Liquidity Risk and Mutual-Fund Performance

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Abstract

This paper demonstrates that the systematic liquidity-risk exposures of mutual funds can predict their performance in the cross-section. The results show that funds that significantly load on liquidity risk subsequently outperform low-loading funds by about 6% annually over the period 1984–2009. The liquidity-risk premium however explains only a small fraction of this outperformance, suggesting that the liquidity-risk exposure of a fund is correlated with its manager's ability to generate abnormal performance. Finally, the liquidity-risk exposure effect in mutual funds can also account for a large part of several other stylized facts such as return persistence, fund size, and smart money.

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1 Introduction

The recent financial crisis highlights the necessity of understanding the liquidity risk of financial securities and institutions. Early works, such as Pástor and Stambaugh (2003), Acharya and Pedersen (2005), and Sadka (2006), demonstrate the pricing of aggregate liquidity risk (beta) in the cross-section of stocks. Following recent events, there is a growing interest in the effect of liquidity risk in the cross-section of other asset classes. This paper studies the ability of mutual fund liquidity-risk exposures to predict the cross-section of their performance.[1]

Most early studies find that the after-fee alphas of mutual funds are either zero or negative (see, e.g., Jensen (1968), Elton, Gruber, Das, and Hlavka (1993), Brown and Goetzmann (1995), and Gruber (1996)). Yet, some recent studies argue that it is possible to identify funds with the skill to generate future risk-adjusted performance based on certain fund characteristics. Examples of such characteristics are the styles that funds follow (Daniel, Grinblatt, Titman, and Wermers (1997)), the location of the stocks that funds hold (Coval and Moskowitz (2001)), the extent to which manager's decisions resemble the decisions of other managers with distinguished performance records (Cohen, Coval, and Pástor (2005)), the industry concentration of fund holdings (Kacperczyk, Sialm, and Zheng (2005)), the motivation for trading (Alexander, Cici, and Gibson (2007)), and fund dependence on analyst recommendations (Kacperczyk and Seru (2007)). This paper contributes to the literature by showing that the liquidity-risk exposure of a fund can predict its relative future performance, and by providing evidence that this finding is likely because a fund's liquidity-risk exposure is indicative of its manager's skill to generate abnormal performance.

We calculate the liquidity-risk exposure of a mutual fund as the covariation of its return with unexpected changes in aggregate liquidity (liquidity beta) using a 12- or 24-month historical rolling window. Our first result shows that funds that significantly load

[1] In terms of economic magnitude, mutual funds are arguably the most important asset class for retail investors. As of 2008 year-end, the value of the assets under management by mutual funds globally is about \$19 trillion compared to less than \$1.8 trillion of global assets managed by hedge funds, while the asset value of U.S. mutual funds is higher than the total U.S. stock-market value.

on liquidity risk subsequently outperform low-loading funds by about 6% annually, on average, over the period 1984−2009. The outperformance of high-liquidity-beta funds is robust to controlling for the Fama and French (1996) size and book-to-market risk factors as well as momentum (e.g., Carhart (1997)) and fixed-income-related factors. In contrast to liquidity risk, the exposures to other commonly used factors do not predict such a return spread in the cross-section of fund returns. Therefore, the results suggest that fund liquidity-risk exposure is a particularly important determinant of the cross-section of mutual-fund future performance. Additionally, as we study a large universe of mutual funds across multiple asset classes, we classify mutual funds into four groups according to their investment style: Growth, Growth and Income, Income and Bonds, and Others. The return spread of high-minus-low liquidity beta mutual funds is present within each group, suggesting that the return spread is not due to differences in investment styles.

The outperformance of high-liquidity-beta funds relative to low-liquidity-beta funds may reflect either a liquidity-risk premium stemming from a large cross-sectional variation in fund liquidity beta or a relation between a fund's liquidity beta and the its manager's ability/skill to generate abnormal performance. We begin by studying whether the mutual-fund liquidity-beta return spread can be explained by compensation for a liquidity-risk premium. Note that the existence of a liquidity-risk premium in the cross-section of tradable assets does not necessarily imply a similar premium in the cross-section of portfolios (e.g., funds) of such assets. For example, if all funds similarly load on liquidity risk to earn the liquidity-risk premium, then the exposure to liquidity risk will not generate a significant cross-sectional variation in mutual-fund returns.[2] When we try to explain the high-minus-low liquidity-beta fund portfolio return spread using a five-factor model (Fama-French four factors plus a traded liquidity factor), at most 20%

[2] Indeed, there are several stylized patterns that are exhibited in the cross-section of asset returns, which do not appear in the cross-section of mutual-fund returns. For example, Massa and Phalippou (2005) show that the illiquid funds, proxied by the illiquidity of their underlying stocks, do not outperform liquid funds, although illiquid stocks outperform liquid stocks. Using a different proxy for fund liquidity, Lo and Khadani (2009) find that illiquid hedge funds outperform liquid hedge funds, yet such an effect, again, is not present in the cross-section of mutual funds. Also, in contrast to the one-month stock return reversal pattern documented by Jegadeesh (1990), there is a one-month return continuation pattern in the cross-section of mutual funds.

of the outperformance of high-liquidity-beta funds relative to low-liquidity-beta funds can be explained by exposures to systematic risk factors.

We further investigate the liquidity beta of fund equity holdings. One explanation for the existence of a liquidity-beta return spread in the cross-section of mutual funds might be that high- and low-liquidity-beta funds hold high- and low-liquidity-beta stocks, respectively, which would imply that the return spread observed in mutual funds is a manifestation of the liquidity-beta spread in stocks, that is the liquidity-risk premium. Yet, we find that high-liquidity-beta funds hold, on average, stocks residing in Decile 6 of liquidity beta in the universe of equities, while the low-liquidity-beta funds hold, on average, stocks in Decile 4 of equity liquidity beta. As the return spread between stocks in Deciles 6 and 4 is quite small, the liquidity-risk premium can at most explain a small fraction of the liquidity-beta return spread in the universe of funds. This result is consistent with the aforementioned finding that the traded liquidity factor can account for only a small part of the observed liquidity-beta return spread in the cross-section of funds. Both findings suggest that mutual funds do not exhibit a wide dispersion in their exposure to liquidity risk. Can the abnormal performance of high-liquidity-beta funds be explained by managers' skillful timing of the exposure to liquidity risk? We apply some timing tests (see, e.g., Henriksson and Merton (1981) and Jagannathan and Korajczyk (1986)), the results of which show no evidence of a superior skill in short-term (monthly) timing of the exposure to liquidity risk.

Overall, the evidence suggest that the relative outperformance of high-liquidity-beta funds is likely due neither to a liquidity-risk premium nor to mangers' skill to time their exposure to liquidity risk on a monthly basis. Rather, the results suggest that a fund's exposure to liquidity risk is positively correlated with its manager's ability to successfully select undervalued securities whose price is corrected by the market in the long-run. Anecdotally, the investment of Berkshire Hathaway (essentially a closed-end fund managed by Warren Buffett) in Goldman Sachs in the midst of the liquidity crisis in September 2008 provides an example of such a security-selection ability.[3] At that time,

[3]See, e.g., "Buffett Buying $5 Billion Stake in Goldman Sachs," September 23, 2008, The Associate

the investment bank exhibited a mildly higher liquidity risk than the average firm (its liquidity beta ranked around Decile 6 in the stock universe in 2008 and 2009). The value of investment in Goldman Sachs however continued to deteriorate with market liquidity conditions and improved only a number of months later. After more than two years of investment, the deal ultimately ends with a significant 14% annual return to investment (which is significantly higher than the risk premium of stocks in Decile 6 of liquidity beta). This example illustrates a manager's skill to generate abnormal returns beyond the normal liquidity-risk premium that average stocks with similar liquidity risk can deliver, while lacking the ability to perfectly time liquidity risk. Our results echo Buffett's own views about investment skill, advocating long-term investing while dismissing the possibility of successfully timing short-term market movements.[4]

We further find that the abnormal outperformance of high-liquidity-beta funds relative to low-liquidity-beta funds is concentrated in periods of relatively moderate liquidity shocks, not in periods of significant positive or negative liquidity shocks, suggesting that the outperformance is not explained by liquidity risk alone. In addition, the high-minus-low liquidity-beta return spread does not exist in the universe of index funds, of which managers are not expected to apply unique skills, and both high- and low-liquidity-risk funds tend to be smaller, they charge higher fees, and trade more frequently than other funds. These results reject the explanation that high-liquidity-beta funds outperform low-liquidity-beta funds because the former are more active and therefore take more risk (and yield high returns), while the latter are more passive and therefore take less risk (and obtain low returns). Instead, the results support an explanation by which a fund's exposure to liquidity risk may signify the fund manager's skill/ability to generate abnormal performance.

Having established the possibility that funds' liquidity-risk exposure is a characteristic related to managerial ability/skill, we examine the relation between the liquidity-risk-exposure effect and several other fund-characteristic-based performance effects. First is

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[4]See, e.g., "Buy American. I Am." By Warren Buffett, The New York Times, October 16, 2008.

performance persistence. As investors tend to chase performance (see, e.g., Chevalier and Ellison (1997) and Sirri and Tufano (1998)), it is useful to understand the sources of performance persistence.[5] In the context of liquidity risk, if a fund's liquidity-risk exposure is correlated with the investment skill of its manager then fund performance should be reasonably persistent. We demonstrate that the liquidity-risk exposure can account for the return-persistence phenomenon as documented in Carhart (1997). Carhart shows that funds with high-prior-year returns continue to outperform funds with low-prior-year returns, yet this outperformance is not predicted by funds' prior-year momentum beta. Using regressions, we decompose a fund's prior 12-month average return into an intercept term, a market-beta component, and a liquidity-beta component. We replicate the main persistence effect, that is sorting funds based on past 12-month return generates a significant spread in future fund returns. Yet, we find that of the three components of prior return, only liquidity beta generates a similar spread in future fund returns. Therefore, funds with high returns in year t tend to outperform during year $t+1$ if year-t returns are mainly driven by high exposures to liquidity risk. These results provide means by which investors can detect persistent managerial skill.

