Liquidity Risk and Mutual Fund Performance

Xi Dong Shu Feng Ronnie Sadka*

Abstract

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This paper hypothesizes that market liquidity constrains mutual fund managers' ability to outperform, which introduces a higher liquidity risk exposure (beta) for skilled managers. Consistently, we document an annual liquidity beta performance spread of 4% in the cross-section of mutual funds over the period 1983-2014. Liquidity risk premia based on traditional passive equity portfolios can explain only an insubstantial part of this spread. Instead, the differential ability of high liquidity beta funds to outperform across high and low market liquidity states, due to either differential rate of mispricing correction or intensity of informed trading, contributes significantly to explaining this spread. Tests of mispricing proxied by a comprehensive set of 68 anomalies and tick-by-tick trades from a large proprietary institutional trading dataset corroborate the contribution of the latter two channels. The findings highlight the complex effect of liquidity risk on active management.

1. Introduction

Systematic liquidity risk has been a focus of recent literature, especially in light of the financial crisis. Prior studies demonstrate the pricing of liquidity risk exposure (beta) in the cross-section of traditional assets such as stocks and bonds. This paper studies the implications of liquidity risk on the cross-section of mutual funds–an asset class with a combined $30 trillion under management globally (ICI 2014 Fact Book). In contrast to passive portfolios of traditional assets, the performance effect of liquidity risk on actively managed portfolios can be more complex. The variation of market liquidity can affect active managers' investment process, which, in turn, affects the value generated from it. Given the availability of fund-level holdings information, mutual funds provide a fertile environment for an in-depth analysis of this issue.[1]

We focus on two potentially important channels by which the liquidity beta of mutual funds can predict the cross-section of their future performance. One channel is the unconditional liquidity risk premium of fund positions. Given the liquidity risk premium among traditional assets, a wide dispersion in the average liquidity risk of fund holdings in mutual funds will translate into a premium in the cross-section of expected mutual-fund returns. The second channel is the difference in risk exposure between funds managed by informed and uninformed managers. Various considerations suggest that informed traders are expected to generate higher abnormal returns during improved market liquidity periods than during periods of decline in market liquidity. This is likely to translate into a higher liquidity beta in the fund return of an informed manager than the return of an otherwise identical, yet uninformed manager. Indeed, theoretical works (see, e.g., Kondor, 2009) show that performance asymmetry across liquidity states results with informed funds, which trade mispriced stocks, carrying a high liquidity beta.

Motivated by the above hypotheses, we examine the relation between the liquidity beta of active mutual funds and their future performance. We find that high liquidity beta funds outperform low liquidity beta funds by 3.4% (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) in the entire fund universe over the period 1983-2014. The relative outperformance of high liquidity beta funds is economically and statistically significant. It is robust to controlling for various risk and style factors as well as to conditional performance models. Focusing on equity funds, for which detailed holding

[1] Sadka (2010) demonstrates the return predictability of liquidity risk exposure in hedge funds. However, the study does not study the different channels by which liquidity risk affects the return of actively managed portfolios.

information is available, we do not find evidence strongly supporting the first channel. Only a small portion (at most 20%) of the liquidity-beta performance spread can be explained by the difference in the liquidity-risk premium of funds' underlying equity holdings. The primary reason is that mutual funds avoid holding stocks with extreme levels of liquidity risk. Therefore, the small cross-sectional dispersion in fund exposure to liquidity risk translates into a low cross-sectional difference in traditional equity liquidity risk premium.

However, our findings suggest that the second channel plays a significant role in explaining the performance spread. Specifically, high liquidity beta funds significantly outperform low liquidity beta funds by at least 2.7% per year after various adjustments for the liquidity risk premium of stocks, for example, a five-factor alpha (Carhart four-factors plus a liquidity risk factor). The relative outperformance is positive in both improved and deteriorated liquidity periods. High liquidity beta funds deliver a significantly positive five-factor alpha on average, but much of their abnormal outperformance stems from improved liquidity periods than from deteriorated liquidity periods. Specifically, they earn a positive five-factor alpha of 3% during improved liquidity periods, outperforming low liquidity beta funds by a five-factor alpha of 4% per year (t-value=3.40). In contrast, they only outperform low liquidity beta funds by a five-factor alpha of 1.2% per year during deteriorated liquidity periods.

We consider two possible reasons for the asymmetry in abnormal fund performance across liquidity states. The first is a higher rate of mispricing correction during improved liquidity periods. This hypothesis posits that informed funds are the funds that hold underpriced and avoid overpriced stocks. Arbitrageurs in the economy trade against mispricing at some point in time, generating abnormal returns in the mispriced stocks and forcing prices to converge to fundamentals. However, mispricing can persist for months (Lamont and Thaler, 2003; Lamont and Stein, 2004) due to limits to arbitrage such as price impacts and trading costs, redemptions, and margin constraints. These limits are more severe during liquidity downturns (see, e.g., Merton, 1987; Shleifer and Vishny, 1997). Higher liquidity is accompanied by greater market efficiency (e.g., Chordia, Roll, and Subrahmanyam, 2008, 2011) as it leads to increased trading against mispricing (see, e.g., Sadka and Scherbina, 2007). Therefore, mispricing is likely to be corrected at a higher rate during improved liquidity periods. Since underpriced stocks are included in the informed funds' portfolios, while overpriced stocks are included in the market portfolio or in other uninformed funds' portfolios, an abnormal performance spread between the informed and the uninformed is likely to be realized during such periods.

Second, the intensity of informed trading of stocks with private information is higher during improved liquidity periods. Theory suggests that during periods of an exogenous increase in noise trading, informed traders trade larger quantities without incurring additional price impacts and therefore earn more profits (see, e.g., Kyle, 1985). It follows that informed funds are more likely to outperform in states of the world for which market liquidity improves, even if mispricing is corrected at a constant rate every period.

We perform several tests indicating both reasons contribute to our findings. First, using a comprehensive set of a total of 68 anomalies documented in academic and practitioner studies as a proxy for mispriced portfolios, we find that the five-factor alpha of anomalies are, on average, more significant and larger during improved liquidity periods. Correspondingly, we find that the stocks held by high liquidity beta funds deliver a significantly positive five-factor alpha (3.3% per year with a t-value of 2.60) during improved liquidity periods, and an insignificant alpha during deteriorated liquidity periods. In contrast, the five-factor alpha of the stocks that low liquidity beta funds hold is insignificantly different from zero in both periods. A mispricing factor, which is computed as the average return of all anomalies, explains a significant portion of the relative outperformance of high liquidity beta funds over the entire sample period as well as during the improved liquidity periods.

Second, using a large proprietary database of tick-by-tick institutional trades from Abel Noser Solutions, we show that informed active funds indeed trade more aggressively and generate higher trading performance during improved liquidity periods than deteriorated ones. The trading performance asymmetry is economically important compared to the total fund performance asymmetry across liquidity states. Informed funds' intensity of trading of mispriced stocks, proxied by stocks' anomaly rankings, is also significantly higher during improved liquidity periods. In fact, such intensity is only significant and in the right direction (buy underpriced and sell overpriced) during improved liquidity periods. It is insignificant and in the wrong direction during deteriorated liquidity periods. In contrast, uninformed funds' trading intensity is insignificantly different from zero during either period. The results provide evidence consistent with the notion that informed trading causes higher mispricing correction during periods of improved liquidity than during periods of deteriorated liquidity.

Additionally, after controlling for stock illiquidity level, high liquidity beta funds trade stocks with significantly smaller size, higher idiosyncratic volatility, and lower analyst following than low liquidity beta funds; these are the type of stocks that funds are more likely to trade when they have private information (see, e.g., Agarwal, Jiang, Tang, and Yang, 2012). They also have significantly higher active share—a measure of the degree to which a fund informatively deviates its stock positions from benchmarks (Cremers and Petajisto, 2009). These significant relations are mostly realized during the improved liquidity periods. Other fund characteristics may also contribute to the liquidity beta performance effects. However, we find little evidence that other concerns such as illiquidity, expenses, trading costs, and different flow-related effects play a major role.

This study contributes to understanding three aspects of the relation between liquidity risk, market efficiency, and active management. First, the recent crisis has provoked a heated discussion in academia and the popular press on the importance of understanding the risk-adjusted performance of financial institutions.[2] Yet successful investors are often described, or describe themselves, as risk takers in various media outlets.[3] Our findings call for caution when it comes to evaluating the liquidity risk of active funds. The essential role of market liquidity in achieving efficient prices and in arbitrage trading suggests that active managers able to identify and dynamically trade mispriced stocks may well be liquidity risk takers at the same time (i.e., introduce liquidity beta to achieve their performance). In contrast to the widely studied effects of liquidity beta on stocks (Pástor and Stambaugh 2003; Acharya and Pedersen, 2005; Sadka, 2006), treasury bonds (Li, Wang, Wu, and He, 2009), and corporate bonds (Lin, Wang, and Wu, 2011), we demonstrate that the effect of liquidity risk on active mutual funds is more complex than its effect pertaining to traditional assets because the effectiveness of active management depends on it. Our results can be interpreted as a concept of liquidity risk inherent in the performance of active funds that is conceptually distinct from the traditional passive traded liquidity factors provided in existing studies.

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[2] See, e.g., Rajan (2005) and the Oscar winning documentary Inside Job (2010) (Screenplay: www.sonyclassics.com/awards-information/insidejob_screenplay.pdf)

[3] A casual Google search with key words "successful investor" and "risk taker" finds connections between the two in various articles and books. For example, Barron's featured value investor, Andrew Burish, described himself as "a risk taker by nature" ("The Best Advice: Value Hunter," 2013); John A. Mulheren, a Wall Street icon, was featured as an avid risk taker in New York Times ("An Avid and Successful Risk-Taker," 1988); Canadian billionaire and fund manager, Eric Sprott, described himself as "a risk-taker and a very successful investor" in his blog ("Is Gold Suitable for Any Investor?" 2013). Successful investors featured in books are also often described as willing or rational risk takers instead of someone who shy away from risk (see, e.g., Volunteer Forty-niners: Tennesseans and the California Gold Rush, 1997, p. 177; The Templeton Touch, 2012, p. 9; The Big Win: Learning from the Legends to Become a More Successful Investor, 2012, p. 181; Investing from Scratch: A Handbook for the Young Investor, 2007, p. 137). In books that summarize the common attributes of successful investors, some authors argue that any successful investor's story is a story of risk taking (The Power of Thinking Differently: An Imaginative Guide to Creativity, 2011, p. 104), and in order to become a successful investor, one has to accept taking certain risk (Random Wisdom, 2012, p. 151).

Second, we contribute to the literature on the relation between liquidity and informed trading. Some studies believe higher liquidity is associated with lower informed trading (at least in the cross-section of stocks). However, dynamically, informed trading intensity and its return and liquidity are predicted to be positively correlated as the informed trade more and/or collect more private information when liquidity increases (Kyle, 1985; Admati and Pfleiderer, 1988). We extend these studies to utilize the positive time-series relation between liquidity, informed trading, and return (i.e., liquidity beta) to identify informed funds. To the best our knowledge, we are the first to provide direct evidence that informed funds' indeed trade more aggressively and earn higher trading profits during improved systematic market liquidity periods.

Third, a recent literature studies the relation between active managers, mispricing, and market efficiency. Kokkonen and Suominen (2015) find evidence in changes in quarterly holdings suggesting hedge funds trade to reduce mispricings especially at times of improving funding liquidity. Jylhä, Rinne and Suominen (2014) shows that hedge funds supply liquidity. Others include Akbas, Armstrong, Sorescu, Subrahmanyam (2015), Avramov, Cheng, Hameed (2015), and Cao, Liang, Lo, Petrasek (2015). These studies provide further evidence supporting the motivation of our second channel. Relatedly, the vast anomaly literature has seen a nascent trend of jointly studying the systematic patterns of an exhaustive set of anomalies from public available databases (e.g., Green, Hand, and Zhang, 2014; Mclean and Pontiff, 2015; Engelberg, McLean, and Pontiff, 2015).

We add to these two strands of literature by showing an implication of the interaction between active managers and mispricing on managers' return patterns, that is, an increased liquidity beta. We document a pervasive effect of liquidity risk on a large number of anomalies. We also provide direct evidence based on actual trades (complementing prior indirect evidence based on the changes in fund quarterly holdings) that shed light on the causal effect of informed trading on the positive relation between market liquidity changes and mispricing-based strategy returns.

Last, we contribute to the literature on predicting mutual fund performance. Given the tremendous resources and interest devoted to selecting fund managers, predicting the outperforming managers is the key challenge. Recent literature has identified several predictors of fund performance. In particular, Huang, Sialm, and Zhang (2011) show that funds that increase (mostly idiosyncratic) risk perform worse than funds that maintain stable risk. In contrast, we provide a separate predictor, which suggests that friction-constrained managers may not be able to avoid assuming systematic liquid risk in order to demonstrate skill. This constraint leads to exposing mispricing-trading funds to liquidity risk. Our results support the view that liquidity is a first-order important friction (see, e.g., Mitchell, Pedersen, and Pulvino, 2007) particularly for arbitrageurs in the process of achieving market efficiency.

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. Section 4 considers the two main hypotheses for this relation. Section 5 provides some additional analysis to control for other alternative explanations and highlight the robustness of the results. Section 6 concludes.

2. Data and Liquidity Risk Measures

Monthly mutual fund return data are obtained from the CRSP Survivor-Bias-Free database for the period 1983–2014. Only funds that report returns on a monthly basis are kept in the sample. To address incubation bias (Evans, 2010), we exclude the first 12-month fund performance. The removal of these young funds also alleviates the concern of cross-subsidization by their respective fund families (Gaspar, Massa, and Matos, 2006). Since we focus on active funds, consistent with prior studies, we exclude money-market, sector, emerging, global, and index funds. We also exclude funds that in the previous month manage less than $15 million.

The returns are based on US dollars and are excess of the risk-free rate. The common-stock holding information for funds holding equities is collected from the Thomson Reuters Mutual Fund Holdings Database. We aggregate into one observation all observations pertaining to different share classes. For the qualitative attributes of funds with multiple share classes (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, 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.

We follow the literature and measure the systematic liquidity risk as unexpected changes in market liquidity (see, e.g., Pástor and Stambaugh, 2003; Acharya and Pedersen, 2005; Li, Wang, Wu, and He, 2009; Lin, Wang, and Wu, 2011). Such changes are measured by various non-traded liquidity factors.

