56)	(4.29)
Ferson-Schadt+PS	-0.18	-0.05	-0.02	0.00	0.13	0.31	-0.33	-0.14	0.00	0.11	0.33	0.66
	(-2.93)	(-1.52)	(-0.68)	(-0.08)	(1.60)	(2.79)	(-3.86)	(-2.50)	(-0.06)	(2.07)	(3.31)	(4.45)
Ferson-Schadt+SadkaPV	-0.14	-0.05	-0.02	0.00	0.09	0.23	-0.27	-0.11	-0.01	0.10	0.28	0.55
	(-2.43)	(-1.37)	(-0.63)	(-0.02)	(1.29)	(2.56)	(-3.26)	(-2.11)	(-0.10)	(2.04)	(3.08)	(4.08)
CPZ+Amihud	-0.11	-0.03	-0.01	0.03	0.18	0.29	-0.24	-0.09	0.04	0.14	0.38	0.62
	(-1.65)	(-0.87)	(-0.22)	(0.80)	(2.26)	(2.63)	(-2.74)	(-1.59)	(0.68)	(2.64)	(4.00)	(4.28)
CPZ+PS	-0.14	-0.04	-0.03	-0.01	0.12	0.26	-0.29	-0.12	0.01	0.11	0.34	0.63
	(-2.17)	(-1.10)	(-0.76)	(-0.29)	(1.42)	(2.35)	(-3.33)	(-2.12)	(0.15)	(2.13)	(3.50)	(4.34)
CPZ+SadkaPV	-0.10	-0.04	-0.02	0.00	0.10	0.21	-0.24	-0.10	0.01	0.11	0.32	0.56
	(-1.72)	(-0.99)	(-0.64)	(0.04)	(1.49)	(2.41)	(-2.85)	(-1.76)	(0.26)	(2.32)	(3.55)	(4.23)

Panel B. Gross Fund Return

	Liq Beta Sorted Portfolios											
	Without Back-testing						With Back-testing					
	1	2	3	4	5	5-1	1	2	3	4	5	5-1
Liquidity Risk Adjusted Alpha	[low]				[high]		[low]				[high]	
Carhart+Amihud	-0.08	0.00	0.03	0.08	0.22	0.29	-0.21	-0.05	0.07	0.18	0.41	0.62
	(-1.23)	(0.09)	(0.77)	(1.79)	(2.64)	(2.66)	(-2.45)	(-0.89)	(1.25)	(3.42)	(4.23)	(4.25)
Carhart+PS	-0.10	0.00	0.01	0.04	0.16	0.26	-0.25	-0.07	0.04	0.16	0.38	0.64
	(-1.63)	(-0.06)	(0.36)	(0.87)	(1.89)	(2.34)	(-2.95)	(-1.34)	(0.79)	(3.07)	(3.87)	(4.32)
Carhart+SadkaPV	-0.07	0.00	0.02	0.05	0.14	0.21	-0.20	-0.06	0.05	0.16	0.35	0.56
	(-1.16)	(-0.02)	(0.42)	(1.19)	(1.97)	(2.36)	(-2.45)	(-1.04)	(0.85)	(3.23)	(3.90)	(4.17)
Ferson-Schadt+Amihud Liquidity	-0.06	0.04	0.08	0.12	0.27	0.33	-0.20	-0.02	0.09	0.21	0.44	0.64
	(-1.00)	(1.17)	(2.32)	(2.94)	(3.43)	(3.01)	(-2.28)	(-0.36)	(1.78)	(4.10)	(4.54)	(4.32)
Ferson-Schadt+PS	-0.08	0.03	0.06	0.09	0.23	0.32	-0.24	-0.05	0.07	0.20	0.42	0.67
	(-1.36)	(0.85)	(1.74)	(2.11)	(2.87)	(2.83)	(-2.81)	(-0.93)	(1.40)	(3.82)	(4.28)	(4.48)
Ferson-Schadt+SadkaPV	-0.04	0.04	0.06	0.09	0.19	0.23	-0.18	-0.03	0.07	0.19	0.37	0.56
	(-0.72)	(1.04)	(1.87)	(2.38)	(2.82)	(2.61)	(-2.17)	(-0.54)	(1.39)	(3.88)	(4.15)	(4.12)
CPZ+Amihud	-0.01	0.05	0.08	0.12	0.28	0.29	-0.15	0.00	0.11	0.22	0.47	0.62
	(-0.17)	(1.31)	(1.97)	(2.89)	(3.55)	(2.67)	(-1.71)	(-0.01)	(2.10)	(4.44)	(5.03)	(4.31)
CPZ+PS	-0.05	0.04	0.06	0.08	0.22	0.26	-0.21	-0.03	0.08	0.20	0.43	0.64
	(-0.71)	(1.05)	(1.42)	(1.82)	(2.68)	(2.40)	(-2.30)	(-0.54)	(1.53)	(3.93)	(4.51)	(4.37)
CPZ+SadkaPV	-0.01	0.05	0.06	0.09	0.21	0.21	-0.15	-0.01	0.09	0.20	0.41	0.56
	(-0.12)	(1.20)	(1.59)	(2.26)	(2.95)	(2.47)	(-1.77)	(-0.18)	(1.66)	(4.18)	(4.64)	(4.26)