Second is the fund-size effect documented by Chen, Hong, Huang, and Kubik (2004). They find that small funds are better able to generate abnormal performance than large funds. In contrast, we focus on liquidity beta, and find that the liquidity-beta return spread is apparent in every fund-size quintile, which confirms that fund size does not explain the liquidity-beta effect. We also find that taken alone, fund size is helpful in identifying the funds that underperform (the largest funds) but not funds that earn a positive alpha. To predict outperforming funds, it is important to consider fund size in conjunction with liquidity-risk exposure, that is, small funds with high liquidity-risk exposure tend to outperform. Our results indicate that large funds with high exposures to liquidity risk experience more losses during severe market liquidity conditions than

[5] A number of studies find persistence in the relative performance of funds (see, e.g., Grinblatt and Titman (1992), Hendricks, Patel, and Zeckhauser (1993), Goetzmann and Ibbotson (1994), Brown and Goetzmann (1995), Grinblatt, Titman, and Wermers (1995), and Gruber (1996)). Most of these articles attribute persistence, at least in part, to funds' managerial skill.

small funds with similar liquidity-risk exposures; their performance nevertheless does not recover as much as small funds when market liquidity conditions improve. This suggests that large funds may not be sufficiently flexible to respond to significant variations in market-wide liquidity conditions, which limits their ability to generate outperformance. While Chen, Hong, Huang, and Kubik (2004) argue that the fund-size effect is likely caused by the large funds' price-impact costs stemming from the idiosyncratic illiquidity of their underlying positions, our results suggest that the lack of ability of large funds to weather significant shifts in systematic liquidity is yet another source of the diseconomies of scale.

The last effect that we study is the smart-money effect, that is, funds that experience investor inflow subsequently outperform funds that experience investor outflow (see, e.g., Gruber (1996) and Zheng (1999)). We find that the liquidity-beta spread is present in both inflow and outflow funds. Consistent with prior studies, our results too indicate that investor flow does not predict fund performance once the momentum factor is included in the performance evaluation (see, e.g., Sapp and Tiwari (2004)). Yet, once the information about funds' liquidity-risk exposure is utilized, the smart-money effect is apparent in funds with high-liquidity-risk exposures. Especially, inflows can predict outperforming funds (those whose alpha is significantly positive) when conditioning on high-liquidity-risk exposure, even after controlling for the momentum factor.

Our conjecture about the correlation between a fund's liquidity-risk exposure and the investment skill of its management is consistent with the economic interpretation of the liquidity factor used for this study (the one proposed in Sadka (2006)). The microstructure literature discusses two main components of liquidity: a pure, non-informational cost component and a component that reflects information asymmetry (see, e.g., Kyle (1985)). Therefore, an exposure to aggregate liquidity risk theoretically reflects two types of uncertainties, corresponding to each component of liquidity: uncertainty about non-informational transaction costs in the marketplace and uncertainty about market-wide information asymmetry. From a natural selection standpoint, a manager who chooses a high exposure to the uncertainty of market-wide information asymmetry may well pos-

sess the skill to utilize private information (e.g., the aforementioned case of Warren Buffett). The liquidity measure used for this study is the permanent-variable price-impact measure of Sadka (2006), which focuses on the information asymmetry component of market liquidity. We find that other liquidity-risk measures, such as Amihud (2002), Pástor and Stambaugh (2003), and the noninformational price-impact measure of Sadka (2006), which do not solely focus on the information asymmetry component, produce directionally consistent, albeit weaker (mostly insignificant) results (see, Dong (2011) for a detailed discussion and comparison of the three above-mentioned liquidity measures). These findings lend further support for our conjecture pertaining to the correlation between a fund's liquidity beta and the investment skill of its management.

Another reason for why the Sadka factor produces more significant results than other liquidity factors may stem from its construction based on systematic movements in volume-induced price impacts that do not reverse quickly. Such trading costs are particularly important for financial institutions because permanent price effects limit their ability to reduce trading costs by splitting-up trades. The systematic nature of the liquidity factor also hampers the ability of these institutions to diversify their search for liquidity. Therefore, funds that are particularly averse to the uncertainty in the permanent component of price impact may be willing to pay a premium (i.e., underperform) to avoid such uncertainty. Taken together, the two attributes of the Sadka liquidity factor, i.e. its interpretation as an informational component of liquidity and its measurement based on permanent price effects, might explain why it can predict fund performance more precisely than other liquidity factors. The findings therefore highlight the particular relevance of the liquidity factor used here to financial institutions.

The rest of this paper is organized as follows. Section 2 describes the data used for this study. Section 3 investigates the relation between liquidity-risk exposure and the cross-section of individual-fund returns and presents the possibility that a fund's liquidity-risk exposure is correlated with its manager's skill to generate abnormal performance. Section 4 studies the manner by which liquidity risk pertains to some stylized facts documented in the mutual-fund literature. Section 5 provides some additional results, and Section 6

concludes.

2 Data

Monthly mutual-fund return data are obtained from the CRSP survivor-bias-free database for the period 1983–2009. Only funds that report returns on a monthly basis and net of all fees (management, incentive, and other expenses) are kept in the sample. Some fund families incubate many private funds and make historical performance available only for the funds that survive (Elton, Gruber, and Blake (2001) and Evans (2004)). In order to address the incubation bias in the data, we exclude the first 12-month fund returns. The removal of these young funds also alleviates a concern that these funds are more likely to be cross-subsidized by their respective fund families (Gaspar, Massa, and Matos (2006)). Consistent with prior studies, we exclude money-market funds and index funds. The returns are based on U.S. dollars and are excess of the risk-free rate. The common-stock holding information for funds that hold equities is collected from the CDA/Spectrum Mutual Fund Holdings Database. The database provides common-stock holding information for all registered mutual funds that report their holdings to the Securities and Exchange Commission (SEC).

Mutual-fund families introduced different share classes in the 1990s. Since different share classes have the same holding composition, we manually aggregate all the observations pertaining to different share classes into one observation. For the qualitative attributes of funds (e.g., name, objectives), we retain the observation of the oldest fund. For the total-net-assets (TNA) under management, we sum the TNAs of the different share classes. Finally, for the other quantitative attributes of funds (e.g., returns, expenses, and loads), we compute the weighted average of the attributes of the individual share classes, where the weights are the lagged TNAs of the individual share classes.

The primary liquidity factor used here is based on the price-impact measures constructed in Sadka (2006), which are extracted from tick-by-tick data. Of the four components of price impact, permanent-fixed, transitory-fixed, permanent-variable, and

transitory-variable, estimated in Sadka (2006), only the permanent-variable component is priced in the cross-section of momentum and post-earnings-announcement-drift portfolios. This paper therefore focuses on the permanent-variable component, henceforth simply referred to as the liquidity factor. In a later section, the transitory-fixed component is also investigated, along with other liquidity-risk measures including Amihud (2002) and Pástor and Stambaugh (2003).

Table 1 reports some summary statistics. The sample includes 13,700 mutual funds. The average number of funds each month varies from 454 in 1983 to 7,138 in 2009. The average monthly mutual-fund return is 20 basis points and the average monthly cross-sectional standard deviation is 2.96%. Comparing the return distribution across the sample years, Panel A shows that minimum returns are more negative (i.e., less than -20%) during 1997–1998 (Asian and Russian financial-crisis periods), 1999–2002 (internet bubble and the subsequent bubble bursting coupled with events such as the 9/11 terrorist attacks and a series of accounting scandals), and 2008–2009 (the recent financial crisis). The maximum returns are also larger during similar periods, suggesting that during volatile periods there are more extreme performers in the cross-section of mutual funds. The percentiles 1, 25, 50, 75, and 99 show similar conclusions.

Panel B of Table 1 reports the summary statistics by investment style. Each fund in the sample is characterized as one of the following investment styles: Growth, Growth and Income, Income and Bonds, and Others (see Appendix for details on the applied classification scheme). Examples of Others are multi-strategy funds, multi-style funds, commodity funds, and real-estate funds. The sample includes 4,207 Growth funds, 1,853 Growth and Income funds, 4,063 Income and Bond funds, and 3,577 Other funds. The different styles exhibit sufficient cross-sectional variation in average return, which is valuable for testing the potential impact of liquidity risk.

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. 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. Following prior works that advocate estimating a fund's risk profile over a short period of time (e.g., Brown, Harlow, and Starks (1996) and Chevalier and Ellison (1997, 1999)), we use a rolling window of 12 months in this section. In any given month, we only include funds with at least 11 non-missing return observations over the prior 12 months. A one-year rolling window allows for time variation in systematic liquidity exposure year by year. The results using longer horizons are analyzed in a later section.

Ten portfolios of mutual funds are formed every month (with equal number of funds in each portfolio) using the past one-year rolling liquidity factor loadings (funds are kept in the portfolios for one month). Portfolio formation begins April 1984 and ends December 2009 (309 monthly observations). Since the liquidity factor ends December 2008, the liquidity betas for funds in 2009 are kept at their estimated levels using the 12-month returns during 2008.

3.1 Full-Sample Analysis

Panels A and B of Figure 1 plot returns and alphas of liquidity-loading deciles (in bars) along with the respective t-statistics (in symbols). Unless otherwise noted, the alphas reported in the paper are returns adjusted by the four factors MKT-RF, SMB, and HML of Fama and French (1993), and UMD of Carhart (1997).[6] The figure shows that the high-liquidity-loading portfolio has the highest average next-month return, 0.57% (alpha=0.16%), while the low-liquidity-loading portfolio has the lowest average next-month return, 0.15% (alpha=–0.36%). The rest of the portfolio returns as well as alphas generally increase with the liquidity loading. The figure also includes the high-minus-low

[6] The four factors are obtained from Kenneth French's website.

liquidity-risk portfolio, whose next-month return is 0.42% and four-factor alpha is 0.51% (6.3% annually) with a t-statistic of 3.21. The significant performance of the portfolio spread suggests that high-liquidity-loading funds significantly outperform low-liquidity-loading funds in the future. These results are also reported in Table 2.

In addition to liquidity beta, the paper also examines whether fund exposures to the four systematic risk factors that are commonly used for explaining the time-series variation in mutual-fund returns can also explain the cross-section of future fund performance. Table 2 reports the returns of decile portfolios sorted by factor loadings with respect to each of the four benchmark risk factors. The results indicate that over the period 1984–2009, none of the four factor sensitivities significantly predicts risk-adjusted fund returns. This result is consistent with Carhart (1997), who finds that funds' prior-year momentum beta does not predict a positive spread in the cross-section of future mutual-fund performance. Therefore, although the benchmark risk factors perform quite well insofar as explaining the contemporaneous time-series variation of mutual-fund returns (as typically reflected by relatively high R^2 of time-series regressions), they do not seem to predict a significant spread in the cross-section of future fund returns in the same manner as the liquidity factor.