The primary factor used here is the permanent-variable price-impact factor obtained from Sadka (2006), which are extracted from the Trades and Quotes (TAQ) tick-by-tick data. First, the components of price impact are estimated monthly, by stock, using tick-by-tick data, which generally provide hundreds or even thousands of observations per month. We estimated the following regression per company per month:

$$\Delta p_t = \Psi D_t + \lambda D_t V_t + \bar{\Psi} \Delta D_t + \bar{\lambda} \Delta D_t V_t + y_t, \tag{A1}$$

where

Δp_t = the change in transaction price

V_t = the order flow (trade size)

D_t = an indicator variable that receives a value of 1 for a buyer-initiated trade and –1 for a seller-initiated trade

y_t = the unobservable pricing error

We classified a trade as buyer (seller) initiated if the trade price was above (below) the midpoint of the quoted bid and ask as of one second before the transaction occurred (trades priced exactly at the midpoint were discarded from the estimation). Equation A1 is further adjusted to account for predictability in order flow and block trades. Specifically, we replaced $D_t V_t$ with unanticipated order flow, calculated as the fitted error term from a five-lag autocorrelation regression of $D_t V_t$. We also replace D_t with its unanticipated component. A dummy variable is used for each of the four terms to separate trades of more than 10,000 shares.

The regression separates four components of price impact: fixed effects unrelated to trade size (Ψ and $\bar{\Psi}$ [permanent and transitory, respectively]) and variable costs (λ and $\bar{\lambda}$ [permanent and transitory, respectively]). A permanent price effect carries on to the next trade; a transitory effect concerns only the current trade price.

Then, these firm-specific estimates are aggregated to form monthly market-wide estimates of each component of liquidity. As liquidity is highly persistent, we follow the literature to generate a time series of uncorrelated shocks for each price-impact component by applying an AR(3) model over the sample period and using the residuals as proxies of shocks. Finally, since price impacts measure illiquidity rather than liquidity, we add a negative sign to each time series, so that a positive shock can be interpreted as an improvement to market liquidity. Sadka provides evidence that only the permanent-variable component is priced in the cross section of stocks.

A permanent change in the stock price depends on the amount of uninformed trading relative to the amount of informed trading (see Kyle, 1985). Since our second hypothesis is based on the implications of time-varying informed trading, the permanent price impact is particularly relevant for the purpose of our study. We therefore focus on this factor, henceforth simply referred to as the liquidity factor. Other liquidity factors offered in the literature, e.g., the Pástor-Stambaugh factor, based on transitory changes, and the Amihud measure, intended to capture total price impact, used by Acharya and Pedersen, produce qualitatively consistent, yet weaker results; we discuss these in a later section.

Table 1 reports the summary statistics of all active mutual funds (Panel A) and active domestic equity mutual funds (Panel B).[4] The sample includes 8,703 distinct 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 increases in recent years. Most characteristics of active equity funds resemble those of all active funds except the turnover ratio, 93.07% for active equity and 165.72% for all active funds.

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; 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 shorter than one year. Therefore, the liquidity beta of funds that buy and hold stocks may also significantly change for horizons longer than one year.

To account for such time variation, we estimate liquidity beta by following previous studies that use a one-year rolling window to estimate time-varying beta or alpha.[5] The liquidity loading of a fund is calculated using a regression of the fund's monthly return on the market return and the liquidity factor over a one-year rolling window.[6] Quintile portfolios of mutual funds are formed

[4] 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, and 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, GI, AGG, GCI, GRI, GRO, LTG, MCG, and 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 shares, then the fund will be included.

[5] See, e.g., Chevalier and Ellison (1999), Nanda, Wang, and Zheng (2004), Lou (2012), and Kacperczyk, Nieuwerburgh, and Veldkamp (2013).

[6] In unreported results, we perform a sensitivity analysis of betas. We sort funds into decile portfolios based on betas estimated using 24-month rolling window, requiring a minimum of 10-month valid fund return

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 2014.

3.1. All Active Funds

Berk and van Binsbergen (2014) advocate examining mutual funds that do not hold only 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. 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 (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.[7]

Since in this section we examine the entire mutual-fund universe, of which bond funds are a large portion, we adopt 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

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observations in each rolling window. Our main results remain qualitatively similar. We do not estimate betas using windows shorter than 12 months as the limited number of observations decrease the precision in estimating beta (and the literature does not offer daily liquidity risk factors).

[7] 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.

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 benchmarks. For example, the relative performance is 0.31% per month (t-value=2.52) using the Carhart+Fixed Income six-factor model. The performance difference is economically significant for active mutual funds. 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 performance measures such as Ferson-Schadt and CPZ.

3.2. Measurement Error and Backtesting

Mamaysky, Spiegel, and Zhang (2007) provide evidence that previous performance studies are subject to estimation problems. Specifically, 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, Mamaysky et. al. suggest using a backtesting 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.

Since our liquidity beta is a statistical measure, and subject to a similar criticism of estimation errors and noise, we mitigate these concerns using the backtesting 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 excess liquidity beta computed using returns between t-13 and t-2 (excess of the average beta in the cross-section of funds computed over the same period). Thus, we keep only funds for which there is a concordance between the lagged excess liquidity beta and the lagged excess return. That is, if a fund's return is above average (i.e., positive excess return), its lagged liquidity beta is also above average. In this way, the liquidity beta of a fund is required to exhibit some predictive success in recent periods before it can be used to predict the returns during 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 backtesting method (e.g., Mamaysky, Spiegel, and Zhang, 2007; Kacperczyk, Sialm, and Zheng, 2008; Dong and Massa, 2014; Boguth and Simutin, 2015). For example, the performance difference for the Carhart+Fixed Income model increases from 0.31% (t-value=2.52) before using backtesting 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 holding exclusively domestic equity to facilitate comparison with prior mutual-fund studies. This restriction also sets the ground for examining the channels leading to such a liquidity beta effect in later sections.

Table 2, Panel B, reports the after-fee portfolio returns of domestic equity fund quintiles. 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 post-ranking liquidity betas of the sorted portfolios as well as the dispersion of their returns, in line with the purpose of the sorting procedure.[8]

The results show that the high liquidity loading portfolio has the highest average next-month return, while the low liquidity loading portfolio has the lowest average next-month return. The rest of the portfolio returns and the alphas generally increase with the liquidity loading. The Carhart four-factor alpha of the high minus low liquidity beta fund return spread is 0.28% per month or 3.4% annually with a t-statistic of 2.47. The performance difference is again economically significant for active equity mutual funds.

The right half of Panel B in Table 2 also includes the results using the backtesting 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 backtested and non-backtested results are similar to those based on all active funds. The results suggest that the liquidity risk exposure of a fund provides valuable information to investors for predicting its future performance.

[8] The equity-fund portfolios remain highly diversified with roughly 300 funds in each quintile per month.The conclusions for the remaining part of the paper are qualitatively similar if using simple sorting methods instead.

Since investors cannot short mutual funds, the strategies assuming a short position in the bottom quintiles and long positions in the top ones are not tradable. However, they demonstrate how, conditioning on liquidity beta, investors can select funds and avoid potential losses that are proportional to the performance differences between the quintiles.

4. Hypotheses

In this section, we investigate the main hypotheses that can support a 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 1 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 cannot invest in such stocks. The figure shows that the cross-sectional dispersion of liquidity beta across fund stock holdings is significantly narrower than the cross-sectional dispersion of liquidity beta across the entire stock universe.

Panel B of Figure 1 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 value of the average quintile rank. For example, for Quintile 5 of funds, the liquidity betas of the stocks that this fund quintile holds have a quintile ranking of 3.6 in the stock universe, thus an arrow linking Quintile 5 of funds to above the midpoint of the box representing Quintile 4 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 ranked closely to each other in the stock universe. They are located between Quintile 2.7 and Quintile 3.6 of liquidity beta in the stock universe on average. The results indicate that the stock holdings of high liquidity beta funds have only a slightly higher average liquidity beta ranking than the stock holdings of low liquidity beta funds.

This narrow dispersion in liquidity beta of stocks generates only a small difference in liquidity risk premium. For example, the return difference between Quintile 3 and Quintile 4 of stocks is minor, with a Carhart alpha of 0.06% per month, which is only 20% of the Carhart alpha of the return spread between high and low liquidity beta funds. Overall, the results suggest 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 correspondingly small difference in stock liquidity risk premium.

4.1.2. Factor Model

Fund holdings do not account for fund managers' activity within the quarter. For example, round-trip transactions within the quarter and trading costs can both affect a fund's actual return. Therefore, for the purpose of evaluating the liquidity beta of a fund's actual performance, a fund's actual net monthly return is a more appropriate return variable. In unreported results, we verify that the liquidity beta based on mutual fund actual returns is not statistically different from the liquidity beta estimated from fund reported holdings on average.

Nevertheless, in this section, we use factor models to formally explain funds' actual net return. This quantifies the fraction of the high minus low liquidity beta actual fund return difference that can be explained by its exposure to the liquidity risk premium in equities. The Carhart four-factor model has often been used as a major benchmark model for domestic equity funds in prior work. It does not directly account for liquidity risk. In Table 3, we try to explain the high minus low liquidity beta fund return by regressing it 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. In addition to Carhart, we use the Ferson-Schadt conditional model and the CPZ model, which extend the Carhart model to consider conditional variables and tradability issues. To interpret the intercept of the five-factor regression as alpha, one needs to use a traded liquidity risk factor. We use three existing widely-used liquidity risk factors "Amihud", "PS", and "SadkaPV". They are based on the liquidity measures from Amihud (2002), Pástor and Stambaugh (2003), and Sadka (2006).[9]

Alternatively, to control for stock characteristics, we also compute the characteristic adjusted returns by taking the return difference between a fund return and its characteristic matched benchmark return based on the fund's stock holdings. The benchmark is an augmented DGTW benchmark that includes the liquidity characteristic (proxied by the Amihud measure) (hence forth DGTW_Liq). Specifically, following the convention (e.g., Fama and French), when there are four dimensions, we divide stocks into 2 size, 4 value, 4 momentum, and 4 liquidity portfolios, to arrive at 128 passive portfolios (in contrast to the original 125 DGTW portfolios).[10]

In addition, to account for the possibility that each factor may capture a different aspect of liquidity, we also consider a seven-factor model by adding all three existing liquidity risk factors (PS, Amihud, and SadkaPV) to the standard Carhart four-factor model. The literature also suggests that stock-level illiquidity and systematic liquidity risk exposure need not bear a simple relation. On the one hand, theory and empirical evidence suggest that when market liquidity declines, investors might prefer to sell liquid stocks in order to save on transaction costs.[11] As a result, Pástor and Stambaugh (2003) argue that the price reaction to aggregate liquidity changes could actually be stronger for stocks that are more liquid. They find that high liquidity beta stocks are more liquid (based on their liquidity measure) and larger in size. On the other hand, there is also evidence that high liquidity beta stocks are positively related to illiquidity when both liquidity beta and illiquidity are calculated based on the Amihud measure (e.g., Acharya and Pedersen, 2005; Watanabe and Watanabe, 2008). Nevertheless, if the relation between liquidity beta and illiquidity is positive, illiquidity could explain the high performance of the high liquidity beta funds studied here. To

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[9] The traded Pástor-Stambaugh factor is obtained from Luboš Pástor's website. The traded Amihud liquidity risk 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 risk factor. The nontraded Amihud liquidity risk 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.

[10] Results are similar if we simply remove the momentum dimension and replace it with the liquidity dimension so that we can construct 125 portfolios just like the original DGTW portfolios.

[11] See Scholes (2000), Brown, Carlin, and Lobo (2010), Ben-David, Franzoni, and Moussawi (2012), Manconi, Massa, and Yasuda (2012).

account for this possibility, we add a liquidity level factor. Following the literature (e.g., Acharya and Pedersen, 2005), the factor is the return difference between illiquid and liquid stocks, where stocks are sorted into decile portfolios based on the Amihud measure of stock illiquidity.[12] To be conservative, we use these factor models to explain the performance spread without backtesting as the spread with backtesting is even stronger and therefore less captured by the existing risk factors.

The results, reported in the right half of Table 3, show the alpha of the performance spread drops by only a small magnitude. The largest drop is from the 0.28% Carhart alpha in Panel B of Table 2 to the 0.23% five-factor Carhart+SadkaPV alpha, which implies that 18% of the performance difference can be explained by the exposure to the liquidity risk premium of equities. In untabulated results, we find the spread does not significantly load on the liquidity level factor, which is consistent with the literature view that liquidity level and systematic liquidity risk exposure need not be related.

The right half of Table 3 reports fund gross performance before fees. The gross fund performance provides a cleaner picture of the value in terms of alpha created by fund managers. 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 (Quintile 1 and 2 of funds). These funds have zero alphas. The five-factor models mainly fail to explain the returns of the funds with higher liquidity betas (Quintile 4 and Quintile 5). For example, Quintile 5 generates a significantly positive annual alpha of 2% to 3% under all performance measures. Therefore, the explanation for the gross performance difference between high and low liquidity beta funds is not low liquidity beta funds' inability to match the benchmark performance but rather high liquidity beta funds' ability to outperform the benchmark before fees.

Overall, the results in Table 3 confirm that only a small portion of the relative outperformance of high liquidity beta funds can be explained by the exposure to the liquidity risk and liquidity level premium of equities. The remaining performance difference is still economically and statistically

[12] The return difference is between Decile 1 (illiquid) and Decile 10 (liquid).

significant. The before-fee performance analysis further supports that the driver of the performance difference is the positive alpha of high liquidity beta funds.[13]

4.2. Hypothesis 2: Risk Exposure Difference between Skilled and Unskilled Funds

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/liquidity premium of stocks and that they deliver significantly positive alpha. These results point to the possibility that funds with higher liquidity beta are likely to be more skillful in generating alpha. This section further examines whether this channel contributes to the performance effect.

4.2.1. Market Liquidity and Asymmetric Abnormal Performance

We first demonstrate that the abnormal performance of high liquidity beta funds is asymmetric between periods with positive (Up) and negative (Down) market liquidity innovations. Unexpected changes in market liquidity are measured by the non-traded Sadka liquidity factor, which has a mean of zero. As explained above, this factor focuses on changes in market-wide informed-to-noise trading ratio and is therefore particularly relevant for investigating our second hypothesis which focuses on the time variation in (relative) informed trading.

It is important to note that we focus on market liquidity conditions measured by innovations 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 systematic liquidity level for our tests would mimic the inclusion of a time dummy variable, comparing the first and second halves of the sample period.[14] Second, in an efficient market, prices react to unexpected 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 quantity and profits is unanticipated. Third, in contrast to other studies,

[13] The small difference in liquidity risk/liquidity premium in the cross section of mutual funds is consistent with the 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, they are prohibited from investing more than 15% of their assets in illiquid securities and restricted in using leverage. Third, a fund return is a value-weighted return of a well-diversified portfolio of stocks.

[14] 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 central 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.

our focus is on the correction rather than the level of mispricing during a particular period. Mispricing level may remain unchanged, thereby realizing a zero alpha for fund managers during a period when the liquidity remains at a low level with little arbitrage trading.