Table 4

Alphas for Improved or Deteriorated Liquidity Periods

Each month mutual funds are sorted into equal-weighted quintile portfolios according to historical liquidity beta. The liquidity beta is calculated using a regression of monthly portfolio returns on the market portfolio and the Sadka factor, using the 12 months prior to portfolio formation. Portfolio returns begin from April 1984, using funds with at least 11 months of returns during the prior year. The table reports the average monthly excess return (in percent) of the quintile portfolios, as well as of the high-minus-low portfolio. The sample is split into the periods when market liquidity improves (Liq Up) and the periods when market liquidity deteriorates (Liq Down). For risk-adjusted returns, we use the one-factor model of CAPM, the four-factor model of Carhart (1997), which includes MKT, SMB, and HML from the three-factor model of Fama and French (1993) and a momentum factor, the four-factor model of CPZ proposed by Cremers, Petajisto and Zitzewitz (2010), the Ferson and Schadt (1996) conditional four-factor model, and the five-factor models, where the five factors are the Sadka liquidity factor plus the four factors from the Carhart, Ferson-Schadt, or CPZ four-factor model. T-statistics are reported in parentheses. The sample includes the CRSP active equity mutual funds for the period April 1983 to December 2010.

	Liq Up Liq Beta Sorted Portfolios						Liq Down Liq Beta Sorted Portfolios					
	1 [low]	2	3	4	5 [high]	5-1	1 [low]	2	3	4	5 [high]	5-1
Return	0.67	0.60	0.62	0.72	0.96	0.29	0.04	0.16	0.18	0.18	0.24	0.19
	(2.45)	(2.67)	(2.77)	(2.95)	(3.38)	(2.28)	(0.10)	(0.48)	(0.54)	(0.51)	(0.57)	(1.07)
Alpha												
CAPM	-0.03	0.01	0.03	0.08	0.26	0.29	-0.28	-0.10	-0.08	-0.09	-0.07	0.21
	(-0.38)	(0.24)	(0.68)	(1.45)	(2.33)	(2.18)	(-2.25)	(-1.48)	(-1.09)	(-1.14)	(-0.49)	(1.17)
Carhart	-0.12	-0.07	-0.06	0.02	0.27	0.39	-0.20	-0.08	-0.07	-0.08	-0.03	0.17
	(-1.45)	(-1.44)	(-1.26)	(0.39)	(2.50)	(2.72)	(-2.13)	(-1.39)	(-1.04)	(-1.02)	(-0.24)	(0.98)
Ferson-Schadt	-0.11	-0.06	-0.05	0.03	0.28	0.38	-0.18	-0.04	0.01	0.01	0.00	0.18
	(-1.30)	(-1.26)	(-1.02)	(0.61)	(2.64)	(2.69)	(-1.97)	(-0.68)	(0.10)	(0.11)	(0.82)	(1.30)
CPZ	-0.05	-0.02	-0.02	0.06	0.32	0.36	-0.16	-0.06	-0.04	-0.05	0.01	0.17
	(-0.55)	(-0.38)	(-0.44)	(1.15)	(3.11)	(2.65)	(-1.62)	(-0.95)	(-0.66)	(-0.70)	(0.07)	(0.98)
Carhart+Liq	-0.12	-0.07	-0.07	0.02	0.26	0.37	-0.17	-0.08	-0.08	-0.11	-0.10	0.07
	(-1.54)	(-1.43)	(-1.30)	(0.36)	(2.80)	(3.40)	(-1.93)	(-1.38)	(-1.35)	(-1.63)	(-0.90)	(0.55)
Ferson-Schadt+Liq	-0.11	-0.06	-0.05	0.03	0.27	0.38	-0.13	-0.04	-0.02	-0.04	0.00	0.13
	(-1.43)	(-1.18)	(-0.97)	(0.59)	(3.06)	(3.45)	(-1.44)	(-0.64)	(-0.29)	(-0.60)	(0.03)	(0.93)
CPZ+Liq	-0.05	-0.02	-0.02	0.06	0.32	0.37	-0.13	-0.06	-0.06	-0.08	-0.05	0.08
	(-0.66)	(-0.40)	(-0.43)	(1.21)	(3.56)	(3.51)	(-1.39)	(-0.90)	(-0.89)	(-1.21)	(-0.49)	(0.55)

Table 5

Stock Holding Performance

Each month mutual funds are sorted into ten equal-weighted portfolios according to historical liquidity beta. The liquidity beta is calculated using a regression of monthly portfolio returns on the market portfolio and the liquidity factor, using the 12 months prior to portfolio formation. Portfolio returns begin from April 1984, using funds with at least 11 months of returns during the prior year. The table reports the average monthly excess return (in percent) of the stock holding portfolios of each fund quintile, as well as of the high-minus-low stock holding portfolio. In Panel A, the sample is split into the periods when market liquidity improves (Liq Up) and the periods when market liquidity deteriorates (Liq Down). In Panel B, the sample is the entire sample period. For risk-adjusted returns, we use the one-factor model of CAPM, the four-factor model of Carhart (1997), which includes MKT, SMB, and HML from the three-factor model of Fama and French (1993) and a momentum factor, the four-factor model of CPZ proposed by Cremers, Petajisto and Zitzewitz (2010), the Ferson and Schadt (1996) conditional four-factor model, and the five-factor models, where the five factors are the Sadka liquidity factor plus the four factors from the Carhart, Ferson-Schadt, or CPZ four-factor model. T-statistics are reported in parentheses. The sample includes the CRSP active equity mutual funds for the period April 1983 to December 2010.