Since we focus on the entire mutual-fund universe, of which bond funds are also a large portion, we add several fixed-income factors to the four-factor model to calculate alphas. Following Sharpe (1992), we consider the Lehman Brothers Long-Term Treasury Bill Index returns, the Government Bond Index returns, Baa Corporate Bond Index returns, and a credit risk factor in the form of the spread between the Baa Index and the Treasury Index returns. Adding these factors to the four-factor model does not significantly change the findings in Table 2. Also, none of the factor loadings with respect to the fixed-income factors generates a positive spread in the cross-section of mutual-fund returns. For brevity, we only report the four-factor results in this paper.

3.2 Style Analysis

To provide some insight as to whether the high-minus-low return spread is driven by different investment styles, Table 3 reports the next-month performance of the liquidity-loading-sorted portfolios separately using the funds in each investment style (these are dependent sorts; the funds in each style are divided into ten equal-size liquidity-beta groups each month). The results show that the four-factor alphas of the high-minus-low portfolios are significantly positive for all investment-style groups. The results suggest that our finding on the ability of liquidity risk to explain the cross-section of future mutual-fund returns does not stem from the difference between investment styles.

3.3 Liquidity-Risk Premium or Managerial Skill?

We study whether the mutual-fund liquidity-beta return spread can be explained by compensation for a liquidity-risk premium. In Table 4, we try to explain the high-minus-low liquidity-beta portfolio return spread for the overall sample and for each individual style by regressing the return spread on a five-factor model, that is the four-factor model plus a traded liquidity factor. The traded liquidity factor is constructed as the return of high-minus-low liquidity-beta deciles of equities, where liquidity beta is calculated through a regression of prior 12-month returns on the market factor and the nontraded liquidity factor. The results show that the return spread using all sample funds drops from 0.51% (four-factor alpha) to 0.41% (five-factor alpha) per month, which implies that roughly 20% of the outperformance of high-liquidity-beta funds relative to low-liquidity-beta funds can be explained by the liquidity-risk exposure. The results within individual styles are generally consistent with the result in the overall sample. We also use alternative ways to constructing traded liquidity factors by either using longer time windows to calculate prior liquidity beta while including the Fama-French factors and momentum as controls, or using other nontraded liquidity factors to estimate liquidity betas (by which a traded factor is formed). These alternative traded liquidity factors can explain much less of the outperformance of the high-minus-low liquidity-beta fund

portfolio.[7]

Overall, these findings suggest that liquidity beta can provide valuable information for investors insofar as manager selection. In contrast to the performance predictability of liquidity beta, fund return exposures to other risk factors do not predict performance. Moreover, a high liquidity-risk exposure of a fund during the ranking period might not imply that part of its future performance is earned through a liquidity-risk premium. Instead, the performance seems to point to the ability of the fund's manager to generate performance over and beyond that which is explained by the fund's systematic risk exposures during the holding period. In sum, the evidence advance that a fund's liquidity beta can predict two sources of performance that are of interest to mutual-fund investors, managerial skill and return compensation for bearing liquidity risk, where most of the performance stems from the former (80%) and only a small portion (at most 20%) is explained by the latter.

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

To further investigate the fund-performance attribution results in the previous section, we obtain the stock holdings of individual funds for the sample period, 1983–2009. Figure 2 plots the relation between the liquidity-beta ranking of funds in the fund universe and the liquidity-beta ranking of funds' stock holdings in the stock universe. In Panel A, on the left-hand side, funds are sorted into decile portfolios according to their liquidity beta, which is calculated using a regression of prior 12 monthly fund returns on the market portfolio and the liquidity factor. On the right-hand side, all the stocks in the CRSP stock universe are also sorted into decile portfolios according to their liquidity beta, where, similar to funds' liquidity beta, the liquidity beta of a stock is calculated using a regression of prior 12 monthly stock returns on the market portfolio and the liquidity

[7] In unreported tests we also replace the equity-based traded liquidity factor with two bond-based traded liquidity factors constructed in Lin, Wang, and Wu (2010). These traded portfolios are based on bond beta spreads with respect to market liquidity as measured in Amihud (2002) or Pástor and Stambaugh (2003). Due to data limitations, the time series of these factors begin in 1994. The results show that the mutual-fund liquidity-beta return spread does not significantly load on either bond-based liquidity factors.

factor. The arrow that links a fund decile to a stock decile indicates the average decile rank of the fund-decile stock holdings in the stock universe. For example, for Decile 1 of funds, the liquidity betas of the stocks that the funds in this decile hold are on average ranked Decile 4 in the stock universe, thus an arrow linking Decile 1 of funds to Decile 4 of stocks.

In Panel B, the horizontal axis includes the fund decile portfolios sorted by fund liquidity beta, while the vertical axis reports (in cubics symbols) the average decile ranks of the fund-decile stock holdings in the CRSP stock universe. The plot also includes the four-standard-deviation range around the average (the bars around each cubic symbol), where the standard deviation is the cross-sectional standard deviation of the average decile ranks of individual funds' stock holdings across the funds in each fund liquidity-beta decile in each month averaged over all months.

One explanation for the existence of a liquidity-beta return spread in the cross-section of mutual funds might be that high-liquidity-beta funds (Decile 10 in the fund universe) hold high-liquidity-beta stocks (Decile 10 in the stock universe) while low-liquidity-beta funds (Decile 1 in the fund universe) hold low-liquidity-beta stocks (Decile 1 in the stock universe). This would imply that the return spread observed in mutual funds is a manifestation of the liquidity-beta return spread in stocks, that is the liquidity-risk premium. However, Figure 2 refutes this simple explanation, because the funds in every liquidity-beta-sorted fund decile hold stocks that are, on average, ranked between Decile 4 and Decile 6 of liquidity beta in the stock universe (Panel A). These findings suggest that most funds do not hold stocks with very high liquidity risk, on average over time, regardless of the fund's liquidity-risk beta ranking in the fund universe. The finding is consistent with the fact that most mutual funds are fairly liquid, allowing for redemptions and inflows on a daily basis. Holding stocks with very high liquidity risk may hamper a fund's ability to accommodate investors' flows if flows have a common component that co-moves with systematic liquidity conditions.

Nevertheless, moving from Decile 1 to Decile 10 of the liquidity-beta fund deciles, the average liquidity beta of fund holdings increases roughly from Decile 4 to Decile 6

in the stock universe. This increase, however, is far from a one-to-one relation between a fund's liquidity beta ranking and the average ranking of its holdings (the dotted 45 degree line on Panel B of the figure). The return spread between Decile 6 stock portfolio and Decile 4 stock portfolio, which is the liquidity-risk premium difference between the stocks residing in Decile 6 and Decile 4, is 0.05% per month, only a fraction of the return spread between Decile 10 fund portfolio and Decile 1 fund portfolio (0.51%). It follows that the liquidity-beta return spread of mutual funds cannot be explained by the relatively small difference in the average liquidity-risk exposure of their reported equity holdings. This result is consistent with the previous finding that the traded liquidity factor can account for only a small part of the observed liquidity-beta return spread in the cross-section of funds.

In addition to a comparison of the rankings of liquidity betas in the fund universe and in the stock universe, in unreported results, we also verify that the average estimated liquidity beta of the funds in each decile is quite similar to the average liquidity beta of the equity holdings of these funds. Although we do not have access to information about the non-equity holdings of mutual funds, the fact that the liquidity beta of a fund is similar to that of its equity holdings suggests that the liquidity beta of the non-equity holdings should be close in magnitude to that of the equity holdings, as well as to that of the entire fund, because the beta of a fund is the weighted average of the betas of its equity and non-equity holdings.

To conclude, it seems that in order to be ranked in liquidity-beta Decile 10 in the fund universe, a fund only needs to hold a portfolio with a mildly higher average liquidity beta than other funds. The outperformance of the high-liquidity-beta funds therefore cannot be explained by the small liquidity-risk premium difference between portfolios with mildly different liquidity betas, but rather by the possibility that the managers of these funds have the ability to select assets that are undervalued, which also tend to, on average, have higher liquidity risk.

3.5 Are Funds Skilled in Timing Liquidity Risk?

To gain further insight as to the type of ability or skill that generates the relative outperformance of high-liquidity-beta funds, this section investigates the time variation of the exposure of the fund liquidity-beta return spread to the traded liquidity factor. As argued in the previous section, the fund return spread is largely not due to a liquidity-risk premium, on average, over time. Yet, a salient feature of high-liquidity-beta assets is that they tend to significantly underperform during liquidity crises while substantially rebounding during post-crisis periods. Thus, a high-liquidity-beta fund can outperform by timing its holdings exposures to the liquidity factor, that is, holding low-liquidity-exposure assets during crisis periods and high-liquidity-exposure assets after crises. Although both timing and security-selection abilities are important skills of fund managers, the alphas reported in Table 4 can be viewed as pure measures of funds' security-selection ability only if the funds lack significant timing ability (see, e.g., Henriksson and Merton (1981) and Jagannathan and Korajczyk (1986)).

Therefore, in Table 5, we investigate whether the returns to the high-minus-low liquidity-beta fund portfolio imply a managerial ability to time the exposure to assets with high liquidity risk. In the spirit of the timing model of Henriksson and Merton (1981), we add the term Max(0, -LIQ) to the five-factor model in Table 4 (LIQ is the traded liquidity factor). In contrast to the ability to time the exposure to the market return studied in Henriksson and Merton (1981), we focus on the ability to time the exposure to the traded liquidity factor. A positive (negative) regression coefficient on Max(0, -LIQ) suggests that the liquidity-beta fund return spread signifies an ability to time liquidity exposure in the right (wrong) direction, that is, having a lower (higher) exposure to liquidity risk during negative liquidity events. Note that the regression intercepts of the timing tests in Table 5 can no longer be interpreted as measures of performance (see, e.g., Ferson (2009)). The results indicate a slightly negative timing ability overall. Using all funds, the coefficient of the liquidity-timing term, Max(0, -LIQ), is negative with a t-statistic of -1.79. This is mostly driven by a significantly negative timing ability of

Growth funds, which display a significantly negative coefficient on the liquidity-timing term. The findings suggest that high-liquidity-beta funds do not have better ability to time exposure to high liquidity-risk assets than low-liquidity-beta funds, on a monthly basis. This is quite reasonable given the fact that liquidity crises tend to emerge as sudden, unpredictable shocks and that most financial institutions were not able to avoid severe losses during past liquidity crises.