Table 4 reports the net alphas of liquidity beta-sorted fund quintiles during Up and Down subperiods. We compute liquidity risk-adjusted alphas by adding liquidity factors to a four-factor model. This is to address the concern that our high minus low liquidity beta fund return is constructed to have a positive (beta) exposure to liquidity risk, which implies, by construction, that a positive or negative liquidity shock on average leads to a corresponding positive or negative excess return or alpha before adjusting for liquidity risk. Any asymmetric performance across Up and Down periods solely due to a positive beta exposure to any of the liquidity factors should disappear after controlling for these factors.

The previous section also shows that five-factor models using either the Amihud or the Pástor-Stambaugh measures to construct traded liquidity factors, in either liquidity risk or liquidity level configurations, explain less of the high minus low liquidity beta fund return than does the Sadka traded factor. Therefore, the five-factor alphas we report henceforth will focus on the Sadka traded liquidity factor.[15] Nevertheless, we also consider the 7-factor model that augments a 4-factor model with all three liquidity risk factors, as well as the 8-factor model that includes all three liquidity risk factors and the liquidity level factor. Including these alternative liquidity factors addresses the concern that the performance of these liquidity factors are all likely to be asymmetric by construction across Up and Down liquidity states. An 8-factor alpha is therefore the abnormal return that all four existing liquidity factors jointly cannot explain.

The results show that high liquidity beta funds outperform low liquidity beta funds in both Up and Down periods. The outperformance, however, is only statistically significant in Up periods. For example, the Carhart+Liquidity five-factor alpha of the high minus low liquidity beta fund return spread is 0.38% per month, or 4.6% per year, with a t-value of 3.40 during Up periods, while it is only 1.2% per year with a t-value of 0.84 during Down periods. Overall, the outperformance in Down periods is about one third to one fourth of the outperformance in Up periods.

During Up periods, high liquidity beta funds deliver significantly positive alphas. For example, the Carhart+Liquidity five-factor alpha of high liquidity beta funds is 0.25% per month with a t-value of 2.68. The difference in the five-factor alpha between the two subperiods is 0.33% per

[15] The results are similar if the Sadka traded factor is replaced with one of the other traded liquidity factors.

month (4.0% per year), which is economically and statistically significant (t-value=2.52). In contrast, there are no significant alpha differences in the performance of low liquidity beta funds between the two periods.

The asymmetry in performance is once again not driven by the possibility that liquidity beta and illiquidity level may be positively related. In that case, illiquid stocks would appreciate in price more on average than liquid stocks when market liquidity rises; and depreciate more on average when market liquidity falls. Yet, such effect would be captured, if not by the liquidity risk factors, then by the liquidity level factor.

Overall, the results suggest that the relative outperformance of high liquidity beta funds is positive in both subperiods, but predominantly driven by the significantly positive alpha of high liquidity beta funds upon improvement in market liquidity. In addition, the results provide further evidence inconsistent with the liquidity risk premium hypothesis. The performance spreads between high and low liquidity beta funds are positive in both Up liquidity states and Down liquidity states. To clearly qualify for a risk 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.

A. Asymmetric Abnormal Performance and Liquidity Beta: The Framework

This subsection lays down the framework explaining why the performance asymmetry in the above section can lead to a positive relation between a fund's liquidity beta and its ability to generate liquidity risk adjusted alpha. Consider the following specification of two funds: One is skilled and the other is unskilled. The two are otherwise identical except for their liquidity risk-adjusted 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 Up periods is driven by the fund's liquidity risk premium and other risk premiums, which are the same as the skilled fund.

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

In Down periods, the expected returns of the two funds are identical 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.[16]

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 an extended period, those months characterized by positive or negative liquidity innovations occur, on average, randomly.[17] If skilled funds tend to generate positive alphas relative to unskilled funds in months with positive liquidity innovations, but generate zero alpha in months with negative liquidity innovations, then they are more likely to have a higher liquidity beta over the period than unskilled funds, ceteris paribus, due to the additional covariation of the skilled fund's abnormal performance with market liquidity when market liquidity switches between Up and Down states.

Overall the analysis in this section suggests that everything else equal, skilled funds are more likely to be high liquidity beta funds if skilled funds create more value from their private signals when market liquidity improves than when it deteriorates.

B. Explanations

One key difference obtains between our concept of an informed fund manager and a traditional informed investor: Informed fund managers are not able to generate alpha irrespective of market liquidity conditions. Literature on the importance of liquidity in the process of achieving market efficiency indicates managers' ability is likely to be more concentrated in Up liquidity states; in Down liquidity states, mispricing is less likely to be corrected and informed managers cannot trade aggressively. This concept has several implications.

First, the restrictive assumption that informed managers' alpha is noticeably different across two liquidity states provides fund performance and mispricing correction a significant degree of independence from market liquidity. The covariation between managers' skill and market liquidity only occurs when the market switches between Up and Down states. Managers can still generate alpha during the Up subperiods, which, by definition, implies performance that does not covary

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16 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.

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

with systematic liquidity risk within the subperiods. Since informed managers generate liquidity risk-adjusted outperformance over uninformed managers in at least one state and similar performance as uninformed managers in the other state (i.e., informed managers' ability is not completely constrained by market liquidity), a performance model with the liquidity factor cannot completely explain away the unconditional relative outperformance of informed managers over the entire sample period either.

The setup also considers that informed trading and therefore mispricing correction are dynamic and can be affected by various forces other than market liquidity alone and that mutual-fund managers do not generally uncover alpha opportunities handily every month. For example, in a particular month of improved market liquidity, a skillful manager may not be able to outperform, either because the mispricing of the stocks she holds is not corrected, or because she was unable to identify mispriced stocks in the beginning of the month even if mispricing correction is dependent on market liquidity in that particular month.

We can alternatively assume there are more than two states. Each state has more than one month. This generally does not change the main message of the framework as long as managers can still generate higher positive alpha within a higher liquidity state. In the robustness section, we show the performance asymmetry still hold if we alternatively partition the sample period into three liquidity states. However, mispricing correction cannot be too state dependent (i.e., there are too many states), given that arbitrageurs hunting for alpha opportunities have always been an important force for achieving market efficiency (e.g., hedge funds). Otherwise, the correction could prove very risky. For example, if fund performance is solely determined by the magnitude of a nondiversifiable liquidity shock each month, there would be little alpha left after adjusting for liquidity risk. Arbitrageurs are not considered informed investors any more if they are evaluated by liquidity risk-adjusted alpha. They are then too constrained by liquidity risk and have little incentive left to trade on mispricing

Second, our hypothesis differs from prevailing studies of fund timing skills. A fund with factor timing ability would exhibit a higher beta when the factor realization is positive and a lower beta when the factor realization is negative than a fund without factor timing ability. Therefore, the average or unconditional beta of the fund over a period with both positive and negative factor realization months does not need to be either higher or lower than that of a fund without a factor timing ability. That is, whether a fund has timing skill or not reveals no information about whether a fund has a high or low unconditional liquidity beta. In our framework, informed fund managers simply hold underpriced assets without advance knowledge of when market liquidity will improve.

In unreported results, we confirm that high and low liquidity beta funds do not have significantly different ability in timing unexpected market liquidity shocks.

Relatedly, our hypothesis does not require that the monthly performance of the skilled fund be more sensitive to market liquidity changes than that of the unskilled fund during the months with positive liquidity innovations. The liquidity beta conditional on positive innovation periods, i.e., the Up liquidity beta β^{+}, does not need to be higher for the skilled funds than for the unskilled fund, as demonstrated in Equations (1) and (2).

In the next three sections, we examine whether the difference in the rate of mispricing correction and the intensity of informed trading could contribute to the fund performance asymmetry discussed above.

4.2.2. Asymmetric Rate of Mispricing Correction: Stock Holdings

In this section, we first investigate whether the mispricing-correction channel contributes to the performance asymmetry by examining the returns of fund holdings. The literature suggests that mispricing is less likely to be corrected in periods of negative liquidity shocks, whereas in periods of positive shocks, the cost of arbitrage drops, which facilitates arbitrage trading and accelerates the convergence of prices to fundamentals. During the periods when mispricing is being corrected, the price of underpriced (overpriced) stocks increases (decreases), realizing a positive (negative) alpha (e.g., Sadka and Scherbina, 2007; Collin-Dufresne and Fos, 2015a). Therefore, a skilled manager who is able to hold underpriced stocks and avoid overpriced stocks is likely to realize a positive alpha in the Up periods.

In Table 5, we report the average monthly stock holding returns of liquidity beta-sorted fund quintiles over the Up and Down subperiods 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 disclosed quarterly stock holdings (value-weighted) and hold them until the next time the fund discloses its holdings.

The results show that the stocks held by high liquidity beta funds significantly outperforms the stocks held by low liquidity beta funds with a Carhart+Liquidity five-factor alpha of 0.34% per month (t-value=2.98) during Up periods. The outperformance is driven by the positive alpha (a five-factor alpha of 0.25% per month) of the stocks held by high liquidity beta funds. The five-factor alpha difference held by high liquidity beta funds between Up and Down periods is significant at 0.25% per month. In contrast, the performance of the stocks held by low liquidity beta funds deliver zero alphas during both subperiods. There are no significant differences in their alphas between the two periods. Controlling for various alternative liquidity risk and liquidity level factors does not affect the results.

Overall, the results provide consistent evidence that high liquidity beta funds hold (and/or avoid) underpriced (overpriced) stocks whose mispricing is particularly corrected in periods with positive liquidity innovations.

It is worth noting that the mispricing of some stocks may exacerbate rather than stabilize during liquidity crises, as arbitrageurs experiencing withdrawals 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, underpriced (overpriced) stocks may realize negative (positive) alpha in the Down periods. This would again induce positive comovement (i.e., beta) between skilled funds' performance and liquidity (see Kondor (2009)), further supporting our hypothesis.

4.2.3. Asymmetric Rate of Mispricing Correction: Anomalies

Mispricing is unobservable; therefore, to more directly support the mispricing correction argument, we follow recent literature (e.g., Stambaugh and Yuan, 2015) by using a wide range of anomalies as a proxy for potential mispricing.[18] Note that mispricing-based anomalies are more likely to disappear post-publication (e.g., Mclean and Pontiff (2015) find anomaly profits are 58% lower post academic publication) than anomalies driven by risk/illiquidity reasons. Therefore, a small set of prominent and surviving anomalies may have a significantly higher chance of being driven by risk/liquidity than other anomalies. For that reason and due to statistical biases, many mispricing-based anomalies that existed in the original sample period used for publication, may not persist in our sample period. Therefore, we examine a large set of return predictors (105 variables) documented in academic and practitioner studies based on the anomalies identified by Green, Hand, and Zhang (2013, 2014, GHZ henceforth).[19]Since the Carhart model has been the most widely-used model for evaluating mutual-fund performance, we use it as the benchmark model. The model carries an implicit assumption that size, value, and momentum-related anomalies are considered passive (risk or style) factors. We therefore exclude all the anomalies based on the three concepts in GHZ, as well as the ones that are directly based on the CAPM model or liquidity factors. Details are provided in the appendix. Due to the concern that some anomalies are due to data snooping, we

[18] Following many studies (see, e.g., Jegadeesh and Titman, 2001; Pástor and Stambaugh, 2003; Wei, Wermers, and Yao, 2014), we remove penny stocks (price<5) that are largely not invested by large institutions to avoid the anomaly returns being driven by microcaps and extreme outliers.

[19] Different arguments are made regarding whether a certain anomaly is due to mispricing or risk. Such debate is beyond the scope of this paper. We only posit that the average of them are mispriced based on the widely-used mutual fund performance evaluation model, i.e., the Carhart 4-factor model.

only keep the anomalies whose Carhart four-factor alpha still has the same sign in our sample period as the sign predicted in the original studies of these anomalies. This results in 68 anomalies. For each anomaly, we then long the underpriced leg and short the overpriced leg to create the return to the trading of mispricing based on that anomaly.

In Table 6, Panel A, we report the performance of a strategy that equal-weights all 68 anomaly return series. The results show this strategy delivers 0.36% (0.20%) more return (five-factor alpha) per month during Up periods than during Down periods. The t-value of the difference is 3.54 (2.78).[20] Among the 68 anomalies, 85% (74%) of them have more significant returns (five-factor alphas) in the Up periods than in the Down periods. The higher statistical significance in Up periods increases the likelihood that fund managers identify the mispricing and capture it during such periods.

Given the virtue of parsimony, we then use the average long-short anomaly return as a mispricing factor and replace the liquidity factor with it in the five-factor model to explain fund performance. The results in Table 6, Panel B show that the high minus low fund performance spread and fund stock holding return spread are more than halved in magnitude and become statistically insignificant over the full sample period as well as during the UP periods, although the remaining alpha is marginally economically meaningful for mutual funds (a monthly return of 0.13% for the full sample period and 0.19% for the Up period).

Overall, the results show consistent evidence that mispricing is on average corrected more during improved liquidity periods, and this asymmetric rate of mispricing correction indeed contributes to a significant portion of the performance asymmetry of high liquidity beta funds. The results suggest that high liquidity beta funds are skilled in investing assets that are mispriced at least relative to the standard performance models for mutual funds.

However, it is important to note that the mispricing proxy is determined *ex post* after observing which anomalies had worked in the specific sample period. One could possibly identify *ex post* a set of anomalies that had worked in a specific sample period and explain a certain portion of the liquidity-beta-based fund performance spread. But, mispriced portfolios (including anomalies), if indeed due to mispricing, are always likely to be different portfolios overtime as old mispricing disappears and new one emerges. This makes a fixed passive rule to identify mispricing *ex ante* highly difficult and imprecise. Furthermore, the next section will show informed managers could

[20] GHZ show that the mean absolute cross-correlation between return predictors is quite small, measuring just 0.08. Therefore, the equal-weighted average return across the anomalies is highly significant.

also dynamically change the intensity of their trading on mispricing across different liquidity states, which can further introduce liquidity state-dependent risk in fund performance. Such changes in trading intensity cannot be precisely observed and measured either.

Therefore, our key message is not the usefulness of specific mispricing factors for understanding active funds' performance, but the positive relation between skill and liquidity beta of active funds when managers' ability to profit from these mispriced portfolios is constrained by liquidity. As long as mispricing correction (and dynamic trading on mispricing) introduces liquidity risk in fund performance, such risk (i.e., liquidity beta) becomes a characteristic of the performance of active funds that trade on mispricing.

4.2.4. Asymmetric Intensity of Trading: Trading Performance and Volume

Informed funds can outperform further in Up periods by trading more aggressively the stocks for which they have private information about the stocks' true value. An exogenous positive liquidity change may induce informed traders to increase their trading quantities, which increases the expected profits from their private signals (e.g., Kyle, 1985). In this section, we examine whether this channel contributes to the performance asymmetry. Our market liquidity shock is a proxy for the exogenous liquidity shock to individual mutual-fund managers. Compared to individual stock liquidity, market liquidity can hardly be endogenously determined by any individual trader of a stock (the total liquidity level of a stock can be decomposed into a market liquidity component and an idiosyncratic liquidity component). A market liquidity shock is therefore a close proxy to the notion of an exogenous shock.