Panel A. Liquidity Up or Down Periods

	Liq Beta Sorted Portfolios					
	Liq Up			Liq Down		
	1 [low]	5 [high]	5-1	1 [low]	5 [high]	5-1
Return	0.93	1.12	0.19	0.22	0.43	0.20
	(2.81)	(3.40)	(1.80)	(0.43)	(0.87)	(1.36)
Alpha						
CAPM	0.08	0.28	0.20	-0.17	0.06	0.22
	(0.84)	(2.65)	(1.90)	(-1.16)	(0.41)	(1.50)
Carhart	0.06	0.30	0.24	-0.08	0.10	0.18
	(0.62)	(2.76)	(2.05)	(-0.69)	(0.84)	(1.29)
Ferson-Schadt	0.07	0.31	0.24	-0.08	-0.12	0.20
	(0.73)	(2.82)	(2.01)	(-0.74)	(1.50)	(1.55)
CPZ	0.12	0.34	0.22	-0.03	0.15	0.18
	(1.22)	(3.23)	(1.97)	(-0.30)	(1.25)	(1.32)
Carhart+Liq	0.06	0.29	0.23	-0.04	0.06	0.10
	(0.70)	(2.93)	(2.46)	(-0.39)	(0.50)	(0.93)
Ferson-Schadt+Liq	0.07	0.31	0.24	-0.02	0.11	0.13
	(0.79)	(3.02)	(2.48)	(-0.16)	(0.98)	(1.18)
CPZ+Liq	0.11	0.35	0.23	0.00	0.11	0.10
	(1.25)	(3.49)	(2.55)	(0.04)	(0.97)	(0.97)

Panel B. Full Sample Period

	Liq Beta Sorted Portfolios					
	1 [low]	2	3	4	5 [high]	5-1
Return	0.61	0.72	0.70	0.70	0.81	0.20
	(2.07)	(2.55)	(2.47)	(2.48)	(2.82)	(2.21)
Alpha						
CAPM	-0.05	0.10	0.08	0.07	0.17	0.22
	(-0.60)	(1.07)	(0.83)	(0.85)	(2.03)	(2.47)
Carhart	-0.05	0.06	0.05	0.05	0.15	0.20
	(-0.64)	(0.69)	(0.52)	(0.56)	(1.91)	(2.22)
Ferson-Schadt	-0.03	0.10	0.08	0.07	0.20	0.23
	(-0.43)	(1.04)	(0.82)	(0.89)	(2.49)	(2.54)
CPZ	0.01	0.12	0.10	0.10	0.21	0.20
	(0.11)	(1.26)	(1.05)	(1.15)	(2.69)	(2.28)
Carhart+Liq	-0.02	0.07	0.06	0.05	0.12	0.14
	(-0.32)	(0.77)	(0.60)	(0.63)	(1.64)	(2.04)
Ferson-Schadt+Liq	0.00	0.10	0.08	0.08	0.16	0.16
	(-0.05)	(1.09)	(0.88)	(0.94)	(2.14)	(2.24)
CPZ+Liq	0.03	0.13	0.11	0.10	0.18	0.15
	(0.47)	(1.36)	(1.14)	(1.23)	(2.51)	(2.15)

Table 6

Determinants of Fund Liquidity Beta

This table performs a Fama-Macbeth regression of funds' liquidity beta on funds' characteristics using Newey-West standard errors with a lag length of 12 months. The liquidity beta is calculated using a regression of monthly portfolio returns on the market portfolio and the liquidity factor, using the 12 months prior to portfolio formation. T-statistics are reported in parentheses. The sample includes the CRSP active equity mutual funds for the period April 1983 to December 2010.

	Full					Liq Up					Liq Down				
Expense Ratio	0.09	0.07	0.07	0.08	0.05	0.11	0.07	0.08	0.10	0.05	0.06	0.07	0.06	0.06	0.05
	(3.10)	(2.61)	(2.56)	(2.79)	(1.73)	(3.64)	(2.74)	(2.65)	(2.96)	(1.69)	(1.59)	(1.70)	(1.56)	(1.59)	(1.18)
Turnover Ratio	-0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.03	-0.03	-0.01	-0.01	0.00	-0.01
	(-0.43)	(0.00)	(0.16)	(0.29)	(0.31)	(0.19)	(0.21)	(0.48)	(0.65)	(0.76)	(-0.96)	(-0.19)	(-0.17)	(-0.10)	(-0.16)
Flow	0.05	0.04	0.04	0.03	0.04	0.04	0.04	0.03	0.03	0.03	0.06	0.05	0.04	0.04	0.05
	(2.22)	(2.41)	(1.85)	(1.83)	(2.00)	(1.95)	(2.32)	(1.64)	(1.57)	(1.76)	(2.04)	(2.16)	(1.79)	(1.81)	(1.99)
Load Dummy	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01
	(0.09)	(0.30)	(0.16)	(0.15)	(0.52)	(0.07)	(-0.12)	(-0.45)	(-0.42)	(0.11)	(0.09)	(0.82)	(1.02)	(0.96)	(0.97)
Fund TNA	-0.02	-0.02	-0.02	-0.01	-0.02	-0.02	-0.01	-0.01	-0.01	-0.01	-0.02	-0.02	-0.02	-0.01	-0.03
	(-1.81)	(-1.09)	(-0.92)	(-0.62)	(-1.30)	(-1.81)	(-0.70)	(-0.64)	(-0.49)	(-0.79)	(-1.43)	(-1.13)	(-0.92)	(-0.56)	(-1.37)
Fund Family TNA	0.03	0.05	0.05	0.06	0.06	0.07	0.07	0.07	0.08	0.07	-0.02	0.03	0.01	0.03	0.04
	(0.35)	(0.57)	(0.50)	(0.63)	(0.77)	(0.92)	(0.88)	(0.93)	(0.98)	(1.17)	(-0.15)	(0.26)	(0.11)	(0.29)	(0.43)
Fund Age	-0.01	0.00	0.00	0.00	-0.01	-0.02	-0.01	0.00	0.00	-0.02	0.00	0.00	0.01	0.01	0.00
	(-1.04)	(-0.22)	(0.14)	(0.70)	(-1.20)	(-2.12)	(-1.06)	(-0.56)	(0.19)	(-2.08)	(0.39)	(0.59)	(0.69)	(0.91)	(0.20)
Stock Illiquidity	0.14	0.02	0.30	0.25	0.42	0.36	0.07	0.62	0.51	0.83	-0.13	-0.04	-0.07	-0.06	-0.06
	(0.61)	(0.16)	(1.12)	(0.97)	(1.29)	(1.02)	(0.39)	(1.46)	(1.25)	(1.58)	(-0.59)	(-0.21)	(-0.33)	(-0.32)	(-0.23)
Trading IVOL		0.17					0.29					0.03			
		(2.02)					(2.31)					(0.49)			
Trading Stock Size			-0.15					-0.17					-0.14		
			(-2.72)					(-2.75)					(-1.93)		
Trading Analyst Following				-0.10					-0.13					-0.08	
				(-2.54)					(-2.79)					(-1.40)	
Active Share					0.04					0.06					0.02
					(1.90)					(2.37)					(0.66)
Adjusted R-square	0.07	0.12	0.11	0.11	0.08	0.06	0.13	0.11	0.11	0.08	0.08	0.11	0.10	0.11	0.09