To further confirm the time-varying property of the high-minus-low liquidity-beta fund portfolio performance, Figure 3 partitions the sample period into quintiles based on the realized returns of the traded liquidity factor. The top (bottom) quintile includes the months for which the factor return is in the top (bottom) 20% of its distribution. The middle quintile (Quintile 3) includes the months with low liquidity risk, where there are neither large positive nor large negative liquidity shocks. The alpha in each month is the constant plus the residual from the four- or five-factor model used to evaluate the high-minus-low fund portfolio performance for the entire sample period. The figure shows that the four-factor alpha of the portfolio increases from significantly negative, when market liquidity condition is low (bottom quintile), to significantly positive, when market liquidity condition is high (top quintile), indicating that the performance (before adjusting for funds' liquidity-risk exposure) covaries with market liquidity conditions. However, once fund performance is adjusted by the five-factor model with the traded liquidity factor included, the adjusted performance is no longer positively correlated with market liquidity conditions. In fact, only the average monthly five-factor alpha in Quintile 3 is significant ($alpha = 0.81\%$ per month and $t = 3.25$), suggesting that the high-minus-low liquidity-beta funds generate most of their performance when there are little liquidity shocks (Quintile 3). This result confirms that the outperformance is due neither to taking high liquidity risk nor to short-term timing of liquidity-risk exposure on a monthly basis.

To summarize, the evidence suggest that the outperformance of high-liquidity-beta funds is largely not a reflection of a liquidity-risk premium, but rather it signifies a superior managerial skill to generate abnormal performance in the long-run. This ability

is especially noticeable during periods that exhibit no large unexpected market-wide liquidity variations.

Perhaps the conclusions in this section and the previous one could be illustrated through a recent example briefly mentioned in the introduction, that is Warren Buffett's recent investment in Goldman Sachs (GS). In the midst of the liquidity crisis, in September of 2008, Buffett's asset-management firm, Berkshire Hathaway—essentially a closed-end fund—decides to invest $5 billion in GS with the belief that GS is undervalued. Due to the general condition of the financial sector during that time, GS exhibits only a mildly higher liquidity beta than the average firm (its stock liquidity beta is ranked around Decile 6 in the stock universe in 2008 and 2009). After more than two years of investment, Buffett closed his position in GS with a significant return.

Nevertheless, this profit is not earned smoothly. Since September 2008, the value of investment in Goldman Sachs continued to deteriorate with market liquidity conditions as the impact of Lehman's collapse unfolds. It improves only a number of months later. Thus, by investing in GS instead of holding cash, Buffett actually increases his fund's liquidity-risk exposure during the crisis. The imperfect timing is ultimately surmounted by about 14% return per year that the GS deal delivers to Buffett, which is significantly higher than the risk premium of the liquidity-beta Decile 6 stock portfolio. This deal exhibits Buffett's ability to generate abnormal returns that are beyond the normal liquidity-risk premium that average stocks with similar liquidity risk can deliver, but does not provide much evidence of his ability to time his fund's liquidity-risk exposure on a monthly basis. If some mutual-fund managers are similarly skillful investors as Warren Buffett, then sorting funds by their liquidity beta is likely to identify such managers.

3.6 Liquidity Beta and Fund Characteristics

This subsection provides some additional analyses supporting the notion that a fund's liquidity-risk exposure could be related to its ability to generate abnormal performance. First, we examine the fund characteristics of each liquidity-beta decile, which are reported in Table 6. The table shows that both high-liquidity-beta funds (Decile 10) and low-

liquidity-beta funds (Decile 1) charge significantly higher fees (an average expense ratio of 1.3%) than funds with average liquidity beta (the average expense ratio of funds in Decile 5 is 0.9%). Since a typical passive index fund charges much lower fees (less than 0.5%), the results regarding the expense ratios suggest that both high- and low-liquidity-beta funds are relatively active. They also trade more frequently (higher turnover ratios) and tend to be smaller than funds with average liquidity beta, providing further evidence that such funds are relatively active.

These results are inconsistent with the hypothesis that high-liquidity-beta funds are more active, take more risk, and earn high returns, while low-liquidity-beta funds are more passive, take less risk, and earn low returns. Therefore, a risk-based explanation is unlikely to explain the outperformance of the high-minus-low liquidity-beta fund portfolio. Yet, active funds are not necessarily skillful funds. As both high- and low-liquidity beta funds tend to be more active, the findings suggest that funds' liquidity-risk exposure can assist investors to distinguish between the active funds that tend to outperform (high-liquidity-beta funds) and those that tend to underperform (low-liquidity-beta funds) in future periods.

To provide further supporting evidence for the conclusion that a fund's liquidity beta is correlated with managerial talent, we also examine index funds. If funds' liquidity beta reflects the liquidity-risk premium rather than skill, we would expect that high-liquidity-beta index funds outperform low-liquidity-beta index funds in a similar manner as in non-index funds. However, using decile sorts of individual index funds, we find that high-liquidity-beta index funds do not outperform low-liquidity-beta index funds. The liquidity betas of the high- and low-liquidity-beta index-fund deciles are close in value to those of the high- and low-liquidity-beta non-index-fund deciles, respectively. This indicates that the liquidity-risk-exposure-induced outperformance is a phenomenon associated with actively managed fund rather than funds that passively follow an index. Since passive funds, in principle, are not supposed to involve significant managerial skill, the finding supports that the outperformance of high-liquidity-beta funds is related to the ability of the fund managers to generate abnormal performance.

4 Liquidity Risk and Other Performance Effects

The previous sections explore the relation between a mutual fund's liquidity-risk exposure and its future performance. A large body of literature documents that mutual-fund future performance can also be predicted by other mutual-fund characteristics such as past return, past flow, and size. This section therefore explores the relation of liquidity risk and these other stylized facts about fund characteristics and future performance.

4.1 Performance Persistence

If a fund's liquidity-risk exposure is correlated with its manager's skill, fund performance should be relatively persistent, as skillful or unskillful managers should repeat themselves at least in the short-run. In this subsection, we examine the effect of liquidity risk on mutual-fund future performance with a focus on the performance-persistence effect documented by Carhart (1997). Carhart finds that sorting funds based on their prior-year returns is useful for predicting their' future performance: Winners continue to outperform while losers continue to underperform during a short period post portfolio formation. Carhart shows that while a fund's momentum beta during the ranking period does not predict the fund's performance persistence during the holding period, a momentum factor exposure during the portfolio holding period can explain a large part of this return persistence effect, that is the magnitude and significance of the return spread between winner and loser funds is significantly reduced after adjusting returns using the momentum risk factor.

Our measure of fund liquidity risk is constructed in a manner that facilitates a study of its relation to the prior-year-return persistence effect because it is estimated using past 12-month returns. In particular, the liquidity beta of fund i for period $t = 0$ is estimated using the following rolling regression over $t = -12... - 1$:

$$R_{i,t} = Const_i + \beta_{i,MKT} \cdot R_{MKT,t} + \beta_{i,Liq} \cdot Liq_t + \epsilon_{i,t}, \tag{1}$$

where $R_{i,t}$ is mutual fund i's return at time t, $R_{MKT,t}$ is the market return at time t, Liq_t denotes the liquidity factor value at time t, and $\epsilon_{i,t}$ is the residual term; all returns are in excess of the risk-free rate. Based on the above regression model, the average of the past 12-month returns can be decomposed into three components as follows:

$$\frac{1}{12}\sum_{t=-12}^{-1} R_{i,t} = \widehat{Const}_i + \widehat{\beta}_{i,MKT} \times \frac{1}{12}\sum_{t=-12}^{-1} R_{MKT,t} + \widehat{\beta}_{i,Liq} \times \frac{1}{12}\sum_{t=-12}^{-1} Liq_t, \tag{2}$$

where the residual term in (1) vanishes because the average of the 12-month residuals is constructed to be zero based on the 12-month rolling regression in (1). If sorting past 12-month returns predicts cross-sectional return differences across mutual funds, then this predictive ability must stem from the three components that decompose past returns, i.e., $\widehat{Const}_i$, $\widehat{\beta}_{i,MKT}$, or $\widehat{\beta}_{i,Liq}$, which are the estimates of the regression (1). Therefore, this decomposition enables the identification of the source of the predictability that past 12-month returns have toward fund future performance.

We first verify that return persistence exists in our sample. Similar to Carhart (1997), we sort funds into decile portfolios based on their average past 12-month returns. We then examine strategies with different post-ranking holding horizons. Specifically, similar to the portfolio construction approach of Jegadeesh and Titman (1993), 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. We also calculate the return difference between the winner fund portfolio (Decile 10) and the loser fund portfolio (Decile 1) for each holding horizon. Carhart (1997) documents return persistence, before adjusting returns using the momentum factor. The results in Table 7 indicate that the raw returns of the winner portfolio outperform those of the loser portfolio for holding periods of up to six months post formation. The Fama-French three-factor alpha of the winner portfolio is significantly higher than that of the loser portfolio for holding periods of up to 12 months post formation. For the one-month holding period strategy, past-12-month winner funds sig-

nificantly outperform loser funds even adjusting for the four factors, although the return spread (adjusted by Fama-French three factors) drops by more than half, from 0.98% to 0.34%, after adding the momentum factor. Its significance is also weakened, with the t-statistic dropping from 3.77 to 2.01, respectively.

After confirming the performance-persistence effect in our sample for holding periods of up to 12 months, we examine which component of the average past 12-month fund returns predicts the cross-sectional differences in future returns. Table 7 reports the 10-minus-1 return spread based on each of the three components of past 12-month returns. For the one-month holding period strategy, where the return-persistence effect remains even after controlling for the four factors, the results show that only the liquidity beta generates a four-factor risk-adjusted return difference in the cross-section of funds. For other holding horizons, where the return-persistence effect remains after controlling for the Fama-French three factors, the power of predicting a three-factor risk-adjusted return difference in the cross-section of funds still mainly stems from the liquidity beta. In fact, for all holding horizons, fund market beta has a reverse implication for funds' future performance, that is, funds that are more sensitive to market risk earn lower returns.