However, since market liquidity shocks are uncorrelated over time, the low-frequency, quarterly fund holdings data limit the power to detect possible trading activity in response to monthly market liquidity changes. We therefore utilize a large proprietary database of active fund trades from Abel Noser Solutions to shed light on this matter. The database includes about 120 million actual trades from thousands of active US funds over a 12-year period. Previous research has shown that Abel Noser institutional clients constitute approximately 10% of the total CRSP daily dollar volume.[21] Therefore, the active funds in the Abel Noser database are likely to overlap with a subset of the active funds in our sample and can allow us to draw inference about the monthly trading patterns of active funds in general.

[21] See, e.g, Puckett and Yan, 2011; Anand, Irvine, Puckett, and Venkataraman, 2012.

For a limited period of time between January, 1999 and September, 2011, Abel Noser provided its academic subscribers with the fund-level identifier in the institutional trading data. Using this dataset, Puckett and Yan (2011) show that at least some active funds are informed traders insofar as they exhibit high trading profits on a quarterly basis. Using a methodology similar to theirs, we identify informed and uninformed traders by estimating the performance of all actual trades of each fund every month.

Specifically, for each fund, we separate all its trades into buys and sells. We then track the return of each buy or sell trade from the execution date (using the execution price) until the end of the month. Our holding-period return calculations account for both stock splits and dividend. We subtract the DGTW_Liq benchmark return over the same holding period to compute abnormal returns. Next, for each fund we compute the average abnormal returns of buy minus sell trades, value-weighted by the value traded. Every quarter, we sort funds into quintiles based on their average monthly trading performance over the prior quarter. It is often reported that Abel Noser fund identifiers are quite noisy. To maximize the signal to noise ratio to capture informed/uninformed funds, we proxy the informed (uninformed) traders using the quintile of funds with the highest (lowest) average monthly trading performance.

The left panel of Table 7 shows that the informed funds deliver significantly positive trading performance, while the uninformed funds deliver low and negative trading performance post ranking, consistent with them indeed being informed and noise traders, respectively. Furthermore, informed funds' trading performance in LIQ Up is almost 3 times that in LIQ Down months (i.e., 0.60% vs 0.20%), while uninformed funds' trading performance exhibits the opposite pattern. This suggests that the relative trading outperformance of informed funds is indeed liquidity-state dependent and it is higher when market liquidity improves.

The right panel of Table 7 shows that informed funds' total monthly trading volume, where daily fund volume is scaled by the total volume of the stock over the corresponding trading day (i.e., to compare the intensity of informed trading relative to the trading of average investors), is significantly higher than that of uninformed funds only in Up states. In Down states, or on average (over the full sample period), the trading volume does not significantly differ across informed and uninformed funds. During the Up state, the difference between the informed and the uninformed funds' trading volume equals 1 day's total trading volume of an average stock in the fund portfolio with a t-value of 3.09. This difference accounts for roughly 30% of the average monthly trading volume of an average informed fund in the sample, which is a relatively large fund in the mutual fund universe (see, e.g., Puckett and Yan, 2011). Informed funds' trading volume in Up states is also roughly 30% higher than their own volume in Down states.

Taken together, these results provide direct evidence that active funds' actual trading performance is indeed liquidity-state dependent and that they trade more aggressively when market liquidity improves.

4.2.5. Asymmetric Intensity of Trading: Trading on Mispricing

Next, we investigate more specifically whether informed funds trade on the mispricing (anomaly) characteristic more intensively when market liquidity improves. We construct two measures to evaluate the relative intensity of informed funds' trading on mispricing. The first measure is the intensity of trading on mispriced stocks based on average anomaly rankings. Specifically, to correspond to the average anomaly results in Table 6, we average all 68-anomaly decile ranks for each stock. Each anomaly is constructed such that its long leg decile is the underpriced decile and its short leg decile is the overpriced decile. Therefore, a higher rank indicates a higher likelihood to be underpriced according to the average score from 68 dimensions of anomaly characteristics. We then sort stocks based on this average mispricing ranking into decile portfolios. Intuitively, we transform the decile ranks into a score between 0 and 100% such that the most overpriced decile (Decile 1) is assigned a score of 0, while the most underpriced decile (Decile 10) is assigned a score of 100%. The average anomaly trading intensity score for the informed or uninformed fund portfolio each month is calculated as the difference between the buy stock scores and sell stock scores, value-weighted by the total trading volume (normalized) of each stock by all funds in the corresponding fund portfolio.

If the informed funds buy stocks with a score of 100% and sell stocks with a score 0, on average, then they are trading perfectly based on signals from average anomalies and therefore receive a score of 100%. If they buy and sell stocks from the same anomaly decile, then the intensity score is zero, which means their trading is anomaly neutral, i.e., they do not appear to trade on anomalies. Likewise, a negative score would indicate a contrarian trading relative to that suggested by the anomaly rankings.

Furthermore, if informed traders trade in the wrong direction of an anomaly, i.e., buy the overpriced and sell the underpriced stocks, their trading cannot cause correction of mispricing. In fact, such trading may pressure the price in the wrong direction. Similarly, a score insignificantly different from zero means trading is anomaly neutral. Such evidence would again suggest trading itself does not appear to help price to converge. In contrast, a highly positive score supports that informed traders are causing the anomaly price to converge.

The results in Table 8 show that informed funds' trading is not anomaly neutral, on average. Their trading score is 16% (t-value=2.74), while the uninformed' trading score is -2% (insignificant). The difference between them is close to 20%, which is roughly a span of 20% of the stocks in the entire cross-section of the stock universe. During LIQ Up states, this difference increases to almost 30% and is highly significant, while during down periods, this difference turns negative to -5% although insignificant. Throughout the sample period, uninformed funds' trading on mispricing is insignificantly different from zero, i.e., anomaly neutral. In contrast, informed funds trade mispriced stocks based on the anomaly rankings, and more aggressively so during periods of improved market liquidity. Assuming anomaly return is linearly increasing with its decile ranking, a 30% trading intensity score implies a 23 bps five-factor alpha per month based on the average anomaly return in Up periods. This amounts to roughly 60% of the 38 bps total outperformance of high-liquidity-beta funds relative to low-liquidity-beta funds in the Up state (Table 4). The results show evidence that trading on mispriced stocks significantly contributes to the state-dependent performance of active funds. In contrast, in down periods, trading does not appear to contribute to the relative outperformance of high-liquidity-beta active funds.[22]

We present additional tests based on a single anomaly, the post-earnings-announcement drift (PEAD). PEAD is one of the most studied anomalies in both finance and accounting literature. It is widely argued that the anomaly is likely due to slow reaction to information contained in earnings surprises, thereby consistent with mispricing. The PEAD trading intensity score is computed in the same manner as the average anomaly trading intensity score, where the average anomaly decile ranking is replaced with the PEAD decile ranking.

The second column of Table 8 shows that the PEAD trading intensity score of informed funds is 10% and significant over the full sample period, while that of uninformed funds is -1% and insignificant. The score difference between the informed and the uninformed funds is 11%. This difference is entirely driven by the fact that informed funds switch to trading PEAD during LIQ Up states. The difference between the informed and the uninformed during Up state is 19% (t-value=3.21), while during Down states, the difference actually turn negative (-7%). The

[22] The comparison is only suggestive as the funds in Abel Noser do not exactly resemble an average mutual fund but are actually bigger. However, smaller funds are likely to be more flexible in trading mispricing pertaining to liquidity (see evidence in, e.g., Dong, Krystyniak, and Peng, 2015). Therefore, the conclusion on the importance of active trading still applies to average mutual funds and could potentially be bigger.

uninformed funds do not exhibit a significant tendency to trade on PEAD during any period and therefore are PEAD neutral.

Taken together, the results offer direct evidence that informed funds indeed trade mispriced stocks more aggressively during improved liquidity states. Furthermore, since only the informed funds exhibit a significant tendency to trade in the right direction of mispricing, and they only do so during Liq Up periods, the results also provide direct evidence that informed trading can cause a positive relation between mispricing correction and liquidity shocks.

4.2.6. Asymmetric Intensity of Trading: Quarterly Holding Evidence

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 stock illiquidity, where the illiquidity measure is the Amihud illiquidity measure. The t-values are calculated based on Newey-West standard errors with a lag length of 12 months.

There are two types of variables of interest. The first type includes established proxies for stock-specific information or information asymmetry. They are the value-weighted averages of idiosyncratic volatility (Durnev, Morck, Yeung, and Zarowin, 2003), stock size (Chari, Jagannathan, and Ofer, 1988; Llorente, Michaely, Saar, and Wang, 2002), and analyst following (Brennan and Subrahmanyam, 1995; Hong, Lim, and Stein, 2000) 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). Reasonably, stocks with higher idiosyncratic volatility, smaller size, or lower analyst following should offer informed investors a better chance to gain an informational advantage over the market. Therefore, the stocks that informed funds trade should be disproportionately such stocks (see evidence in Agarwal, Jiang, Tang, and Yang, 2012), particularly during Up periods. To control with greater refinement for illiquidity, we include the value-weighted average illiquidity measures of both the stocks a fund holds at the beginning of a quarter and those it trades during a quarter. The second type includes active share. It measures the degree by which a fund informatively deviates its stock positions from its benchmark (Cremers and Petajisto, 2009). By the same logic, informed funds should particularly deviate from their benchmarks, i.e., higher active share, during Up periods. Table 9 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 confirm the stocks that high liquidity beta funds trade are disproportionately stocks with significantly smaller size, higher idiosyncratic volatility, lower analyst following, and higher active share. In the next two vertical panels, the sample period is divided into the months where their corresponding aggregate (calendar) quarterly liquidity innovations are positive, and the months where their corresponding aggregate quarterly liquidity innovations are negative.[23] We perform Fama-MacBeth regressions for the two subsample periods separately. The results show that the significant relations between fund liquidity beta and idiosyncratic volatility, size, analyst following, and active share are almost entirely driven by the periods when market liquidity improves. For example, a one standard deviation increase in Trading IVOL results in a 0.34 standard deviation increase in liquidity beta during Up periods but no increase during Down periods.

It is worth noting that the above relations are obtained after controlling for the stock illiquidity that a fund holds and/or trades.[24] In addition, the results also show that fund liquidity beta is not significantly related to the illiquidity level of the stocks that a fund holds or trades. These results confirm the earlier discussion: there need not be a simple relation between liquidity risk exposure and liquidity level, which provides further evidence that the relationship between fund future performance and liquidity beta is not driven by the liquidity level of individual stocks.

Overall, the results provide consistent evidence that high liquidity beta funds trade on stocks with private information more aggressively 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

Funds may differ in liquidity beta due to other characteristic differences. If these characteristics are also correlated with performance, they may explain the liquidity beta performance effect. In this section, we perform Fama-MacBeth regressions of fund performance on multiple lagged control variables that might be correlated with both liquidity beta and fund performance (Table 10). The performance measure we focus on is the five-factor alpha (Carhart four factors plus the Sadka

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

[24] The results are similar if we do not control for one of the two illiquidity measures or both of them for multicollinearity concerns.

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 Newey-West standard errors with a lag length of 12 months.

These regressions address several concerns. First are fund flow related concerns. Fund flows predict fund performance (e.g., Zheng, 1999; Sapp and Tiwari, 2004). Flow volatility may also impose liquidity costs on fund managers and consequently hurt their performance. 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.[25]

The second concern is funding liquidity risk. Since market liquidity and funding liquidity reinforce each other (e.g., Brunnermeier and Pedersen, 2009), 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 AR(2) model of the TED spread.

The third concern entails illiquidity and cost concerns. Fund performance difference could be illiquidity/cost-based differences due to differences in fund expenses, fees, managers' trading frequency (turnover), and the individual stock-level illiquidity of fund holdings (Amihud, 2002). Fourth, relatedly, is the relation of fund size to fund performance due to funds with different capital under management incurring different liquidity-based costs (e.g., Chen, Hong, Huang, and Kubik, 2004). The fifth concern is business expansions and recessions (Kacperczyk, Nieuwerburgh, and Veldkamp, 2013). We 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. A one-standard-deviation increase in the liquidity beta increases the future fund return by roughly 10 basis points per month. This relation is also only significant during Liq Up periods.

[25] 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.

Other concerns do not seem to drive the liquidity beta performance effects. For example, fund future performance cannot be predicted by the illiquidity level of fund stock holdings. This is consistent with Massa and Phalippou (2005), who find fund future performance is unconditionally independent of the illiquidity of fund holdings. Our analysis (unreported) suggests this is again due to the cross-sectional dispersion of value-weighted illiquidity level of fund holdings being small, further suggesting that illiquidity (level) premium cannot drive our performance effects.[26]

Additionally, Kacperczyk, Nieuwerburgh, and Veldkamp (2013) argue that expansions and recessions drive the relative importance of timing and stock picking skills for skilled funds. They identify a type of skilled fund that can consistently outperform as a result of timing the market well in recessions while simultaneously picking stock well in expansions. The subperiod results suggest that the type of funds in their study differ from the high liquidity beta funds. First, aggregate liquidity shocks (rather than absolute liquidity levels) and business cycles are independent concepts. The table shows the percentage of months with positive liquidity shocks during either expansions or recessions are not far from 50%, suggesting that positive and negative liquidity shocks are almost equally likely to occur in expansions and recessions. 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 most important difference is that the ability of the high liquidity beta funds to outperform is related to liquidity shocks rather than business cycles. Second, 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, consistent with our earlier analysis that high liquidity beta funds do not have timing ability.[27]

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[26] Lynch and Yan (2012) also studies the effect of liquidity level and liquidity risk on fund performance. Their focus is on documenting the performance effects, while ours is on how liquidity risk can generate a fund performance effect. The only publicly available version of their paper we found is at EFMA (June, 2012); ours is posted on SSRN in March, 2011.

[27] Huang (2013) shows that funds that hold liquid assets during periods of high expected volatility outperform following such periods. His explanation is that expected volatility provides a good estimate for future volatility, and some fund managers can time the market by tilting towards liquid assets as liquidity provision amid large redemptions. However, Ben-Rephael (2014) finds that the reason mutual funds reduce their holdings of illiquid stocks when expected market volatility increases is a result of larger withdrawals from funds that hold less liquid stocks, and not of fund manager strategic trading decisions. Nevertheless, our high liquidity beta funds outperform during periods with unexpectedly increased liquidity. Volatility and liquidity are conceptually different but high volatility often corresponds to low liquidity. Expected volatility also differs from future unexpected liquidity shocks (an insignificant correlation of -9% between VIX and next-month Sadka liquidity factor). Therefore, the outperformance of our high liquidity beta funds is driven by a different, and largely opposite, market state from that of Huang's funds. Our interpretation is based on mispricing correction during unexpected, favorable liquidity states, while his is based on cost saving during

Lastly, we also perform a subsample analysis by splitting the sample period into half. The results show that the liquidity beta performance effect is robust in both the first half and the second half of the sample period. In untabulated results, we verify that there is no significant difference between the two subperiods.