Table 7

Predictive Regressions of Fund Performance

This table reports the coefficients of Fama-Macbeth regressions of monthly fund five-factor alphas on various lagged fund characteristics. The liquidity beta is calculated using a regression of monthly portfolio returns on the market portfolio and the liquidity factor, using the 12 months prior to portfolio formation. The dependent variable is a fund's five-factor alpha, which adds the liquidity factor to the Carhart 4-factor model. T-statistics computed using Newey-West standard errors with 12 lags are reported in parenthesis. The sample includes the CRSP active equity mutual funds for the period April 1983 to December 2010.

	Carhart+Liq								
	Full	Liq Up	Liq Down	Expansion	Recession	Expansion Liq Up	Expansion Liq Down	Recession Liq Up	Recession Liq Down
	(321 Months)	(117 Months)	(114 Months)	(285 Months)	(36 Months)	(160 Months)	(125 Months)	(17 Months)	(19 Months)
Liq Beta	0.10	0.14	0.04	0.10	0.07	0.14	0.05	0.13	0.01
	(2.81)	(3.00)	(0.80)	(2.52)	(0.95)	(2.74)	(0.78)	(2.08)	(0.21)
Expense Ratio	-4.31	4.04	-14.57	-1.82	-23.95	7.05	-13.18	-24.22	-23.71
	(-1.06)	(0.91)	(-2.49)	(-0.45)	(-2.87)	(1.56)	(-2.18)	(-2.40)	(-1.83)
Turnover Ratio	0.01	0.00	0.03	0.02	0.00	0.00	0.04	0.02	-0.02
	(0.99)	(0.07)	(1.16)	(1.08)	(0.02)	(-0.07)	(1.28)	(0.44)	(-0.39)
Flow	-0.02	-0.02	-0.01	-0.02	0.00	-0.02	-0.02	-0.01	0.01
	(-3.06)	(-3.14)	(-1.70)	(-3.17)	(0.11)	(-2.76)	(-1.99)	(-0.60)	(0.44)
Load Dummy	0.01	-0.01	0.04	0.02	-0.03	-0.01	0.05	-0.03	-0.03
	(0.67)	(-0.40)	(1.38)	(0.85)	(-0.28)	(-0.27)	(1.51)	(-0.19)	(-0.46)
Log of Fund TNA	-0.03	-0.03	-0.04	-0.03	-0.06	-0.02	-0.04	-0.05	-0.08
	(-3.30)	(-2.03)	(-2.93)	(-2.66)	(-2.56)	(-1.89)	(-2.50)	(-0.89)	(-2.56)
Log of Fund Family TNA	0.18	0.28	0.04	-0.10	2.35	0.25	-0.55	0.57	3.95
	(0.19)	(0.24)	(0.03)	(-0.10)	(1.09)	(0.20)	(-0.31)	(0.68)	(1.28)
Fund Age	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01
	(0.60)	(-0.55)	(1.11)	(-0.17)	(2.08)	(-0.86)	(0.42)	(0.51)	(7.20)
Flow Volatility	-0.23	-0.12	-0.36	-0.25	-0.10	-0.35	-0.12	1.97	-1.95
	(-0.77)	(-0.31)	(-0.75)	(-0.73)	(-0.11)	(-0.70)	(-0.24)	(1.65)	(-1.44)
Systematic Flow Risk	0.01	0.02	-0.01	0.01	0.02	0.02	-0.02	0.01	0.03
	(0.61)	(1.76)	(-0.73)	(0.50)	(0.50)	(1.95)	(-1.31)	(0.17)	(0.61)
Funding Liq Risk	-0.01	-0.04	0.02	-0.01	-0.06	-0.04	0.04	-0.05	-0.06
	(-0.79)	(-1.75)	(0.76)	(-0.38)	(-1.94)	(-1.64)	(1.09)	(-1.15)	(-0.87)
Prior-year Return	2.18	2.07	2.31	2.27	1.42	2.14	2.44	1.35	1.47
	(4.60)	(3.16)	(3.17)	(4.39)	(1.29)	(3.05)	(2.86)	(1.32)	(1.09)
Adjusted R-square	0.25	0.24	0.27	0.25	0.26	0.24	0.27	0.28	0.25