Overall, the results show that the ability of past returns to predict future fund performance mainly stems from the liquidity-risk exposure of the past 12-month fund returns. Carhart finds that funds with high-momentum loadings do not outperform those with low-momentum loadings (which also holds in our sample, as shown in Table 2). His explanation for the return-persistence effect is therefore that winner funds happen to load (by luck) on momentum winners during the portfolio holding period. Our results show that performance persistence occurs only in conjunction with liquidity risk: Funds with high returns in year t tend to outperform during year $t+1$ if year-t returns are mainly driven by a high exposure to liquidity risk. Given the association of liquidity beta with skill, as discussed above, another interpretation for these results is that skill-related performance seems to persist.[8]

[8] Carhart also examines another type of return persistence, whereby funds are sorted based on their prior-36-month four-factor alpha. In a later section, we note that the liquidity beta estimated using 36-month rolling windows does not significantly predict fund performance, and, therefore, our analyses

4.2 The Fund-Size Effect

The fund-size effect is documented in Chen, Hong, Huang, and Kubik (2004). They find that small funds have better ability to generate abnormal performance than large funds, and offer an explanation based on the liquidity level of their underlying positions. Since individual-fund liquidity may have a common, systematic component, we examine the relation between fund size and systematic liquidity risk.

To alleviate the concern that the liquidity-beta return spread is due to the fund-size effect, we first remove funds with TNAs less than 15 million dollars each month. We then sort the remaining funds into five portfolios according to fund size (TNA) and then into five portfolios according to fund liquidity beta, estimated using the prior 12 months. Table 8 shows that the return spread of the high-minus-low liquidity-beta portfolio is significant in all size quintiles, suggesting that fund size does not explain the liquidity-beta effect.

Table 8 also confirms the fund-size effect in the last column. The largest fund quintile underperform the smallest fund quintile by 0.08% (four-factor alpha) per month (t-statistic of 2.41). However, taken alone, fund size is only helpful in identifying the funds that underperform (the largest funds); the smallest fund quintile does not earn a positive alpha. To help investors predict outperforming funds, it is important to consider fund size in conjunction with liquidity-risk exposure, that is, small funds with high liquidity-risk exposure tend to outperform. For example, the smallest size and highest liquidity-beta funds have a positive alpha of 0.23% per month with t-statistic of 2.55.

In addition, the double-sort results show that the fund-size effect is significant only among the most liquidity sensitive funds (within the highest liquidity-beta quintile, large funds underperform small funds by 0.15% per month with a t-statistic of -2.67). To further investigate this result, we partition the sample into liquidity-crisis periods and non-crisis periods. Since liquidity crises are rare events, we classify months for which the liquidity factor innovations belong to the bottom 20% of the distribution as a proxy for

focus on the one-year return-persistence effect alone.

months of liquidity crises and the rest of the months in the sample period are defined as non-crisis periods. In unreported results, we find that large, high-liquidity-beta funds experience more losses during severe market liquidity conditions (crisis periods) than small funds with similar liquidity-risk exposures; their performance nevertheless does not recover as much as small funds when market liquidity conditions improve (non-crisis periods). This suggests that large funds are not sufficiently flexible to respond to significant variations in market-wide liquidity conditions, limiting their ability to generate performance. The fund-size effect is not present in funds with low liquidity betas, suggesting that size does not significantly matter for funds whose returns are insensitive to market liquidity variations.

In sum, while Chen, Hong, Huang, and Kubik (2004) argue that the fund-size effect is likely caused by large funds' lack of ability to avoid high transaction costs due to the idiosyncratic illiquidity of their underlying positions, our results suggest that the lack of ability of large funds to handle a high exposure to systematic liquidity risk is another source of the diseconomies of scale.

4.3 The Smart-Money Effect

The final effect that we study is the smart-money effect, that is, funds that experience investor inflow subsequently outperform funds that experience investor outflow (see, e.g., Gruber (1996) and Zheng (1999)). As fund flow can generate price pressure on the underlying securities it holds (e.g., Coval and Stafford (2007)), it is natural to examine the relation between the smart-money effect and aggregate liquidity conditions.

Following the literature, the percentage net flow to fund i during month t is measured as

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1 + R_{i,t}) - MergeTNA_{i,t}}{TNA_{i,t-1}}, \tag{3}$$

where $TNA_{i,t}$ is measured at the end of month t, $R_{i,t}$ is the fund's return for month t, and $MergeTNA_{i,t}$ is the increase in the TNA due to mergers during month t.

In Table 9, funds are first sorted into those with inflows versus those with outflows during the previous month. Within each group, funds are further sorted into five portfolios based on fund liquidity beta, measured using the prior 12 months. The results show that the liquidity-beta return spread is present in both inflow and outflow funds. Note that outflow funds seem more constrained than inflow funds in choosing assets with different liquidity-risk exposures because the liquidity-beta return spread among outflow funds is smaller and less significant than that of inflow funds (the four-factor alpha is 0.35% and 0.60%, respectively, with t-statistics of 2.84 and 3.71). One possible explanation is that funds with outflows may require managers to liquidate positions quickly, while funds with inflows may choose to slowly engage capital into new investments.

In unreported results, we confirm the smart-money effect: inflow funds outperform outflow funds by 0.19% per month (Fama-French three-factor alpha) with a t-statistic of 2.37. Sapp and Tiwari (2004) argue that momentum can explain the smart-money effect. Their argument is also confirmed in our sample: after including the momentum factor, the performance (four-factor alpha) difference between inflow and outflow funds becomes insignificant.

Yet, when the information about funds' liquidity-risk exposure is utilized, the double-sort results show that the smart-money effect is significant among the high-liquidity-beta funds. The fund-flow return spread in the high-liquidity-beta group remains significant after controlling for the momentum factor, with a four-factor alpha of 0.25% and a t-statistic of 2.91. Notably, the high-liquidity-beta funds with recent inflows earn a positive alpha of 0.36% per month (t-statistic of 3.08), even after controlling for the momentum factor. Low-liquidity-beta, outflow funds can also predict significant underperformance.

5 Additional Tests

5.1 Alternative Liquidity-Risk Measures

It is well recognized that liquidity can be measured in various ways, and different measures may capture different aspects of liquidity (see Korajczyk and Sadka (2008)). We

conjecture that the correlation between fund liquidity beta and managerial ability stems from the fact that liquidity risk reflects two types of uncertainties——uncertainty about pure, non-informational transaction costs in the marketplace and uncertainty about market-wide information asymmetry. The liquidity measure used for this study is the permanent-variable price-impact measure of Sadka (2006), which focuses on the information asymmetry component of market liquidity (see, e.g., Kyle (1985)). From a natural selection standpoint, a manager who chooses a higher exposure to the uncertainty of market-wide information asymmetry may well have the skill to utilize private information.

Therefore, the analysis in this section repeats the liquidity-loading portfolio sorts while using several other measures of liquidity risk: the Amihud (2002) measure, the measure of Pástor and Stambaugh (2003), and the transitory-fixed price-impact component of Sadka (2006).[9] These alternative measures do not particularly focus on the information asymmetry component of market liquidity.

Table 10 reports the returns and alphas of the high-minus-low liquidity-beta portfolio using the different liquidity factors. The results show that all other liquidity-risk measures produce directionally consistent, albeit weaker (mostly insignificant) results. Replacing the traded liquidity factor in Table 4 with the traded Amihud factor or the traded Pástor-Stambaugh factor also shows consistent, but weaker effects pertaining to the liquidity-beta return spread. That is, although the liquidity loadings of the liquidity-beta return spread are still significantly positive, the reduction of the risk-adjusted return spread from using the four-factor model to using the five-factor model is smaller than that reported in Table 4.[10]

In addition, the liquidity factor measures systematic movements in volume-induced

[9] The Amihud-based measure is a non-traded liquidity-risk factor constructed following the procedure outlined in Acharya and Pedersen (2005). The Pástor-Stambaugh measure is the non-traded liquidity-risk factor obtained from Pástor's website.

[10] The traded Amihud liquidity factor is constructed as the decile return spread of liquidity beta of equities, where liquidity beta is calculated through a regression of prior 12-month (or 60-month) returns on the market factor (or the Fama-French four factors) and the nontraded Amihud liquidity factor. The traded Pástor-Stambaugh factor is obtained from Pástor's website.

price impacts that do not reverse quickly, while the Amihud factor focuses on total contemporaneous volume-induced price impact and the Pástor-Stambaugh factor focuses on volume-induced price impacts that reverse the following trading day (see, e.g., Dong (2011) for a detailed discussion). Permanent price impacts are particularly important for large financial institutions because they limit the ability to reduce trading costs by splitting-up trades across multiple periods. The systematic nature of the liquidity factor also hampers the ability of these institutions to diversify their search for liquidity. Therefore, funds that are especially averse to the uncertainty in the permanent component of price impact may be willing to pay a premium (i.e., underperform) to avoid such uncertainty. Taken together, the two attributes of the Sadka liquidity factor, i.e. its interpretation as an informational component of liquidity and its permanent effect, might explain why it can predict performance more precisely than other liquidity factors. These results therefore highlight the particular relevance of the main liquidity factor used here for financial institutions.

5.2 Liquidity Level and Liquidity Risk

Although this paper focuses on liquidity risk, the liquidity level and the liquidity risk of a fund may be related. In unreported results, we also evaluate the robustness of our findings to controlling for fund-level liquidity in two ways. First, we compute fund-level liquidity using the return-autocorrelation measure advanced in Getmansky, Lo, and Makarov (2004) and Khandani and Lo (2009). Sorting funds first by fund-level liquidity and then by liquidity beta, we find that the liquidity-beta return spread remains significant.

Second, we construct an illiquidity return spread as the return of high-minus-low Amihud illiquidity measure deciles of equities. We then try to explain our liquidity-beta return spread using an augmented five-factor model (the four factors plus the Amihud-based illiquidity return spread). The results indicate that the liquidity-beta return spread does not significantly load on the Amihud-based illiquidity return spread, and the alpha of the liquidity-beta return spread using the five-factor model is quite similar to that

of the four-factor model. The analysis therefore suggests that our main results are not driven by fund-level liquidity.