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 managers 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 outflows. 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 due to suboptimal response to flows, we view such a fund lacking fund managerial skill in making optimal investment decisions.

In addition, trading costs cannot be fully captured by turnover, size, expense ratio, and illiquidity of fund holdings. 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 alpha during Up periods. The positive alpha is also observed for tests based on gross fund return in Table 3, as well as for results over the full sample period in Table 2 and Table 3, especially after backtesting. Taken together, the results suggest that high liquidity beta funds outperform not simply because of low difficult-to-measure trading costs.

5.3. Other Predictors of Manager Skill

In this section, we test whether a fund's liquidity beta has incremental performance prediction over and above other documented performance predictors. Table 11 reports the Fama-MacBeth

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expected, unfavorable volatility states. Relatedly, Cao, Chen, Liang, and Lo (2013) find some hedge funds have ability to especially time a persistent market liquidity level measure. As discussed in an earlier section, liquidity timing ability and unconditional liquidity beta need not bear any particular relationship. We find high and low liquidity beta mutual funds are equally skilled (or not skilled) in their ability to time unexpected liquidity shocks. Therefore, the high minus low liquidity beta fund performance difference cannot be due to a difference in their liquidity timing ability.

regression results controlling for the active share measure of the return gap measure of Kacperczyk, Sialm, and Zheng (2008), Cremers and Petajisto (2009), 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.

5.4. Performance Persistence

If a fund manager has the skill to generate alpha, we would expect persistence in the fund's 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 2.[28]

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. The length of persistence is comparable to other studies discussed in the previous section that identify fund performance predictors.

5.5. Passive Portfolios

We also perform placebo tests by examining the relation between the liquidity beta and the alpha of portfolios that can proxy for passive benchmarks of active funds. That is, the portfolios that are comparable to the portfolios that active funds invest in. We utilize the 125 DGTW portfolios that are commonly used as mutual fund benchmarks. We treat each of these portfolios as a fund and estimate the rolling liquidity betas for these hypothetical funds. Table 12 reports the liquidity beta-sorted quintiles of these "funds."

The results first show that the high minus low liquidity beta return spread is not significant especially after the five-factor model is used. Additionally, all of the liquidity beta quintile portfolios do not generate positive five-factor alpha. These two results are in stark contrast to the patterns of the before-fee results in Table 3 (since benchmark portfolios do not involve significant

[28] 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.

costs and expenses, the results based on before-fee fund returns in Table 3 are directly comparable). The conclusion is similar if we use passive index mutual funds.[29]

It is worth noting that existing asset pricing models may fail to price extreme small and value portfolios or, relatedly, equal-weighted portfolios. To mitigate this extreme portfolio effect, we only group funds into quintiles in our earlier tests. Additionally, fund return is a value-weighted return. These two considerations dilute the effect of any extreme small/illiquid stocks.

Overall, the analysis suggests the factor models we use completely explain the high minus low liquidity beta return spread for passive portfolios that are comparable to the portfolios invested by active funds.

5.6. Extreme Negative States

One concern regarding the main results in Table 4 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 negative states with other mild negative states, we may no longer detect such poor performance.

Figure 3 provides an alternative way to partition the sample period based on market liquidity. The sample period is divided into three states (i.e., N=3): months for which the liquidity innovation is one standard deviation below its mean, one standard deviation above its mean, and the remaining months. This division allows us to narrow the focus to extreme market liquidity changes.

The figure plots the Carhart+Liquidity five-factor alpha of the high minus low liquidity beta fund return. The result confirms that as market liquidity improves, the relative outperformance of high liquidity beta funds becomes increasingly positive. However, during the worst liquidity states (one standard deviation below the mean), high liquidity beta funds still perform marginally better than the low liquidity beta funds.

In unreported tests, we also examine 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 due to the small number of observations. Given the small number, the alpha of high liquidity beta funds during these months would need to be substantially lower than that of low

[29] The index-fund results are subject to the concern that there are not many index funds in the earlier part of the sample period. We therefore focus on DGTW portfolios which are commonly accepted benchmarks.

liquidity beta funds to support a risk compensation explanation. However, we find that the five-factor alpha of the high minus low liquidity beta return spread still 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, which is still inconsistent with a risk compensation explanation.

6. Conclusion

This paper highlights the importance of understanding the liquidity risk exposure of mutual funds. Fund managers can choose to generate performance by taking high liquidity risk. However, given the importance of market liquidity to achieving market efficiency and determining the intensity of informed trading, truly informed funds may not be able to avoid their performance being correlated with market liquidity, thus introducing liquidity risk due to active management itself.

We find evidence consistent with these hypotheses, while the risk-premium hypothesis does not appear to play a substantial role based on existing widely-used liquidity factors for evaluating fund performance. Our results indicate that the ability of skilled fund managers to generate alpha from mispricing is at least partly dependent on market liquidity conditions. This dependence leads to economically meaningful cross-sectional differences in fund liquidity risk exposures, contributes to the understanding of the relation between market liquidity and informed traders, and helps predict fund performance.

Appendix

This appendix discuss the anomalies used in Table 6.

The anomalies are based on the anomalies in GHZ (2013, 2014), who constructed 100 return predictive signals (RPS) that can be calculated using the commonly available databases including CRSP, Compustat, and I/B/E/S (programs provided on Jeremiah Green's website). The RPS are from both academic and practitioner papers. We further update their 100 anomaly list (Table 1 of GHZ (2014)) by incorporating a few developments in the anomaly studies cited in their list. This also results in 5 additional RPS added to the list. They are: (1) Betting-against-beta. It utilizes market beta to predict return in an opposite manner to that in the CAPM theory. Therefore, it complements the CAPM-based beta anomaly in the list. (2) Asset turnover. It is in Novy-Marx (2013) final published version but is missing in the list. (3) Return on assets. (4) Return on book equity. (5) Return on market equity. Chen and Zhang (2010) was retracted from the Journal of Finance, which resulted in an alternative working paper by Chen, Novy-Marx, and Zhang (2010) with a different set of RPS. We make the corresponding adjustment in the list and add the above three RPS.

The full list of anomaly-based RPS is reported in Table A.1. For ease of comparison, we use the same Acronym as in the Table 1 of GHZ (2014) when possible.

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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 2014.

	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

2 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 net-of-expenses 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 (2013), 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 the results with and without backtesting. The backtesting method is similar to the backtesting/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 2014.

	Liq Beta Sorted Portfolios											
	Without Backtesting						With Backtesting					
	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	0.38	0.42	0.43	0.48	**0.63**	**0.25**	0.30	0.38	0.45	**0.57**	**0.81**	**0.51**
	(1.68)	(2.20)	(2.28)	(2.36)	**(2.63)**	**(2.36)**	(1.12)	(1.75)	(2.21)	**(2.69)**	**(3.35)**	**(3.55)**
CAPM	-0.16	-0.04	-0.02	-0.01	0.10	**0.26**	-0.28	-0.11	0.00	**0.10**	**0.30**	**0.59**
	(-2.34)	(-1.06)	(-0.59)	(-0.20)	(1.00)	**(2.40)**	(-3.13)	(-1.88)	(-0.06)	**(1.69)**	**(2.91)**	**(4.12)**
Carhart	-0.18	-0.08	-0.06	-0.03	0.10	**0.28**	-0.31	-0.14	-0.02	**0.09**	**0.29**	**0.61**
	(-3.04)	(-2.08)	(-1.56)	(-0.64)	(0.92)	**(2.47)**	(-3.69)	(-2.63)	(-0.42)	**(1.66)**	**(2.99)**	**(4.17)**
Ferson-Schadt	-0.16	-0.04	-0.01	0.01	**0.14**	**0.30**	-0.30	-0.11	0.01	**0.12**	**0.33**	**0.62**
	(-2.76)	(-1.23)	(-0.38)	(0.35)	**(1.77)**	**(2.83)**	(-3.48)	(-2.14)	(0.10)	**(2.32)**	**(3.33)**	**(4.24)**
CPZ	-0.13	-0.03	-0.02	0.01	**0.15**	**0.27**	-0.26	-0.10	0.02	**0.13**	**0.35**	**0.61**
	(-2.01)	(-0.91)	(-0.51)	(0.24)	**(1.83)**	**(2.65)**	(-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. The table reports the results for net fund return and 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 (2013), or the Ferson and Schadt (1996) conditional four-factor model. We also use the characteristic adjusted alpha by augmenting the DGTW benchmark with the liquidity characertic (the Amihud measure). We control for liquidity level by using the Carhart model augmented with the Amihud liquidity-level factor. We also include a 7-factor model in which all three liquidity risk factors are added into the Carhart model (Carhart+3Liq), and a 8-factor model in which the Amihud liquidity-level factor is added in the 7-factor model (Carhart+3Liq+Liq Level). T-statistics are reported in parentheses. The sample includes the CRSP active equity mutual funds for the period April 1983 to December 2014.

	Liq Beta Sorted Portfolios											
	Net Fund Return						Gross Fund Return					
	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	-0.07	-0.05	-0.02	0.10	**0.27**	-0.07	0.01	0.03	0.07	**0.21**	**0.27**
	(-2.79)	(-1.93)	(-1.46)	(-0.43)	(1.06)	**(2.37)**	(-1.17)	(0.39)	(0.78)	(1.61)	**(2.34)**	**(2.42)**
Carhart+PS	-0.19	-0.08	-0.07	-0.05	0.05	**0.24**	-0.09	0.01	0.02	0.03	**0.15**	**0.24**
	(-3.18)	(-2.08)	(-1.83)	(-1.27)	(0.67)	**(2.38)**	(-1.57)	(0.23)	(0.41)	(0.82)	**(1.95)**	**(2.43)**
Carhart+SadkaPV	-0.17	-0.07	-0.06	-0.03	0.05	**0.23**	-0.08	0.01	0.02	0.06	**0.15**	**0.23**
	(-3.15)	(-2.06)	(-1.66)	(-0.86)	(0.65)	**(2.67)**	(-1.39)	(0.28)	(0.64)	(1.39)	**(2.18)**	**(2.72)**
DGTW+Liq	-0.14	-0.15	-0.08	-0.06	0.09	**0.23**	-0.04	-0.08	-0.01	0.01	**0.19**	**0.24**
	(-1.41)	(-0.86)	(-0.83)	(-0.41)	(0.81)	**(2.22)**	(-0.45)	(-0.45)	(-0.49)	(0.06)	**(2.30)**	**(2.38)**
Ferson-Schadt+Amihud	-0.15	-0.03	-0.01	0.02	**0.13**	**0.28**	-0.05	0.05	0.08	0.11	**0.23**	**0.29**
	(-2.54)	(-1.02)	(-0.21)	(0.53)	**(1.77)**	**(2.71)**	(-0.90)	(1.46)	(2.29)	(2.76)	**(3.11)**	**(2.76)**
Ferson-Schadt+PS	-0.17	-0.05	-0.03	-0.01	0.09	**0.27**	-0.08	0.04	0.06	0.08	**0.20**	**0.27**
	(-2.93)	(-1.36)	(-0.75)	(-0.22)	(1.24)	**(2.56)**	(-1.30)	(1.11)	(1.76)	(2.05)	**(2.57)**	**(2.60)**
Ferson-Schadt+SadkaPV	-0.15	-0.04	-0.02	0.00	0.10	**0.25**	-0.05	0.04	0.07	0.09	**0.20**	**0.25**
	(-2.75)	(-1.18)	(-0.50)	(0.11)	(1.39)	**(2.91)**	(-0.96)	(1.32)	(2.06)	(2.59)	**(3.00)**	**(2.97)**
CPZ+Amihud	-0.11	-0.03	-0.01	0.02	**0.15**	**0.25**	-0.01	0.06	0.07	0.11	**0.25**	**0.26**
	(-1.69)	(-0.71)	(-0.31)	(0.57)	**(1.94)**	**(2.44)**	(-0.14)	(1.55)	(1.95)	(2.68)	**(3.26)**	**(2.48)**
CPZ+PS	-0.14	-0.04	-0.03	-0.02	0.10	**0.24**	-0.04	0.05	0.05	0.07	**0.20**	**0.24**
	(-2.19)	(-0.96)	(-0.81)	(-0.40)	(1.26)	**(2.28)**	(-0.66)	(1.29)	(1.45)	(1.77)	**(2.57)**	**(2.32)**
CPZ+SadkaPV	-0.12	-0.03	-0.02	0.01	**0.12**	**0.23**	-0.02	0.05	0.06	0.09	**0.22**	**0.24**
	(-2.04)	(-0.88)	(-0.57)	(0.13)	**(1.72)**	**(2.78)**	(-0.38)	(1.39)	(1.72)	(2.41)	**(3.16)**	**(2.84)**
Carhart+Liq Level	-0.17	-0.07	-0.05	-0.02	0.07	**0.24**	-0.07	0.01	0.03	0.07	**0.17**	**0.24**
	(-2.88)	(-1.98)	(-1.42)	(-0.50)	(0.82)	**(2.24)**	(-1.25)	(0.34)	(0.82)	(1.53)	**(2.08)**	**(2.29)**
Carhart+3Liq	-0.17	-0.07	-0.07	-0.05	0.07	**0.23**	-0.07	0.02	0.02	0.04	**0.17**	**0.24**
	(-3.04)	(-1.89)	(-1.85)	(-1.34)	(0.67)	**(2.57)**	(-1.26)	(0.41)	(0.42)	(0.93)	**(2.18)**	**(2.63)**
Carhart+3Liq+Liq Level	-0.16	-0.07	-0.06	-0.04	0.06	**0.23**	-0.07	0.02	0.02	0.05	**0.17**	**0.23**
	(-2.96)	(-1.81)	(-1.67)	(-1.11)	(0.81)	**(2.63)**	(-1.20)	(0.47)	(0.58)	(1.16)	**(2.33)**	**(2.68)**

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. To adjust for liquidity risk, we use a five-factor model, where the five factors are the Sadka liquidity risk factor (Liq) plus four factors from the four-factor model of Carhart (1997), the four-factor model of CPZ proposed by Cremers, Petajisto and Zitzewitz (2013), or the Ferson and Schadt (1996) conditional four-factor model. We also include a 7-factor model in which all three liquidity risk factors (Amihud, PS, or SadkaPV) are added into the Carhart model (Carhart+3Liq), and a 8-factor model in which the Amihud liquidity-level factor is added in the 7-factor model (Carhart+3Liq+Liq Level). The sample is split into the periods when market liquidity improves (Liq Up) and the periods when market liquidity deteriorates (Liq Down). In the last two columns, we report the difference in alpha between Up and Down periods for Quintile 5 and 1, respectively. T-statistics are reported in parentheses. The sample includes the CRSP active equity mutual funds for the period April 1983 to December 2014.