Table 8

Fama-French 100 Size and Book-to-Market Portfolios

Each month the Fama-French 100 size and book-to-market value-weighted portfolios are sorted into equal-weighted quintiles according to their historical liquidity beta. The liquidity beta is calculated using a regression of monthly size and book-to-market portfolio returns on the market portfolio and the liquidity factor, using the 12 months prior to portfolio formation. Portfolio returns begin from April 1984, using 12 months of returns during the prior year. The table reports the average monthly excess return (in percent) of each quintile, as well as of the high-minus-low portfolio. For risk-adjusted returns, we use the one-factor model of CAPM, three-factor model of Fama and French (1993), the four-factor model of Carhart (1997), which includes MKT, SMB, and HML from the three-factor model of Fama and French (1993) and a momentum factor, and the five-factor models, where the five factors are the Sadka liquidity factor plus the four factors from the Carhart four-factor model. T-statistics are reported in parentheses. The sample includes the CRSP active equity mutual funds for the period April 1983 to December 2010.

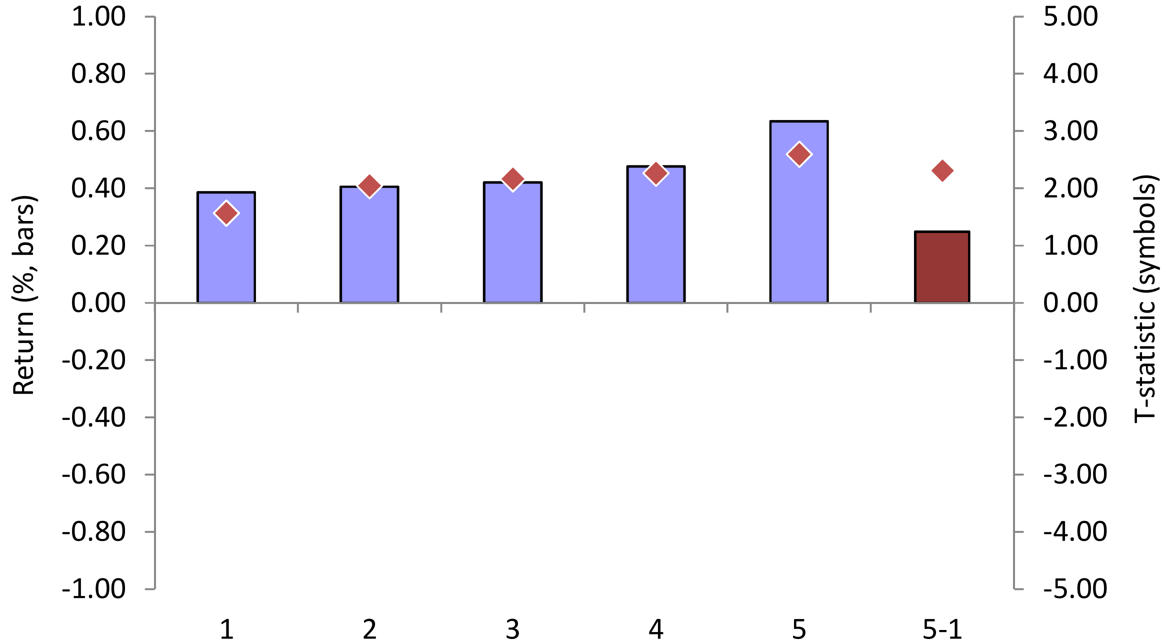
	Liq Beta Sorted Portfolios					
	1 [low]	2	3	4	5 [high]	5-1
Return	0.29	0.70	0.77	0.79	0.46	0.17
	(0.91)	(2.47)	(2.74)	(2.75)	(1.55)	(0.90)
Alpha						
CAPM	-0.35	0.10	0.18	0.20	-0.13	0.23
	(-2.37)	(1.00)	(1.69)	(1.64)	(-0.84)	(1.16)
FF3	-0.38	-0.02	0.05	0.03	-0.31	0.07
	(-3.22)	(-0.31)	(0.89)	(0.43)	(-2.69)	(0.39)
Carhart	-0.42	0.00	0.09	0.11	-0.21	0.21
	(-3.43)	(-0.07)	(1.61)	(1.45)	(-1.83)	(1.13)
Carhart+Liq	-0.37	-0.01	0.07	0.08	-0.25	0.12
	(-3.27)	(-0.14)	(1.34)	(1.10)	(-2.38)	(0.72)