5.3 Longer Holding and Ranking Periods

The analyses in this paper are mainly based on liquidity-beta-sorted portfolios that are held for a period of one month. This section examines the performance of the liquidity-beta return spread over longer holding periods. Table 11, Panel A, reports the results. We follow the portfolio construction approach of Jegadeesh and Titman (1993). Specifically, the table utilizes average returns of multiple portfolios with the same holding horizon. For example, the January return of a three-month holding period strategy is an average of the January returns of three liquidity-risk portfolios that are constructed in October, November, and December of the previous year. The results indicate that the high-liquidity-beta portfolio outperforms the low-liquidity-beta portfolio for up to 60 months. Yet, the performance of the high-minus-low liquidity-loading portfolio decreases over long holding horizons; it is significant for holding periods equal to or less than 12 months. The finding is consistent with Berk and Green (2004), who advance an explanation for the lack of long-lived performance persistence, even in the presence of managerial skill (note that the performance-persistence section highlights that return is persistent only within a year post portfolio formation).

We also examine the performance of liquidity-beta portfolios using longer rolling windows to calculate fund liquidity beta. Table 11, Panel B, repeats the analysis of Table 3, while using liquidity betas that are constructed based on 12, 24, 36, 48, and 60 prior monthly returns. At any given period of time, funds with non-missing returns for at least 11, 18, 24, 36, and 48 months are used, respectively. The results demonstrate that the liquidity-beta return spread decreases with the ranking period and remains significant for rolling windows of up to 36 months. The insignificant liquidity-beta return spread for rolling windows of over 36 months seems similar to that using the momentum factor. Carhart (1997) finds that funds that follow a long-term momentum strategy do not outperform funds that follow a long-term contrarian strategy. These findings

suggest that short-term liquidity-beta measures are more precise in predicting future fund performance. The difference between the performance predictability of long- and short-term liquidity beta supports the notion that a high-liquidity beta can signify a fund manager's superior investment skill. If a fund manager has a consistent strategy to generate performance by simply earning a liquidity-risk premium, then one would not expect the fund to change its liquidity-risk exposure quickly over time. The fact that although funds choose a short period of time to be exposed to liquidity risk and then outperform in the subsequent year suggests that the fund manager may know some additional information, and the outperformance is not simply due to a liquidity-risk premium. Management skill (to generate risk-adjusted performance) once again emerges as a likely explanation.

5.4 Subperiod Analysis

Last, to further examine the time-varying property of the liquidity-beta return spread, we split the sample into two equally long subperiods and conduct a subperiod analysis using the same methodology as in Table 2. Panels A and B of Table 12 report the results of the subperiods 1984–1997 and 1998–2009, respectively. The liquidity-beta return/alpha spread is present in both early and recent subperiods. The liquidity-beta return spread is therefore not driven by a particular subperiod.

6 Conclusion

This paper highlights the importance of considering funds' liquidity-risk exposure as an a determinant of the cross-section of mutual-fund performance. Funds with a high liquidity-risk exposure earn significantly high future returns during 1984–2009. However, only a fraction of the outperformance of high-liquidity-beta funds relative to low-liquidity-beta funds can be explained by systematic risk factors, suggesting that most of this outperformance may stem from funds' ability/skill to generate abnormal performance. The liquidity-risk-exposure effect is also related to several other documented

effects, such as return persistence, fund size, and smart money.

The results of this study have several implications. First, since we find that fund exposures to liquidity risk generate an alpha spread in the cross-section of mutual funds, which we largely associate with investment skill, this paper offers means by which investors can select mutual-fund managers. In contrast, funds' past-return exposures to other risk factors do not exhibit such performance predictability. Second, as the liquidity-risk-exposure effect can account for a large part of several other stylized effects, it is important for investors to examine these other fund characteristics together with fund liquidity-risk exposure in order to predict mutual-fund performance. Finally, from a risk-management standpoint, the paper offers an additional tool for evaluating the liquidity-risk exposure of mutual funds.

Appendix

The sample funds are assigned to one of four broad investment objectives, using the information provided by CRSP regarding classifications by Policy Code (Policy), Wiesenberger (Wiesenberger OBJ), Lipper objectives (LIPPER OBJ), and Strategic Insight (SI OBJ). We apply the following classification scheme:

1. *Growth funds*: Wiesenberger OBJ: AGG, G, G-S, GRO, LTG, MCG, SCG, S-G; SI OBJ: AGG, EIG, G, GRO, SCG; LIPPER OBJ: G, SG.

2. *Growth and Income funds*: Wiesenberger OBJ: GCI, G-I, G-I-S, G-S-I, I-G, I-G-S, I-S-G, S-G-I, S-I-G, GRI; SI OBJ: GRI, ING; LIPPER OBJ: GI.

3. *Income and Bonds funds*: Policy: B & P, Bonds, Flex, GS, I-S, I, Pfd, TF, TFE, TFM; Wiesenberger OBJ: I, I-S, IEQ, CBD, CHY, GOV, MTG, IFL, MBD, MHY, MSS; SI OBJ: ING, BGG, BGN, BGS, CGN, CHQ, CHY, CIM, CMQ, CPF, CPR, CSI, CSM, GBS, GGN, GIM, GMA, GMB, GSM, IMX,IAZ, ICA, ICO, ICT, IFL, IGA, IHI, IKS, IKY, IMA, IMD, IMI, IMN, IMT, INC, IND, INJ, INM, INY, IOH, IOR, IPA, ISC, ISD, ITN, ITX, IVA, IVT, IWA, IWV, LCA, LFL, LKY, LMA, LMD, LMI, LNC, LNY, LTN, LVA, MAL, MAR, MAZ, MCA, MCO, MCT, MDE, MFL, MGA, MGN, MHI, MHY,

MIA, MID, MIL, MIM, MIN, MIS, MKS, MKY, MLA, MMA, MMD, MME, MMI, MMN, MMO, MMS, MMT, MNC, MND, MNE, MNH, MNJ, MNM, MNY, MOH, MOK, MOR, MPA, MPR, MRI, MSC, MSD, MSM, MTN, MTX, MUT, MVA , MVT, MWA, MWI, MWV, TAL, TAZ, TBG, TCA, TCT, TFG, TFI, TFL, TGA, TMA, TMD, TMI, TMN, TNC, TNJ, TNY, TOH, TPA, TTN, TTX, TVA; LIPPER OBJ: I, EI, EIEI, CV, FX, GB, GUT, GX, I, IUT, SUT CAM, AL, AZ, CAG, CAI, CAS, CAT, CO, CT, FL, FLI, FLT, GA, GM, HI, HM, IMD, KS, KY, LA, MA, MD, MDI, MI, MN, MO, NC, NJ, NY, NYI, NYT, OH, OHT, OST, OTH, PA, PAT, SC, SIM, SMD, SSIM, TN, TX, VA, VAT, WA.

4. *Other funds*: The remaining, unclassified sample funds.

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Table 1
Summary Statistics

This table reports summary diagnostics of the sample of mutual funds. The statistic N is either the number of different mutual funds for each year (Panel A) or for each investment style (Panel B) or for all funds (Panel C). The rest of the statistics (minimum; 1, 25, 50, 75, and 99 percentiles; maximum; and standard deviation) are time-series averages of monthly cross-sectional statistics: In Panel A statistics are averages over the 12 months of each year; in Panel B the statistics except N are first obtained each month from the cross-section of mutual funds in each investment style, then averaged over the 12months in each year, and at last averaged over the 27 years of the sample. Panel C reports the number of mutual funds in the sample as well as other statistics averaged over the 12 months in each year and then averaged over the 27 years of the sample. The sample includes all mutual fund in CRSP for the period 1983-2009.

	N	Min	P1	P25	P50	P75	P99	Max	Std
Panel A. All funds per year									
1983	454	-0.1085	-0.0592	-0.0116	0.0042	0.0187	0.0749	0.1614	0.0272
1984	540	-0.1505	-0.0862	-0.0220	-0.0036	0.0112	0.0567	0.1160	0.0273
1985	690	-0.1125	-0.0466	-0.0019	0.0118	0.0254	0.0833	0.2034	0.0253
1986	947	-0.1442	-0.0568	-0.0111	0.0075	0.0244	0.0896	0.2119	0.0285
1987	1,353	-0.1737	-0.0732	-0.0295	-0.0013	0.0259	0.0967	0.2017	0.0391
1988	1,678	-0.1045	-0.0477	-0.0067	0.0035	0.0144	0.0583	0.2000	0.0210
1989	1,809	-0.1002	-0.0397	-0.0071	0.0028	0.0174	0.0621	0.1300	0.0210
1990	1,905	-0.1844	-0.0800	-0.0232	-0.0045	0.0113	0.0584	0.1739	0.0288
1991	2,177	-0.1555	-0.0430	-0.0049	0.0087	0.0275	0.0787	0.2391	0.0266
1992	2,451	-0.1434	-0.0532	-0.0073	0.0032	0.0123	0.0565	0.2001	0.0209
1993	2,992	-0.1233	-0.0364	-0.0020	0.0063	0.0167	0.0742	0.1640	0.0212
1994	3,590	-0.1957	-0.0519	-0.0154	-0.0071	0.0047	0.0416	0.1935	0.0192
1995	3,979	-0.1415	-0.0400	0.0004	0.0091	0.0208	0.0638	0.1707	0.0203
1996	4,159	-0.1170	-0.0476	-0.0081	0.0014	0.0172	0.0684	0.1721	0.0234
1997	4,470	-0.2339	-0.0751	-0.0079	0.0061	0.0224	0.0722	0.1662	0.0289
1998	4,849	-0.2624	-0.0841	-0.0206	0.0025	0.0313	0.0953	0.3406	0.0392
1999	5,353	-0.2930	-0.0601	-0.0139	0.0030	0.0268	0.1333	0.4887	0.0399
2000	5,686	-0.3928	-0.1344	-0.0280	-0.0019	0.0212	0.1232	0.3727	0.0510
2001	5,817	-0.3232	-0.1223	-0.0351	-0.0060	0.0218	0.0924	0.3625	0.0456
2002	5,738	-0.2869	-0.1097	-0.0382	-0.0101	0.0200	0.0721	0.3402	0.0408
2003	5,623	-0.1660	-0.0325	-0.0035	0.0167	0.0341	0.0830	0.2260	0.0261
2004	5,532	-0.1523	-0.0445	-0.0060	0.0066	0.0194	0.0626	0.1685	0.0212
2005	5,451	-0.1422	-0.0415	-0.0113	0.0020	0.0152	0.0588	0.1684	0.0210
2006	5,617	-0.1988	-0.0425	-0.0072	0.0043	0.0167	0.0563	0.1554	0.0200
2007	5,767	-0.1700	-0.0523	-0.0127	0.0010	0.0147	0.0635	0.5233	0.0254
2008	6,365	-0.4199	-0.1481	-0.0543	-0.0318	-0.0021	0.0939	0.6043	0.0457
2009	7,138	-0.4191	-0.1068	-0.0047	0.0203	0.0440	0.1353	0.3774	0.0437
Panel B. Full Sample, by investment style									
Growth	4,207	-0.1484	-0.0677	-0.0112	0.0039	0.0195	0.0806	0.2052	0.0292
Growth and Income	1,853	-0.0986	-0.0452	-0.0065	0.0039	0.0143	0.0549	0.1137	0.0198
Income and Bond	4,063	-0.1003	-0.0354	-0.0048	0.0016	0.0081	0.0415	0.1049	0.0155
Others	3,577	-0.1670	-0.0809	-0.0149	0.0022	0.0201	0.0929	0.2001	0.0328
Panel C. All funds, full sample									
	13,700	-0.2011	-0.0673	-0.0146	0.0020	0.0198	0.0780	0.2536	0.0296