Alpha	Liq Up						Liq Down						Up Minus Down	
	Liq Beta Sorted Portfolios						Liq Beta Sorted Portfolios							
	1 [low]	2	3	4	5 [high]	5-1	1 [low]	2	3	4	5 [high]	5-1	1 [low]	5 [high]
Carhart	-0.13	-0.06	-0.07	0.00	**0.25**	**0.38**	-0.20	-0.07	-0.06	-0.06	-0.04	0.15	0.07	**0.28**
	(-1.51)	(-1.22)	(-1.42)	(-0.02)	**(2.25)**	**(2.51)**	(-2.16)	(-1.27)	(-0.92)	(-0.85)	(-0.28)	(0.96)	(0.67)	**(2.00)**
Carhart+Liq	-0.13	-0.06	-0.07	0.01	**0.25**	**0.38**	-0.18	-0.07	-0.06	-0.08	-0.08	0.10	0.05	**0.33**
	(-1.83)	(-1.27)	(-1.37)	(0.13)	**(2.68)**	**(3.40)**	(-2.12)	(-1.24)	(-1.08)	(-1.26)	(-0.76)	(0.84)	(0.45)	**(2.52)**
Ferson-Schadt+Liq	-0.12	-0.04	-0.04	0.02	**0.26**	**0.39**	-0.14	-0.03	0.00	-0.02	0.02	0.15	0.02	**0.25**
	(-1.70)	(-0.92)	(-0.90)	(0.49)	**(2.96)**	**(3.48)**	(-1.67)	(-0.48)	(-0.01)	(-0.29)	(0.08)	(1.39)	(0.15)	**(2.35)**
CPZ+Liq	-0.07	-0.02	-0.03	0.04	**0.30**	**0.38**	-0.14	-0.05	-0.04	-0.06	-0.02	0.12	0.06	**0.33**
	(-0.97)	(-0.38)	(-0.62)	(0.84)	**(3.39)**	**(3.47)**	(-1.55)	(-0.77)	(-0.65)	(-0.84)	(-0.33)	(0.84)	(0.59)	**(2.62)**
Carhart+3Liq	-0.13	-0.06	-0.08	-0.01	**0.25**	**0.38**	-0.16	-0.06	-0.06	-0.09	-0.06	0.10	0.03	**0.31**
	(-1.77)	(-1.20)	(-1.55)	(-0.19)	**(2.54)**	**(3.22)**	(-1.96)	(-1.09)	(-1.03)	(-1.44)	(-0.82)	(0.73)	(0.32)	**(2.51)**
Carhart+3Liq+Liq level	-0.12	-0.05	-0.07	0.00	**0.23**	**0.36**	-0.16	-0.06	-0.06	-0.09	-0.09	0.09	0.04	**0.32**
	(-1.67)	(-0.99)	(-1.31)	(0.07)	**(2.43)**	**(3.07)**	(-1.98)	(-1.09)	(-1.04)	(-1.47)	(-0.86)	(0.62)	(0.37)	**(2.53)**

Table 5

Stock Holding Performance

Each month mutual funds are sorted into five 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. To adjust for liquidity risk, we use a five-factor model, where the five factors are the Sadka liquidity risk factor (Liq) plus four factors from the four-factor model of Carhart (1997), the four-factor model of CPZ proposed by Cremers, Petajisto and Zitzewitz (2013), or the Ferson and Schadt (1996) conditional four-factor model. We also include a 7-factor model in which all three liquidity risk factors (Amihud, PS, or SadkaPV) are added into the Carhart model (Carhart+3Liq), and a 8-factor model in which the Amihud liquidity-level factor is added in the 7-factor model (Carhart+3Liq+Liq Level). The sample is split into the periods when market liquidity improves (Liq Up) and the periods when market liquidity deteriorates (Liq Down). In the last two columns, we report the difference in alpha between Up and Down periods for Quintile 5 and 1, respectively. T-statistics are reported in parentheses. The sample includes the CRSP active equity mutual funds for the period April 1983 to December 2014.

	Liq Beta Sorted Portfolios							
	Liq Up			Liq Down			Up Minus Down	
	1	5	5-1	1	5	5-1	1	5
Alpha	[low]	[high]		[low]	[high]		[low]	[high]
Carhart	-0.09	**0.23**	**0.34**	-0.04	0.03	0.07	-0.05	**0.20**
	(-0.76)	**(2.20)**	**(2.54)**	(-0.38)	(0.19)	(0.34)	(0.51)	**(1.80)**
Carhart+Liq	-0.09	**0.25**	**0.34**	-0.02	0.00	0.02	-0.06	**0.25**
	(-0.92)	**(2.60)**	**(2.98)**	(-0.24)	(0.03)	(0.12)	(-0.81)	**(2.16)**
Ferson-Schadt+Liq	-0.09	**0.23**	**0.35**	0.00	0.01	0.02	-0.09	**0.22**
	(-0.85)	**(2.55)**	**(2.85)**	(-0.03)	(0.11)	(0.11)	(-0.96)	**(2.03)**
CPZ+Liq	-0.07	**0.30**	**0.37**	0.00	0.02	0.01	-0.08	**0.28**
	(-0.93)	**(3.69)**	**(3.37)**	(0.03)	(0.14)	(0.09)	(-0.66)	**(2.68)**
Carhart+3Liq	-0.10	**0.24**	**0.35**	0.05	0.01	-0.04	-0.15	**0.23**
	(-1.20)	**(2.51)**	**(3.03)**	(0.50)	(0.10)	(-0.22)	(-1.58)	**(2.09)**
Carhart+3Liq+Liq level	-0.10	**0.26**	**0.36**	0.04	-0.01	-0.05	-0.15	**0.27**
	(-0.80)	**(2.96)**	**(3.05)**	(0.45)	(-0.08)	(-0.35)	(-1.28)	**(2.42)**

Table 6

Mispricing Portoflios

Panel A reports the performance of a strategy that equal-weights the returns of 68 anomalies over the period of April 1983 to December 2014. The last column reports the percentage of individual anomalies whose return or alpha has a higher t-statistic during the Liq Up period than during the Liq Down period. Panel B reports the performance comparison between the Carhart+Liq model and the model that replaces the Liq factor with a mispricing factor, where the factor is the equal-weighted average anomaly return from Panel A. T-statistics are reported in parentheses.

Panel A.

	Average				
	Full	Liq Up	Liq Down	Up Minus Down	% of t_{Up}>t_{Down}
Return	0.78	0.95	0.59	**0.36**	**85%**
	(19.06)	(20.48)	(8.24)	**(3.54)**	
Carhart	0.65	0.75	0.56	**0.19**	**74%**
	(15.35)	(14.55)	(7.85)	**(2.47)**	
Carhart+Liq	0.64	0.75	0.55	**0.20**	**74%**
	(15.06)	(14.54)	(7.63)	**(2.78)**	

Panel B.

	Fund Return								Holding Return	
	Full						Liq Up	Liq Down	Liq Up	Liq Down
	1 [low]	2	3	4	5 [high]	5-1	5-1	5-1	5-1	5-1
Carhart	-0.18	-0.08	-0.06	-0.03	0.10	**0.28**	**0.38**	0.15	**0.34**	0.07
	(-3.04)	(-2.08)	(-1.56)	(-0.64)	(0.92)	**(2.47)**	**(2.51)**	(0.96)	**(2.54)**	(0.34)
Carhart+Liq	-0.17	-0.07	-0.06	-0.03	0.05	**0.23**	**0.38**	0.10	**0.34**	0.02
	(-3.15)	(-2.06)	(-1.66)	(-0.86)	(0.65)	**(2.67)**	**(3.40)**	(0.84)	**(2.98)**	(0.12)
Carhart+Mispricing	-0.17	-0.05	-0.11	-0.10	-0.04	0.13	0.19	0.07	0.14	0.07
	(-2.01)	(-0.98)	(-1.82)	(-1.57)	(-0.64)	(0.57)	(1.61)	(0.44)	(0.94)	(0.31)

Table 7

Trading Performance and Trading Volume

Institutional trading data are obtained from Abel Noser Solutions. during the period from January 1, 1999 to September, 2011. For each trade, we calculate the raw cumulative stock return from the execution price until the end of the month. We adjust the raw cumulative return by the DGTW_LIQ benchmark return over the same period. To compute the net trading performance of each fund in each month, we then take the value-weighted average buy minus sell returns (DGTW_LIQ adjusted) of the fund. We sort all funds into quintile portfolios based on their monthly trading performance over the prior quarter. We report the trading attributes in the subsequent month for the fund portfolios with the lowest (uninformed) and the highest (informed) prior trading performance, as well as the difference in these attributes between the two fund portfolios. The attributes reported are the average DGTW_LIQ adjusted trading performance and the monthly trading volume nomalized by dividing the stock's total trading volume on the corresponding trading day. All returns are expressed in percent. Numbers in parentheses are t-statistics with Newey-West standard errors.

Prior Trading Performance	Post Ranking					
	Trading Performance			Trading Volume		
	Full	Liq Up	Liq Down	Full	Liq Up	Liq Down
Low (uninformed)	-0.15	-0.18	-0.05	2.65	2.45	2.99
	(-1.67)	(-1.87)	(-0.25)	(8.50)	(7.83)	(7.97)
High (informed)	0.50	0.60	0.20	3.09	3.39	2.60
	(4.39)	(4.60)	(1.95)	(13.00)	(12.36)	(10.00)
High-Low (informed-uninformed)	0.64	0.78	0.25	0.44	0.95	-0.39
	(4.21)	(4.84)	(1.83)	(1.79)	(3.09)	(-1.01)

Table 8

Intensity of Trading of Mispriced Stocks

Institutional trading data are obtained from Abel Noser Solutions. during the period from January 1, 1999 to September, 2011. For each trade, we calculate the raw cumulative stock return from the execution price until the end of the month. We adjust the raw cumulative return by the DGTW_LIQ benchmark return over the same period. To compute the net trading performance of each fund in each month, we then take the value-weighted average buy minus sell returns (DGTW_LIQ adjusted) of the fund. We sort all funds into quintile portfolios based on their monthly trading performance over the prior quarter. We report the trading attributes in the subsequent month for the fund portfolios with the lowest (uninformed) and the highest (informed) prior trading performance, as well as the difference in these attributes between the two fund portfolios. The attributes reported are the buy minus sell ranking score value-weighted by nomalized trading volume, where the ranking score of each stock is a number between 0 and 100% based on a stock's overall anomaly ranking or the post earnings annoucement drift (PEAD) ranking. Numbers in parentheses are t-statistics with Newy-West standard errors.

Prior Trading Performance	Average Anomaly Trading Intensity Score			PEAD Trading Intensity Score		
	Full	Liq Up	Liq Down	Full	Liq Up	Liq Down
Low (uninformed)	-2%	-5%	5%	-1%	-4%	6%
	(-0.66)	(-1.33)	(0.71)	(-0.06)	(-0.89)	(1.06)
High (informed)	16%	24%	0%	10%	15%	-1%
	(2.74)	(3.52)	(0.04)	(2.68)	(3.14)	(0.26)
High-Low (informed-uninformed)	19%	29%	-5%	11%	19%	-7%
	(2.52)	(3.77)	(-0.49)	(2.02)	(3.21)	(-0.89)

Table 9

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 2014.

	Full					Liq Up					Liq Down				
Expense Ratio	0.09	0.08	0.08	0.09	0.07	0.10	0.08	0.09	0.10	0.07	0.08	0.08	0.08	0.08	0.08
	(3.16)	(3.05)	(3.05)	(3.09)	(2.72)	(2.68)	(2.51)	(2.57)	(2.60)	(2.12)	(2.33)	(2.42)	(2.27)	(2.27)	(2.22)
Turnover Ratio	0.00	-0.01	-0.01	0.00	-0.01	0.05	0.04	0.04	0.05	0.05	-0.05	-0.05	-0.05	-0.05	-0.05
	(-0.16)	(-0.30)	(-0.30)	(-0.18)	(-0.19)	(2.10)	(1.84)	(1.85)	(2.03)	(2.04)	(-1.60)	(-1.61)	(-1.66)	(-1.61)	(-1.57)
Flow	0.03	0.03	0.03	0.03	0.03	0.05	0.05	0.04	0.04	0.05	0.02	0.02	0.02	0.02	0.02
	(1.81)	(1.81)	(1.56)	(1.58)	(1.69)	(2.18)	(2.11)	(1.94)	(2.01)	(2.11)	(0.73)	(0.78)	(0.63)	(0.61)	(0.67)
Load Dummy	0.00	0.00	0.00	0.00	0.00	-0.01	-0.01	-0.01	-0.01	0.00	0.00	0.00	0.00	0.00	0.00
	(-0.63)	(-0.71)	(-0.68)	(-0.69)	(-0.31)	(-0.44)	(-0.47)	(-0.55)	(-0.53)	-0.08	(-0.56)	(-0.67)	(-0.50)	(-0.54)	(-0.46)
Fund TNA	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.01	-0.02	-0.01	(-0.01)	-0.02	-0.03	-0.02	-0.02	-0.03
	(-1.77)	(-1.77)	(-1.64)	(-1.51)	(-2.00)	(-1.60)	(-1.04)	(-1.23)	(-1.19)	-1.28	(-1.43)	(-1.76)	(-1.48)	(-1.32)	(-1.82)
Fund Family TNA	0.02	0.02	0.01	0.02	0.02	-0.01	-0.02	-0.01	-0.01	(-0.00)	0.05	0.05	0.04	0.05	0.03
	(0.32)	(0.25)	(0.22)	(0.31)	(0.27)	(-0.38)	(-0.85)	(-0.51)	(-0.52)	-0.05	(0.55)	(0.64)	(0.47)	(0.59)	(0.40)
Fund Age	-0.01	0.00	0.00	0.00	-0.01	-0.02	-0.01	-0.01	-0.01	(-0.02)	0.00	0.00	0.00	0.00	0.00
	(-0.92)	(-0.53)	(-0.33)	(-0.15)	(-0.97)	(-1.60)	(-1.10)	(-0.93)	(-0.74)	-1.56	(0.11)	(0.21)	(0.31)	(0.40)	(0.05)
Stock Illiquidity	0.08	-0.12	0.01	0.03	0.03	0.31	-0.10	0.20	0.23	0.20	-0.12	-0.13	-0.15	-0.15	-0.10
	(0.40)	(-0.87)	(0.08)	(0.16)	(0.17)	(0.89)	(-0.54)	(0.74)	(0.82)	(0.61)	(-0.69)	(-0.79)	(-0.85)	(-0.85)	(-0.60)
Trading Illiquidity		0.02	0.03	0.02			0.01	0.03	0.02			0.03	0.02	0.02	
		(1.47)	(1.70)	(1.23)			(0.56)	(1.29)	(1.03)			(1.54)	(1.17)	(0.80)	
Trading IVOL		**0.16**					**0.34**					-0.01			
		(2.07)					**(2.79)**					(-0.18)			
Trading Stock Size			**-0.16**					**-0.23**					-0.10		
			(-2.82)					**(-3.26)**					(-1.47)		
Trading Analyst Following				**-0.10**					**-0.14**					-0.06	
				(-2.60)					**(-2.67)**					(-1.69)	
Active Share					**0.05**					**0.11**					0.01
					(1.83)					**(2.88)**					(0.28)
Adjusted R-square	0.06	0.08	0.07	0.07	0.07	0.05	0.08	0.08	0.08	0.07		0.07	0.07	0.07	0.07

Table 10

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 2014.