Table 9

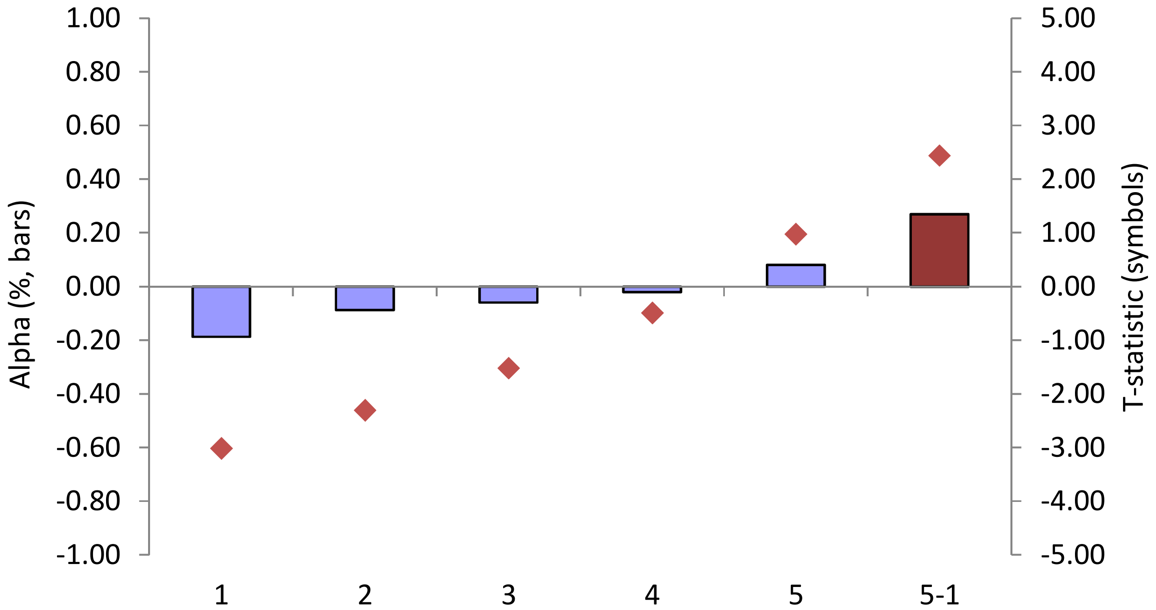
Predictive Regressions of Fund Performance with Other Skill Predictors

This table reports the coefficients of Fama-Macbeth regressions of monthly fund five-factor alphas on various lagged fund characteristics plus several lagged fund skill predictors. The lagged predictors are the active share measure of Cremers and Petajisto (2009), the return gap measure of Kacperczyk, Sialm, and Zheng (2008), and the R^2 measure of Amihud and Goyenko (2013). The liquidity beta is calculated using a regression of monthly portfolio returns on the market portfolio and the liquidity factor, using the 12 months prior to portfolio formation. The dependent variable is the five-factor alpha, which adds the liquidity factor to the Carhart four factor model. T-statistics computed using Newey-West standard errors with 12 lags are reported in parenthesis. The sample includes the CRSP active equity mutual funds for the period April 1983 to December 2010.

			Carhart+Liq		
Liq Beta	0.10	0.10	0.10	0.10	0.09
	(2.81)	(2.85)	(2.71)	(3.05)	(3.07)
Expense Ratio	-4.31	-4.26	-5.57	-5.77	-6.35
	(-1.06)	(-1.05)	(-1.35)	(-1.19)	(-1.33)
Turnover Ratio	0.01	0.01	0.02	0.02	0.02
	(0.99)	(1.08)	(1.14)	(1.32)	(1.44)
Flow	-0.02	-0.02	-0.02	-0.02	-0.02
	(-3.06)	(-3.02)	(-3.01)	(-3.08)	(-2.97)
Load Dummy	0.01	0.01	0.02	0.00	0.01
	(0.67)	(0.70)	(0.88)	(0.18)	(0.32)
Log of Fund TNA	-0.03	-0.03	-0.03	-0.03	-0.03
	(-3.30)	(-3.18)	(-3.17)	(-3.71)	(-3.52)
Log of Fund Family TNA	0.18	-0.05	0.10	0.37	0.21
	(0.19)	(-0.05)	(0.10)	(0.43)	(0.23)
Fund Age	0.00	0.00	0.00	0.00	0.00
	(0.60)	(0.69)	(0.57)	(1.16)	(0.97)
Flow Volatility	-0.23	-0.20	-0.24	-0.30	-0.26
	(-0.77)	(-0.66)	(-0.82)	(-1.02)	(-0.90)
Systematic Flow Risk	0.01	0.01	0.01	0.01	0.01
	(0.61)	(0.63)	(0.77)	(1.04)	(1.06)
Funding Liq Risk	-0.01	-0.01	-0.01	-0.01	0.00
	(-0.79)	(-0.86)	(-0.41)	(-0.57)	(-0.12)
Prior-year Return	2.18	2.10	2.17	2.12	2.08
	(4.60)	(4.37)	(4.63)	(4.71)	(4.59)
Return Gap		0.05			0.03
		(5.60)			(3.36)
Active Share			0.04		0.03
			(1.37)		(1.03)
R^2				-0.01	-0.01
				(-0.33)	(-0.35)
Adjusted R-square	0.25	0.26	0.27	0.28	0.30