Table 2
Factor Beta Portfolios

Each month mutual funds are sorted into ten equally weighted portfolios according to various historical factor betas. The factor beta is calculated using a regression of monthly portfolio returns on the market portfolio and the factor (other than the market portfolio itself), 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 years. The factors analyzed are the Fama-French three factors (MKT, SMB, and HML), the momentum factor (UMD) of Carhart (1997), and the liquidity factor. The table reports the average monthly excess return (in percent) of the decile portfolios, as well as of the high-minus-low portfolio. Risk-adjusted return (alpha; in percent) is the return adjusted by Fama-French four factors. T-statistics are reported in square brackets. The sample includes the CRSP mutual-fund universe for the period April 1983 to December 2009.

Factor	Factor Beta Deciles										Decile Spread	
	1 [low]	2	3	4	5	6	7	8	9	10 [high]	10-1 Return	10-1 Alpha
MKT	0.04	0.14	0.18	0.23	0.29	0.34	0.38	0.43	0.49	0.48	0.43	-0.09
	[0.84]	[0.84]	[0.84]	[0.84]	[0.84]	[0.84]	[0.84]	[0.84]	[0.84]	[0.84]	[0.84]	[0.84]
SMB	0.04	0.14	0.19	0.26	0.30	0.35	0.38	0.43	0.46	0.45	0.42	-0.08
	[0.68]	[2.51]	[2.56]	[2.29]	[1.89]	[1.75]	[1.68]	[1.71]	[1.62]	[1.25]	[1.14]	[-0.80]
HML	0.02	0.13	0.16	0.24	0.25	0.34	0.40	0.47	0.51	0.46	0.44	-0.05
	[0.43]	[2.26]	[2.33]	[2.11]	[1.50]	[1.66]	[1.69]	[1.85]	[1.89]	[1.42]	[1.35]	[-0.47]
UMD	0.03	0.14	0.18	0.22	0.28	0.35	0.38	0.45	0.49	0.47	0.44	-0.06
	[0.50]	[2.35]	[2.50]	[1.90]	[1.71]	[1.74]	[1.66]	[1.80]	[1.77]	[1.38]	[1.29]	[-0.60]
Liquidity	0.15	0.21	0.19	0.19	0.21	0.27	0.27	0.37	0.49	0.57	0.42	0.51
	[0.59]	[1.09]	[1.26]	[1.47]	[1.85]	[2.20]	[1.96]	[2.21]	[2.47]	[2.37]	[2.65]	[3.21]

Table 3
Liquidity-Beta Portfolios: Style Analysis

Each month mutual funds are sorted into ten equally 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 Sadka factor, using the 12 months prior to portfolio formation. Portfolio returns begin April 1984, using funds with at least 11 months of returns during the prior years. The portfolios are separately formed using mutual funds in particular investment styles. The table reports the average monthly excess return and the risk-adjusted return, i.e., alpha (in percent) of the decile portfolios, as well as the high-minus-low portfolio. Alphas are returns adjusted by Fama-French three factors (MKT, SMB, and HML) and the momentum factor (UMD) of Carhart (1997). T-statistics are reported in square brackets. The sample includes the CRSP mutual-fund universe for the period April 1983 to December 2009.

Investment Style	Liquidity Beta Deciles										Decile Spread	
	1	2	3	4	5	6	7	8	9	10	10-1	
	[low]									[high]	Return	Alpha
Growth	0.20	0.40	0.42	0.46	0.46	0.46	0.51	0.54	0.51	0.54	0.34	0.40
	[0.68]	[1.46]	[1.58]	[1.78]	[1.81]	[1.83]	[2.01]	[2.05]	[1.93]	[1.92]	[1.89]	[2.20]
Growth and Income	0.25	0.36	0.38	0.44	0.38	0.40	0.44	0.47	0.49	0.51	0.25	0.30
	[1.07]	[1.69]	[1.80]	[2.11]	[1.86]	[1.93]	[2.10]	[2.28]	[2.36]	[2.28]	[2.47]	[2.85]
Income and Bond	0.13	0.15	0.15	0.15	0.17	0.15	0.17	0.21	0.25	0.36	0.23	0.27
	[1.08]	[1.89]	[2.17]	[2.09]	[2.29]	[2.00]	[2.43]	[2.86]	[3.10]	[2.96]	[2.23]	[2.62]
Others	0.15	0.23	0.27	0.27	0.20	0.21	0.29	0.41	0.55	0.61	0.46	0.50
	[0.53]	[1.27]	[1.99]	[2.51]	[1.97]	[1.82]	[2.13]	[2.36]	[2.58]	[2.36]	[2.47]	[2.61]

Table 4
Liquidity-Beta Porfotlio and the Liquidity-Risk Premium

The table reports the results of time-series regressions of the high-minus-low liquidity-beta portfolio return on the Fama-French three factors (MKT, SMB, and HML), the momentum factor (UMD) of Carhart (1997), and the traded liquidity factor (LIQ). The traded liquidity factor is constructed as the value weighted return spread of high-minus-low liquidity beta deciles of equities, where liquidity beta is calculated through a regression of prior 12-month returns on the market factor and the nontraded Sadka permenent-variable liquidity factor. The high-minus-low liquidity-beta portfolios are formed either using the overall sample (first row) or using mutual funds in particular investment styles. T-statistics are reported in parentheses. The sample includes the CRSP mutual-fund universe for the period April 1983 to December 2009.

	Alpha	MKT-RF	SMB	HML	UMD	LIQ	Adj.R^2
All Sample	0.51	-0.12	-0.06	0.02	-0.05		0.04
	[3.20]	[-3.25]	[-1.17]	[0.31]	[-1.62]		
	0.41	-0.10	-0.02	-0.04	-0.06	0.30	0.34
	[3.13]	[-3.28]	[-0.52]	[-0.82]	[-2.17]	[11.74]	
Growth	0.40	-0.09	-0.07	0.12	-0.07		0.05
	[2.20]	[-2.03]	[-1.20]	[1.81]	[-1.86]		
	0.29	-0.06	-0.02	0.05	-0.08	0.36	0.38
	[1.94]	[-1.82]	[-0.51]	[0.94]	[-2.54]	[12.75]	
Growth and Income	0.30	-0.07	-0.03	-0.01	0.00		0.02
	[2.85]	[-2.79]	[-0.96]	[-0.30]	[-0.18]		
	0.24	-0.06	-0.01	-0.05	-0.01	0.20	0.34
	[2.72]	[-2.75]	[-0.24]	[-1.60]	[-0.45]	[12.27]	
Income and Bond	0.27	-0.02	-0.07	-0.05	-0.03		0.01
	[2.62]	[-0.68]	[-2.06]	[-1.40]	[-1.38]		
	0.25	-0.01	-0.06	-0.07	-0.03	0.08	0.06
	[2.43]	[-0.48]	[-1.80]	[-1.84]	[-1.49]	[4.04]	
Others	0.50	-0.10	-0.06	0.08	0.00		0.03
	[2.61]	[-2.24]	[-1.01]	[1.21]	[-0.04]		
	0.39	-0.08	-0.02	0.02	-0.01	0.35	0.31
	[2.40]	[-2.06]	[-0.35]	[0.30]	[-0.26]	[11.13]	

Table 5
Liquidity Risk Timing

The table reports the results of the timing regressions:

$$R_{i,t} = Const_i + \beta i_{,MKT}\, R_{MKT,t} + \beta_{i,SMB} R_{SMB,t} + \beta_{i,HML} R_{HML,t} + \beta_{i,UMD} R_{UMD,t} + \beta_{i,LIQ} LIQ_t + \beta_{i,LIQ\_Timing}\, MAX(0, -LIQ_t) + \varepsilon_{i,t}$$

where $R_{i,t}$ is the high-minus-low liquidity-beta portfolio return in all sample or in particular investment styles. The independent variables include the Fama-French three factors (MKT, SMB, and HML), the momentum factor (UMD) of Carhart (1997), the traded liquidity factor (LIQ), and a timing-related term max(0, -LIQ). The traded liquidity factor is constructed as the value-weighted return spread of high-minus-low liquidity beta deciles of equities, where liquidity beta is calculated through a regression of prior 12-month returns on the market factor and the nontraded Sadka permenent-variable liquidity factor. T-statistics are reported in parentheses. The sample includes the CRSP mutual-fund universe for the period April 1983 to December 2009.