	Carhart+Liq										
	Full	Liq Up	Liq Down	Expansion	Recession	Expansion Liq Up	Expansion Liq Down	Recession Liq Up	Recession Liq Down	First Half	Second Half
Liq Beta	**0.10**	**0.14**	0.04	**0.10**	0.07	**0.14**	0.05	**0.15**	0.00	0.11	0.09
	(2.97)	**(3.76)**	(0.78)	**(2.75)**	(1.18)	**(3.44)**	(0.79)	**(2.04)**	(-0.07)	**(2.36)**	**(2.02)**
Expense Ratio	-4.21	5.21	-15.72	-1.51	-25.71	6.95	-12.25	-11.20	-38.70	-5.17	-3.34
	(-1.08)	(1.45)	(-2.75)	(-0.43)	(-2.14)	(1.80)	(-2.34)	(-1.02)	(-2.66)	(-1.48)	(-0.50)
Turnover Ratio	0.02	0.01	0.03	0.02	0.04	0.01	0.03	0.05	0.03	0.02	0.02
	(1.40)	(0.67)	(1.23)	(1.21)	(1.07)	(0.42)	(1.11)	(1.19)	(0.91)	(1.09)	(0.93)
Flow	-0.02	-0.02	-0.02	-0.02	-0.01	-0.02	-0.02	-0.01	0.00	-0.01	-0.02
	(-3.54)	(-3.38)	(-2.34)	(-3.39)	(-0.35)	(-2.78)	(-2.40)	(-0.59)	(-0.16)	(-1.69)	(-3.47)
Load Dummy	0.00	-0.02	0.02	0.00	0.02	-0.02	0.02	-0.01	0.04	-0.01	0.01
	(-0.03)	(-0.77)	(0.67)	(-0.13)	(0.23)	(-0.64)	(0.52)	(-0.17)	(0.59)	(-0.61)	(0.37)
Log of Fund TNA	-0.03	-0.02	-0.04	-0.03	-0.05	-0.02	-0.03	-0.03	-0.08	-0.04	-0.02
	(-3.48)	(-2.02)	(-3.27)	(-2.82)	(-2.95)	(-1.70)	(-2.74)	(-1.13)	(-3.89)	(-3.90)	(-1.72)
Log of Fund Family TNA	0.95	1.01	0.87	0.77	2.39	1.03	0.43	0.85	3.78	1.59	0.36
	(1.10)	(1.01)	(0.71)	(0.82)	(1.13)	(0.95)	(0.32)	(1.18)	(1.18)	(0.90)	(3.09)
Fund Age	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
	(1.32)	(-0.61)	(1.98)	(0.64)	(2.60)	(-1.27)	(1.47)	(0.97)	(4.83)	(1.72)	(0.20)
Flow Volatility	0.09	0.21	-0.05	0.11	-0.04	0.17	0.04	0.62	-0.63	-0.16	0.32
	(0.34)	(0.57)	(-0.14)	(0.39)	(-0.04)	(0.41)	(0.10)	(1.03)	(-0.63)	(-0.39)	(0.93)
Systematic Flow Risk	0.01	0.02	0.00	0.01	0.01	0.02	0.00	0.01	0.01	0.02	0.00
	(1.44)	(2.22)	(0.30)	(1.67)	(0.34)	(2.42)	(0.21)	(0.35)	(0.31)	(1.39)	(0.53)
Funding Liq Risk	-0.01	-0.03	0.02	0.00	-0.05	-0.03	0.03	-0.05	-0.06	0.00	-0.01
	(-0.39)	(-1.31)	(0.70)	(-0.03)	(-1.46)	(-1.17)	(0.97)	(-1.12)	(-0.62)	(-0.09)	(-0.49)
Prior-year Return	2.12	2.04	2.21	2.18	1.60	2.09	2.30	1.63	1.57	1.70	2.50
	(4.65)	(3.19)	(3.27)	(4.36)	(1.45)	(3.03)	(2.94)	(1.57)	(1.08)	(2.56)	(4.09)
Stock Illiquidity	0.00	0.03	-0.04	-0.02	0.12	0.03	-0.07	0.07	0.17	-0.02	0.01
	(-0.08)	(0.91)	(-0.90)	(-0.83)	(1.06)	(0.73)	(-1.92)	(1.14)	(1.01)	(-0.55)	(0.33)
Adjusted R-square	0.24	0.22	0.26	0.24	0.26	0.22	0.26	0.28	0.25	0.22	0.25

Table 11

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 2014.

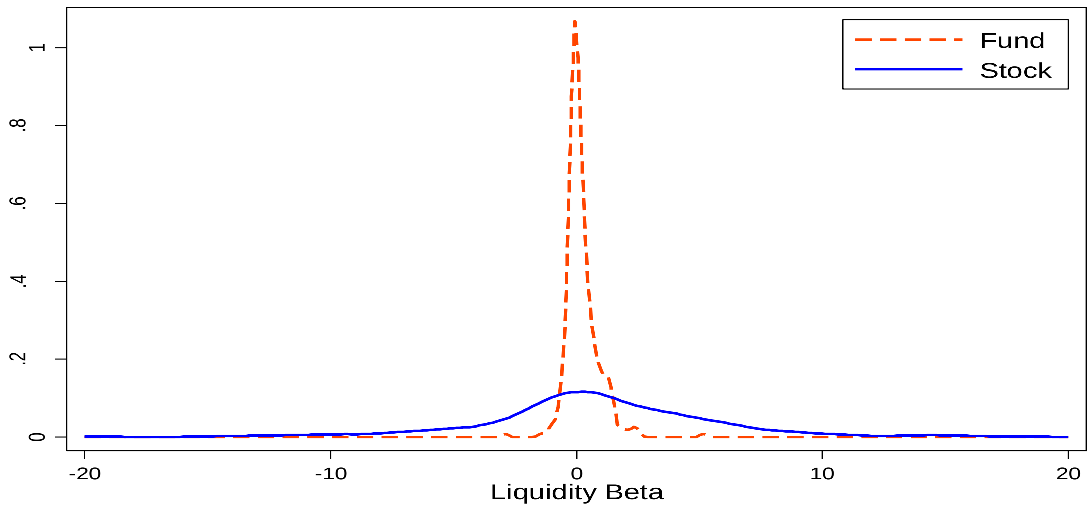
	Carhart+Liq				
Liq Beta	**0.10**	**0.10**	**0.10**	**0.09**	**0.09**
	(2.97)	**(2.82)**	**(3.04)**	**(2.68)**	**(3.06)**
Expense Ratio	-4.21	-4.93	-5.63	-6.00	-6.30
	(-1.08)	(-1.10)	(-1.17)	(-1.34)	(-1.32)
Turnover Ratio	0.02	0.02	0.02	0.02	0.02
	(1.40)	(1.40)	(1.18)	(1.54)	(1.30)
Flow	-0.02	-0.02	-0.02	-0.02	-0.02
	(-3.54)	(-3.22)	(-3.04)	(-3.20)	(-2.95)
Load Dummy	0.00	0.01	0.01	0.01	0.01
	(-0.03)	(0.52)	(0.42)	(0.57)	(0.53)
Log of Fund TNA	-0.03	-0.03	-0.03	-0.03	-0.03
	(-3.48)	(-3.30)	(-3.69)	(-3.24)	(-3.48)
Log of Fund Family TNA	0.95	0.14	0.50	0.19	0.36
	(1.10)	(0.15)	(0.59)	(0.20)	(0.40)
Fund Age	0.00	0.00	0.00	0.00	0.00
	(1.32)	(1.02)	(1.03)	(0.84)	(0.89)
Flow Volatility	0.09	-0.22	-0.27	-0.23	-0.24
	(0.34)	(-0.75)	(-0.98)	(-0.80)	(-0.86)
Systematic Flow Risk	0.01	0.01	0.01	0.01	0.01
	(1.44)	(1.40)	(1.10)	(1.38)	(1.08)
Funding Liq Risk	-0.01	-0.01	-0.01	0.00	0.00
	(-0.39)	(-0.38)	(-0.35)	(0.06)	(0.06)
Prior-year Return	2.12	2.09	2.11	2.15	2.07
	(4.65)	(4.41)	(4.66)	(4.65)	(4.58)
Stock Illiquidity	0.00	-0.01	-0.02	-0.01	-0.01
	(-0.08)	(-0.47)	(-0.64)	(-0.41)	(-0.59)
Return Gap		0.03			0.03
		(3.68)			(3.37)
Active Share			0.01		0.01
			(0.40)		(0.38)
R^2				-0.04	-0.04
				(-1.35)	(-1.18)
Adjusted R-square	0.24	0.25	0.28	0.26	0.29

Table 12

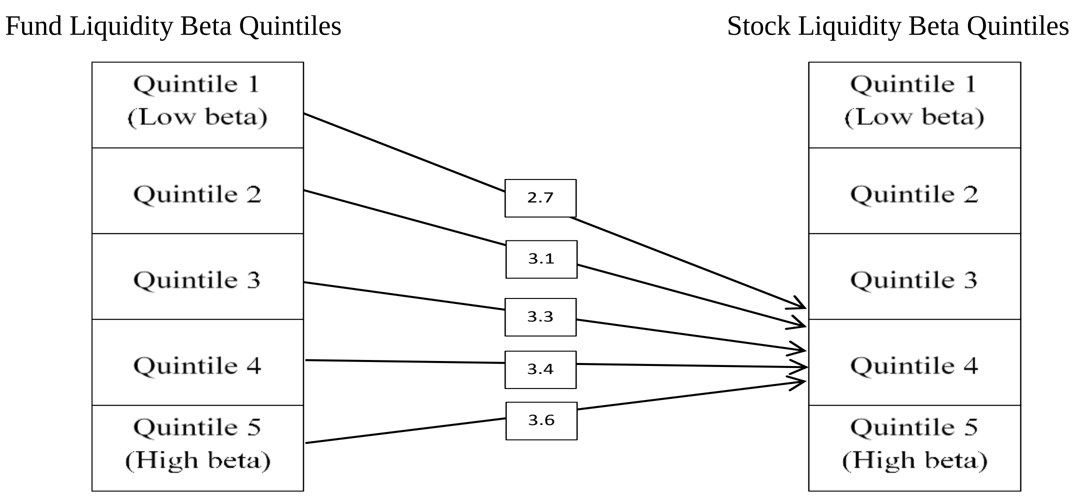
DGTW 125 Passive Portfolios

Each month the DGTW 125 portfolios are sorted into equal-weighted quintiles according to their historical liquidity beta. The liquidity beta is calculated using a regression of monthly DGTW 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 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 2014.

	Liq Beta Sorted Portfolios					
	1 [low]	2	3	4	5 [high]	5-1
Return	0.65	0.72	0.77	0.79	0.82	0.16
	(2.30)	(2.70)	(2.90)	(2.95)	(2.81)	(1.18)
Carhart	-0.03	0.02	0.06	0.07	0.07	0.11
	(-0.47)	(0.48)	(1.05)	(1.42)	(1.06)	(1.04)
Carhart+Liq	0.01	0.02	0.03	0.04	0.04	0.04
	(0.10)	(0.32)	(0.49)	(0.94)	(0.47)	(0.23)



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 1. 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 2014.

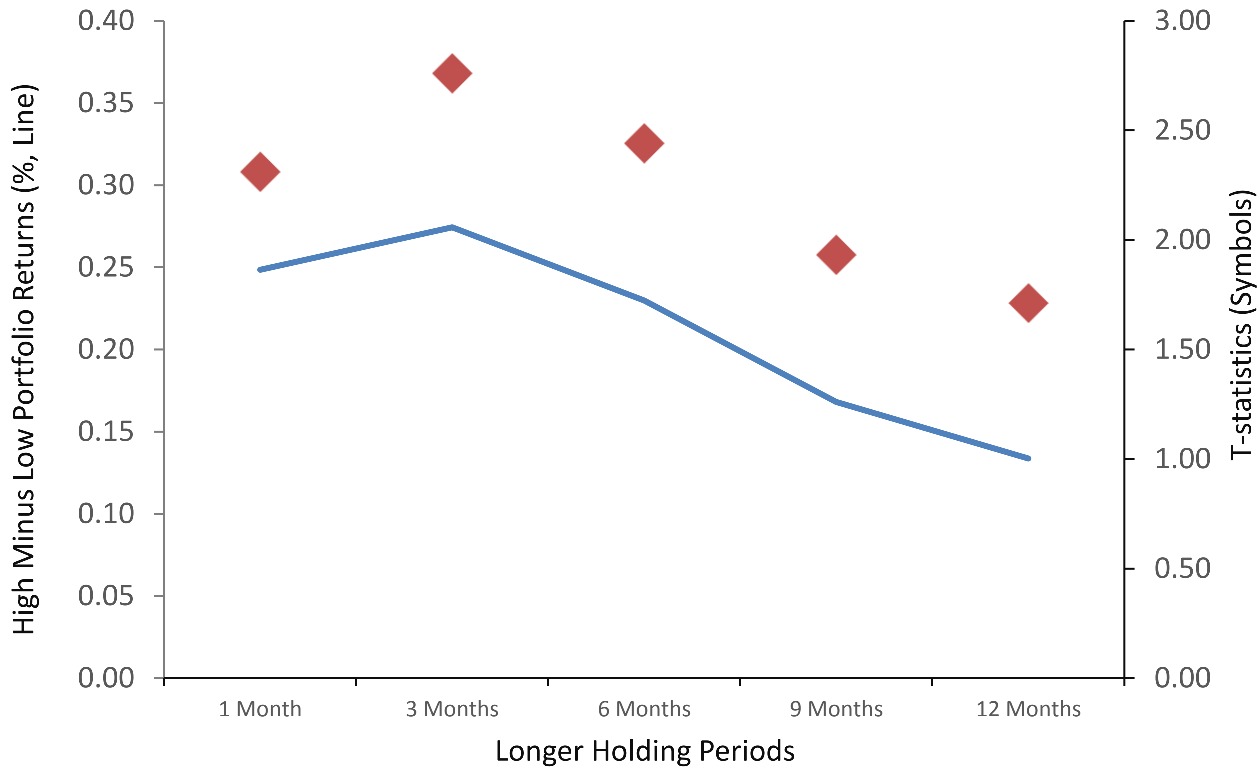


Figure 2. We rank funds into quintiles based on their liquidity beta at time 0 and then report the high minus low fund performance spread over holding periods of 1, 3, 6, 9, and 12 months after portfolio formation. The sample includes active equity mutual funds for the period April 1983 to December 2014.