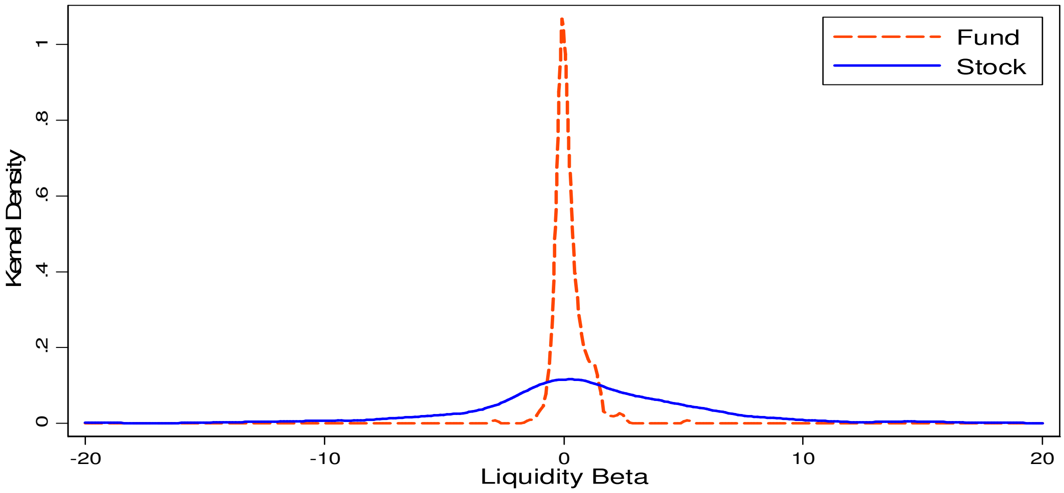


Panel A. Monthly Returns of Liquidity Beta Portfolios

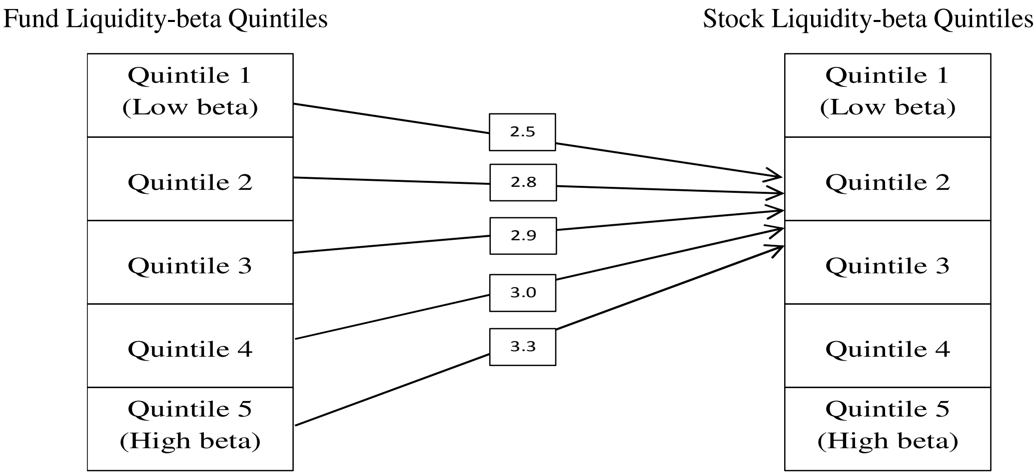


Panel B. Monthly Alphas of Liquidity Beta Portfolios

Figure 1. The figure plots the monthly returns (Panel A) and Carhart four-factor alphas (Panel B) of liquidity-beta-sorted portfolios as well as the high-minus-low portfolio. Each month mutual funds are first sorted into equal-weighted quintile portfolios according to historical liquidity beta. The liquidity beta is calculated using a regression of monthly portfolio returns on the market portfolio and the liquidity factor, using the 12 months prior to portfolio formation. Portfolio returns begin April 1984, using funds with at least 11 months of returns during the prior years. The sample includes the active mutual fund universe for the period April 1983 to December 2010.



Panel A. Distribution of Stock and Fund Liquidity Betas



Panel B. The Ranking of the Stock Holdings of Liquidity-Beta-Sorted Fund Quintile in the Stock Universe

Figure 2. Panel A plots the distribution of fund liquidity beta and that of stock liquidity beta. Panel B plots where the stock holdings of each liquidity-beta-sorted fund quintile are ranked in the stock universe. On left-hand side, funds are sorted into quintile portfolios according to their fund liquidity beta. On the right-hand side, all the stocks in the stock universe are also sorted into quintile portfolios according to the stock liquidity beta. The arrow that links a fund quintile to a stock quintile indicates the average rank of the fund-quintile stock holdings in the stock universe. The box in the middle of the figure provides the exact value of the average quintile rank. The liquidity-beta rank of the stock holdings of each fund is computed as the value-weighted average rank of the individual stock liquidity betas in the stock universe. The rank of the fund-quintile stock holdings for each fund quintile is then computed as the equal-weighted average of the liquidity-beta rank of the stock holdings of each fund in the fund quintile portfolio. The fund's (stock's) liquidity-beta is calculated using a regression of monthly fund (stock) returns on the market portfolio and the liquidity factor, using the 12 months prior to portfolio formation. The sample includes active equity mutual funds and NYSE, AMEX and NASDAQ common stocks (removing stocks with price lower than 5 dollars) for the period April 1983 to December 2010.