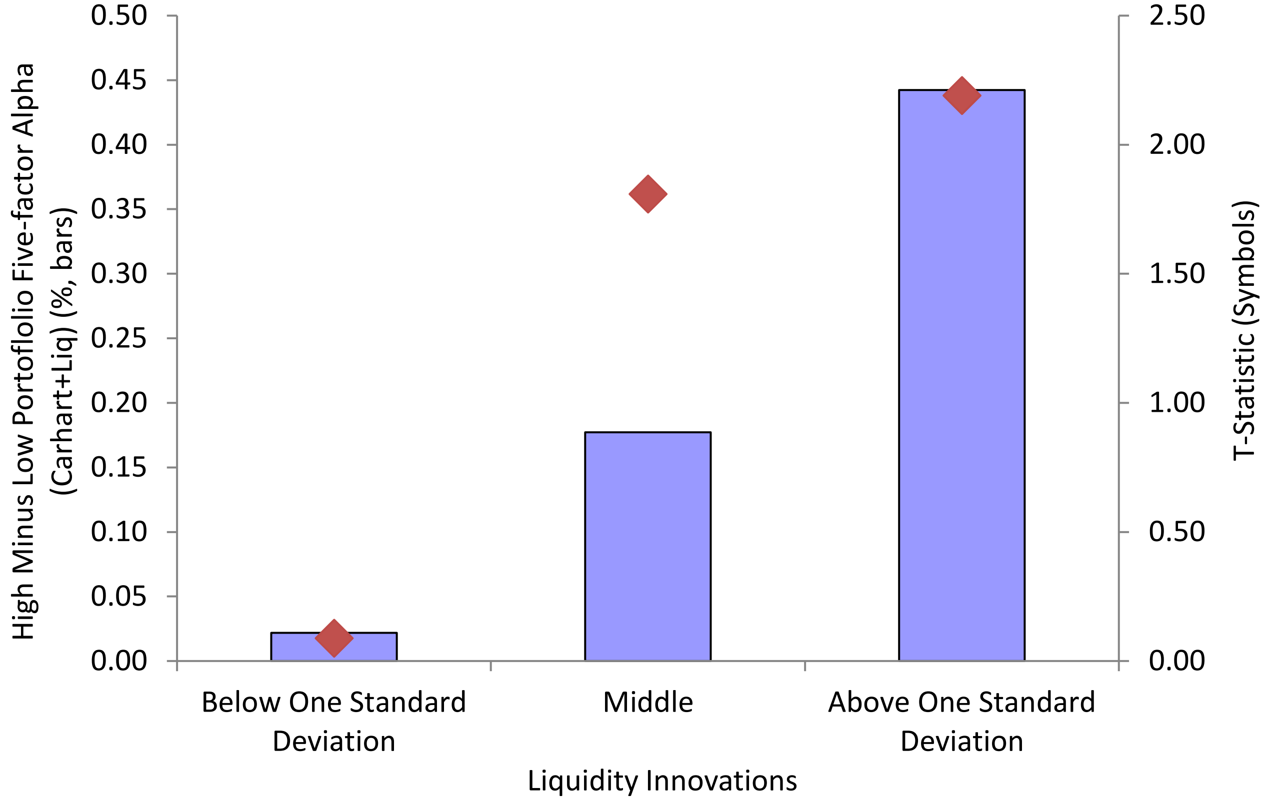


Figure 3. The figure plots the Carhart+Liquidity five-factor alpha of the high minus low liquidity beta-sorted fund-quintile return spread during different market liquidity conditions. The sample period is divided into three subperiods: the months for which liquidity innovation is one standard deviation 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 2014.

Table A.1

This table reports the list of anomalies based on Green, Hand, and Zhang (2014) that are included or excluded in Table 6 of this study. For anomalies that are excluded, the reasons of the exclusion are listed in the last two columns. The first reason is that the anomaly is based on positive market beta premium, the concepts of Value, Size, and Momentum anomalies, or directly based on an illiquidity factor. The second reason is that the sign of the anomaly return is opposite to that expected based on prior literature.

#	**RPS**	**Acronym**	**Author(s)**	**Date, Journal**	**Included**	**Mkt, Value, Size, MOM, LIQ**	**Inconsistent Sign**
1	Beta Arbitrage	*BAB*	Black;Frazzini & Pedersen	1972, JB; 2014, JFE	Y		
2	Beta	*beta*	Fama & MacBeth	1973, JPE	N	1	1
3	Beta squared	*betasq*	Fama & MacBeth	1973, JPE	N		1
4	Earnings-to-price	*ep*	Basu	1977, JF	N		1
5	Firm size (market cap)	*mve*	Banz	1981, JFE	N	1	
6	Dividends-to-price	*dy*	Litzenberger & Ramaswamy	1982, JF	N		1
7	Unexpected quarterly earnings	*sue*	Rendelman, Jones & Latane	1982, JFE	Y		
8	Change in forecasted annual EPS	*chfeps*	Hawkins, Chamberlin & Daniel	1984, FAJ	Y		
9	Book-to-market	*bm*	Rosenberg, Reid & Lanstein	1985, JPM	N	1	
10	36-month momentum	*mom36m*	De Bondt & Thaler	1985, JF	N	1	1
11	Forecasted growth in 5-year EPS	*fgr5yr*	Bauman & Dowen	1988, FAJ	N		1
12	Leverage	*lev*	Bhandari	1988, JF	N		1
13	Current ratio	*currat*	Ou & Penman	1989, JAE	Y		
14	% change in current ratio	*pchcurrat*	Ou & Penman	1989, JAE	N		1
15	Quick ratio	*quick*	Ou & Penman	1989, JAE	Y		
16	% change in quick ratio	*pchquick*	Ou & Penman	1989, JAE	N		1
17	Sales-to-cash	*salecash*	Ou & Penman	1989, JAE	N		1
18	Sales-to-receivables	*salerec*	Ou & Penman	1989, JAE	Y		
19	Sales-to-inventory	*saleinv*	Ou & Penman	1989, JAE	Y		
20	% change in sales-to-inventory	*pchsaleinv*	Ou & Penman	1989, JAE	Y		
21	Cash flow-to-debt	*cashdebt*	Ou & Penman	1989, JAE	N		1
22	Illiquidity (bid-ask spread)	*baspread*	Amihud & Mendelson	1989, JF	N	1	1
23	1-month momentum	*mom1m*	Jegadeesh	1990, JF	N	1	1
24	6-month momentum	*mom6m*	Jegadeesh & Titman	1990, JF	N	1	
25	12-month momentum	*mom12m*	Jegadeesh	1990, JF	N	1	
26	Depreciation-to-gross PP&E	*depr*	Holthausen & Larcker	1992, JAE	Y		
27	% change in depreciation-to-gross PP&E	*pchdepr*	Holthausen & Larcker	1992, JAE	N		1
28	Industry-adjusted firm size	*mve_ia*	Asness, Porter & Stevens	1994, WP	N	1	
29	Industry-adjusted cash flow-to-price ratio	*cfp_ia*	Asness, Porter & Stevens	1994, WP	N		1
30	Industry-adjusted book-to-market	*bm_ia*	Asness, Porter & Stevens	1994, WP	N	1	
31	Annual sales growth	*sgr*	Lakonishok, Shleifer & Vishny	1994, JF	Y		
32	Industry-adjusted change in employees	*chempia*	Asness, Porter & Stevens	1994, WP	Y		
33	New equity issue	*IPO*	Loughran, Ritter & Ritter	1995, JF	Y		
34	Dividend initiation	*divi*	Michaely, Thaler & Womack	1995, JF	N		1
35	Dividend omission	*divo*	Michaely, Thaler & Womack	1995, JF	Y		
36	Sales-to-price	*sp*	Barbee, Mukherji & Raines	1996, FAJ	Y		
37	Working capital accruals	*acc*	Sloan	1996, TAR	Y		
38	Share turnover	*turn*	Datar, Naik & Radcliffe	1998, JFM	N		1
39	% change in sales - % change in inventory	*pchsale_pchinvt*	Abarbanell & Bushee	1998, TAR	Y		
40	% change in sales - % change in accounts receivable	*pchsale_pchrect*	Abarbanell & Bushee	1998, TAR	N		1
41	% change in CAPEX - industry % change in CAPEX	*pchcapx_ia*	Abarbanell & Bushee	1998, TAR	Y		
42	% change in gross margin - % change in sales	*pchgm_pchsale*	Abarbanell & Bushee	1998, TAR	Y		
43	% change in sales - % change in SG&A	*pchsale_pchxsga*	Abarbanell & Bushee	1998, TAR	Y		
44	# of consecutive earnings increases	*nincr*	Barth, Elliott & Finn	1999, JAR	Y		

45	Industry momentum	*indmom*	Moskowitz & Grinblatt	1999, JF	N	1	
46	Financial statements score	*ps*	Piotroski	2000, JAR	Y		
47	Dollar trading volume in month t-2	*dolvol*	Chordia, Subrahmanyam & Anshuman	2001, JFE	N		1
48	Volatility of dollar trading volume	*std_dolvol*	Chordia, Subrahmanyam & Anshuman	2001, JFE	N		1
49	Volatility of share turnover	*std_turn*	Chordia, Subrahmanyam & Anshuman	2001, JFE	N		1
50	Scaled analyst forecast of one year ahead earnings	*sfe*	Elgers, Lo & Pfeiffer	2001, TAR	N		1
51	# of analysts covering stock	*nanalyst*	Elgers, Lo & Pfeiffer	2001, TAR	Y		
52	Dispersion in forecasted eps	*disp*	Diether, Malloy & Scherbina	2002, JF	Y		
53	Changes in inventory	*chinv*	Thomas & Zhang	2002, RAS	Y		
54	Idiosyncratic return volatility	*idiovol*	Ali, Hwang & Trombley	2003, JFE	N		1
55	Growth in long term net operating assets	*grltnoa*	Fairfield, Whisenant & Yohn	2003, TAR	Y		
56	RD_increase	*rd*	Eberhart, Maxwell & Siddique	2004, JF	N		1
57	Corporate investment	*cinvest*	Titman, Wei & Xie	2004, JFQA	N		1
58	Taxable income to book income	*tb*	Lev & Nissim	2004, TAR	Y		
59	Cash flow-to-price	*cfp*	Desai, Rajgopal & Venkatachalam	2004, TAR	Y		
60	Earnings volatility	*roavol*	Francis, LaFond, Olsson & Schipper	2004, TAR	Y		
61	Change in long-term debt	*lgr*	Richardson, Sloan, Soliman & Tuna	2005, JAE	Y		
62	Change in common shareholder equity	*egr*	Richardson, Sloan, Soliman & Tuna	2005, JAE	Y		
63	Illiquidity	*ill*	Acharya & Pedersen	2005, JF	N	1	
64	# of years since first Compustat coverage	*age*	Jiang, Lee & Zhang	2005, RAS	Y		
65	Financial statements score	*ms*	Mohanram	2005, RAS	Y		
66	Price delay	*pricedelay*	Hou & Moskowitz	2005, RFS	Y		
67	R&D-to-sales	*rd_sale*	Guo, Lev & Shi	2006, JBFA	Y		
68	R&D-to-market cap	*rd_mve*	Guo, Lev & Shi	2006, JBFA	Y		
69	Return volatility	*retvol*	Ang, Hodrick, Xing & Zhang	2006, JF	Y		
70	Industry sales concentration	*herf*	Hou & Robinson	2006, JF	Y		
71	% change over two years in CAPEX	*grcapex*	Anderson & Garcia-Feijoo	2006, JF	Y		
72	Zero-trading days	*zerotrade*	Liu	2006, JFE	Y		
73	Change in 6-month momentum	*chmom*	Gettleman & Marks	2006, WP	N	1	
74	Return on invested capital	*roic*	Brown & Rowe	2007, WP	Y		
75	Abnormal volume in earnings announcement month	*aeavol*	Lerman, Livnat & Mendenhall	2007, WP	Y		
76	Change in # analysts	*chnanalyst*	Scherbina	2007, WP	Y		
77	Asset growth	*agr*	Cooper, Gulen & Schill	2008, JF	Y		
78	Change in shares outstanding	*chcsho*	Pontiff & Woodgate	2008, JF	Y		
79	Industry-adjusted change in profit margin	*chpmia*	Soliman	2008, TAR	N		1
80	Industry-adjusted change in asset turnover	*chatoia*	Soliman	2008, TAR	Y		
81	3-day return around earnings announcement	*ear*	Brandt, Kishore, Santa-Clara & Venkatachalam	2008, WP	Y		
82	Revenue surprise	*rsup*	Kama	2009, JBFA	Y		
83	Cash flow volatility	*stdcf*	Huang	2009, JEF	Y		
84	Debt capacity-to-firm tangibility	*tang*	Hahn & Lee	2009, JF	Y		
85	Sin stock	*sin*	Hong & Kacperczyk	2009, JFE	N		1
86	Employee growth rate	*hire*	Bazdresch, Belo & Lin	2009, WP	Y		
87	Cash productivity	*cashpr*	Chandrashekar & Rao	2009, WP	Y		
88	ROA	*roaq*	Balakrishnan, Bartov & Faurel	2010, JAE	Y		
89	Investment	*invest*	Chen, Novy-Marx, Zhang	2010, WP	Y		
90	Return-on-book equity	*Returnonbookequity*	Chen, Novy-Marx, Zhang	2010, WP	Y		
91	Return-on-market equity	*Returnonmarketequity*	Chen, Novy-Marx, Zhang	2010, WP	Y		
92	Return-on-assets	*Returnonassets*	Chen, Novy-Marx, Zhang	2010, WP	Y		
93	Real estate holdings	*realestate*	Tuzel	2010, RFS	Y		
94	Absolute accruals	*absacc*	Bandyopadhyay, Huang & Wirjanto	2010, WP	Y		
95	Accrual volatility	*stdacc*	Bandyopadhyay, Huang & Wirjanto	2010, WP	N		1

96	Change in tax expense	*chtx*	Thomas & Zhang	2010, WP	Y	
97	Maximum daily return in prior month	*maxret*	Bali, Cakici & Whitelaw	2011, JFE	Y	
98	Percent accruals	*pctacc*	Hafzalla, Lundholm & Van Winkle	2011, TAR	Y	
99	Cash holdings	*cash*	Palazzo	2012, JFE	Y	
100	Gross profitability	*gma*	Novy-Marx	2013, JFE	Y	
101	Asset Turnover	*AssetTurnover*	Novy-Marx	2013, JFE	Y	
102	Organizational capital	*orgcap*	Eisfeldt & Papanikolaou	2013, JF	Y	
103	Secured debt-to-total debt	*secured*	Valta	2015, JFQA	Y	
104	Secured debt indicator	*securedind*	Valta	2015, JFQA	Y	
105	Convertible debt indicator	*convind*	Valta	2015, JFQA	N	1