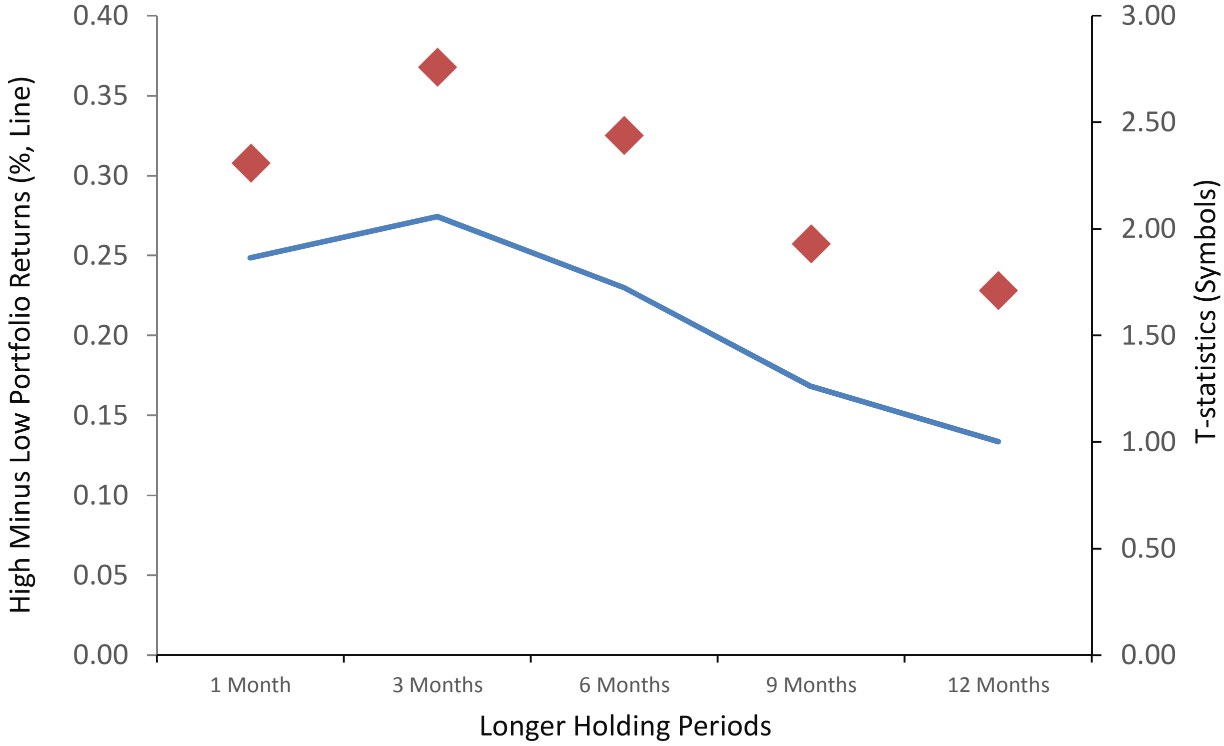


Figure 3. We rank funds into quintiles based on their liquidity beta at time 0 and then report the high-minus-low fund performance spread over holding periods of 1, 3, 6, 9, and 12 months after portfolio formation. The sample includes active equity mutual funds for the period April 1983 to December 2010.

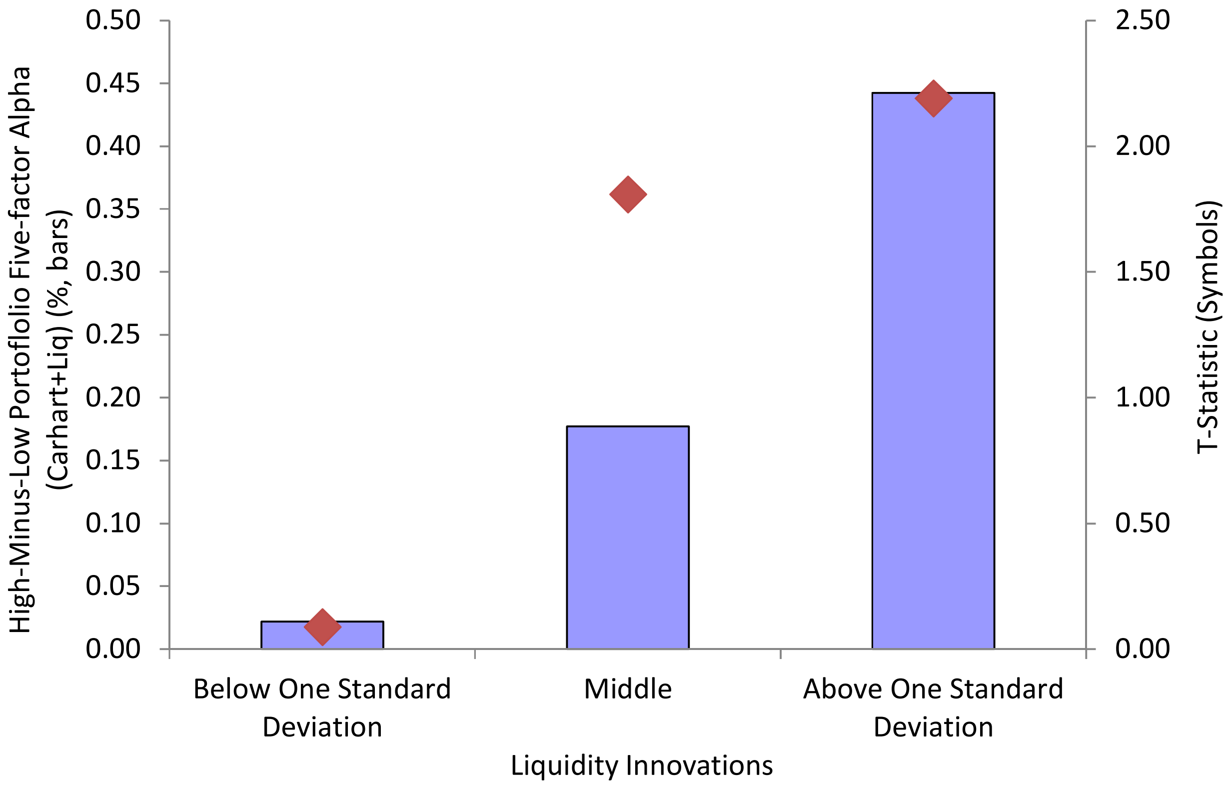


Figure 4. The figure plots the Carhart+Liquidity five-factor alpha of the high-minus-low liquidity-beta-sorted fund-quintile return spread during different market liquidity conditions. The sample period is divided into three subperiods: the months for which liquidity innovation is one standard deviation below its mean, the months for which it is one standard deviation above its mean, and the remaining months. The sample includes active equity mutual funds for the period April 1983 to December 2010.