	Intercept	MKT-RF	SMB	HML	UMD	LIQ	LIQ_Timing
All Sample	0.65	-0.11	-0.02	-0.04	-0.06	0.24	-0.13
	[3.49]	[-3.49]	[-0.56]	[-0.89]	[-2.29]	[5.98]	[-1.79]
Growth	0.68	-0.07	-0.03	0.04	-0.08	0.27	-0.21
	[3.27]	[-2.17]	[-0.57]	[0.85]	[-2.74]	[5.99]	[-2.66]
Grwoth and Income	0.23	-0.06	-0.01	-0.05	-0.01	0.20	0.00
	[1.86]	[-2.71]	[-0.24]	[-1.59]	[-0.44]	[7.74]	[0.09]
Income and Bond	0.16	-0.01	-0.06	-0.06	-0.03	0.10	0.05
	[1.09]	[-0.36]	[-1.78]	[-1.80]	[-1.42]	[3.22]	[0.89]
Others	0.60	-0.08	-0.02	0.01	-0.01	0.30	-0.12
	[2.63]	[-2.21]	[-0.38]	[0.25]	[-0.35]	[5.96]	[-1.31]

Table 6
Fund Characteristics and Liqiudity Risk Exposure

This table summarizes the average characteristics of the liquidity-beta sorted mutual fund decile portfolios. The liquidity-factor 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 differences in characteristics are computed on a monthly basis using Newey-West standard errors with a lag length of 12 months. T-statistics are reported in square brackets. The sample includes the CRSP mutual-fund universe for the period April 1983 to December 2009.

Liquidity Beta Deciles		Net Assets (millions)	Family Size (millions)	Expense Ratio (percent)	Turnover (percent)	Flow (percent)	Load Fund Dummy	Age
1	[low]	473.60	19107.48	1.3%	1.12	1.30	0.47	19.45
2		598.41	19089.58	1.1%	0.97	0.94	0.39	20.29
3		608.55	18657.81	0.9%	0.97	0.87	0.32	20.54
4		605.12	19129.66	0.9%	0.92	0.90	0.27	20.44
5		658.78	19795.83	0.9%	0.86	0.44	0.26	20.36
6		659.81	19128.32	0.9%	1.30	0.62	0.28	20.27
7		646.69	18832.23	1.0%	0.90	0.72	0.32	20.18
8		638.06	19441.56	1.0%	0.93	1.01	0.39	20.10
9		591.02	19797.98	1.2%	0.99	0.98	0.46	19.94
10	[high]	433.14	20210.70	1.3%	1.08	1.15	0.50	19.54
(1)-(5)		-185.19	-688.35	0.4%	0.25	0.88	0.21	-0.90
		[-4.92]	[-0.83]	[11.51]	[3.70]	[1.33]	[7.62]	[-4.33]
(10)-(5)		-225.64	414.87	0.5%	0.21	0.69	0.23	-0.81
		[-4.84]	[0.53]	[14.30]	[4.05]	[1.42]	[9.19]	[-3.41]
(10)-(1)		-40.45	1103.22	0.1%	-0.04	-0.12	0.03	0.09
		[-1.30]	[0.82]	[1.77]	[-0.92]	[-0.43]	[0.89]	[0.58]

Table 7

Liquidity Risk Exposure and Return Persistence

Individual fund betas are estimated using the following regression of past 12-month returns on the market factor and the liquidity risk factor.

$$r_{i,t} = Const_i + \beta_{i,MKT} \cdot r_{MKTt} + \beta_{i,Liq} \cdot Liq_t + \varepsilon_{i,t},$$

where $r_{i,t}$ is mutual fund i's return at time t, r_{MKTt} is the market return at time t, Liq_t denotes the non-traded liquidity factor value at time t, and $\varepsilon_{i,t}$ is the residual term; all returns are excess of the risk-free rate. Based on the above regression, a funds' average past 12-month returns can be decomposed into three components as follows:

$$\frac{1}{12}\sum_{t=-12}^{-1} r_{i,t} = \widehat{Const}_i + \hat{\beta}_{i,MKT} \times \frac{1}{12}\sum_{t=-12}^{-1} r_{MKTt} + \hat{\beta}_{i,Liq} \times \frac{1}{12}\sum_{t=-12}^{-1} Liq_t.$$

In each of the sorting criterion column below, funds are sorted into ten decile portfolios based on the average past 12-month returns, the constant term, the market beta term, and the liquidity beta term, respectively. Strategies with post-ranking holding periods of 1 month, 3 months, 6 months, and 12 months are examined. The monthly returns of longer holding-period strategies are calculated from an equal weighted average of the monthly returns of a series of portfolios. For example, the return of Decile 1 of the 3-month holding period strategy on January is an equal weighted average of the January returns of the Decile 1 portfolios sorted in December, November, and October of the previous year. T-statistics are reported in square brackets. 3-Factor Alpha are monthly returns adjusted by Fama-French three factors (MKT, SMB, and HML). 4-Factor Alpha are monthly returns adjusted by Fama-French three factors (MKT, SMB, and HML) and the momentum factor (UMD) of Carhart (1997). The sample includes the CRSP mutual-fund universe for the period April 1983 to December 2009.

Portfolio Holding Period	Sorting Variable											
	$\frac{1}{12}\sum_{t=-12}^{-1} r_{i,t}$			$\widehat{Const}_i$			$\hat{\beta}_{i,MKT}$			$\hat{\beta}_{i,Liq}$		
	Return	3-Factor Alpha	4-Factor Alpha	Return	3-Factor Alpha	4-Factor Alpha	Return	3-Factor Alpha	4-Factor Alpha	Return	3-Factor Alpha	4-Factor Alpha
1 month												
1	0.04	-0.44	-0.14	0.15	-0.31	-0.16	0.03	0.02	-0.02	0.15	-0.35	-0.36
	[0.17]	[-3.06]	[-1.32]	[0.64]	[-2.65]	[-1.43]	[0.57]	[0.39]	[-0.44]	[0.59]	[-3.96]	[-4.00]
10	0.79	0.54	0.20	0.61	0.13	-0.01	0.48	-0.12	-0.07	0.57	0.12	0.16
	[3.13]	[3.79]	[1.98]	[2.28]	[1.10]	[-0.10]	[1.34]	[-1.41]	[-0.79]	[2.37]	[1.09]	[1.41]
10-1	0.75	0.98	0.34	0.46	0.44	0.15	0.45	-0.14	-0.04	0.42	0.46	0.51
	[2.71]	[3.77]	[2.01]	[2.25]	[1.83]	[0.82]	[1.23]	[-1.25]	[-0.39]	[2.65]	[2.95]	[3.21]
3 months												
1	0.19	-0.28	0.01	0.23	-0.29	-0.19	0.06	0.05	0.01	0.19	-0.32	-0.32
	[0.83]	[-2.12]	[0.11]	[0.94]	[-2.98]	[-2.09]	[1.18]	[0.98]	[0.20]	[0.73]	[-4.05]	[-3.90]
10	0.55	0.25	-0.05	0.48	0.00	-0.11	0.48	-0.13	-0.09	0.58	0.14	0.16
	[2.10]	[1.89]	[-0.54]	[1.81]	[-0.00]	[-1.03]	[1.32]	[-1.69]	[-1.11]	[2.49]	[1.30]	[1.48]
10-1	0.36	0.53	-0.06	0.25	0.29	0.08	0.41	-0.19	-0.10	0.39	0.46	0.48
	[1.40]	[2.22]	[-0.40]	[1.47]	[1.66]	[0.50]	[1.13]	[-1.75]	[-0.93]	[2.63]	[3.11]	[3.16]
6 months												
1	0.18	-0.29	-0.04	0.24	-0.28	-0.20	0.07	0.06	0.02	0.22	-0.30	-0.26
	[0.82]	[-2.37]	[-0.41]	[1.00]	[-3.04]	[-2.40]	[1.25]	[1.04]	[0.29]	[0.87]	[-3.90]	[-3.41]
10	0.49	0.18	-0.08	0.47	0.00	-0.09	0.48	-0.12	-0.08	0.58	0.15	0.16
	[1.88]	[1.51]	[-0.86]	[1.80]	[-0.04]	[-0.88]	[1.34]	[-1.61]	[-1.08]	[2.54]	[1.51]	[1.52]
10-1	0.31	0.47	-0.04	0.22	0.28	0.12	0.41	-0.18	-0.10	0.36	0.45	0.42
	[1.30]	[2.19]	[-0.25]	[1.46]	[1.67]	[0.79]	[1.14]	[-1.74]	[-0.97]	[2.46]	[3.20]	[2.93]
12 months												
1	0.19	-0.27	-0.06	0.34	-0.21	-0.16	0.07	0.05	0.01	0.27	-0.24	-0.20
	[0.90]	[-2.32]	[-0.56]	[1.37]	[-2.78]	[-2.13]	[1.36]	[0.96]	[0.28]	[1.08]	[-3.38]	[-2.73]
10	0.42	0.09	-0.13	0.43	-0.03	-0.07	0.49	-0.10	-0.08	0.50	0.07	0.05
	[1.64]	[0.85]	[-1.39]	[1.69]	[-0.36]	[-0.80]	[1.38]	[-1.40]	[-1.11]	[2.17]	[0.79]	[0.57]
10-1	0.23	0.37	-0.07	0.09	0.18	0.09	0.42	-0.15	-0.09	0.23	0.31	0.25
	[1.02]	[1.81]	[-0.44]	[0.68]	[1.41]	[0.70]	[1.19]	[-1.54]	[-0.97]	[1.85]	[2.60]	[2.05]

Table 8
Fund Size and Liquidity Risk Exposure

Each month mutual funds are first sorted into five portfolios according to their size and then sorted into five portfolios according to their liquidity factor betas within each size portfolio. The liquidity-factor 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 years. The table reports the average monthly excess return (in percent) of the liquidity-beta and the fund-size quintile portfolios, as well as of the high-minus-low liquidity-beta and the large-minus-small fund size portfolios. Alphas are four-factor alphas, where returns are adjusted by Fama-French three factors (MKT, SMB, and HML) and the momentum factor (UMD) of Carhart (1997). T-statistics are reported in square brackets. The sample includes the CRSP mutual-fund universe for the period April 1983 to December 2009.

Size Portfolios	Liquidity Beta Portfolios						
	1	2	3	4	5		
	[low]				[high]	High-Low	All
1	-0.24	-0.10	-0.02	0.01	0.23	0.47	-0.02
[small]	[-3.06]	[-1.66]	[-0.41]	[0.15]	[2.55]	[3.49]	[-0.59]
2	-0.25	-0.10	-0.07	0.08	0.18	0.43	-0.03
	[-3.23]	[-1.54]	[-1.13]	[1.05]	[1.98]	[3.17]	[-0.76]
3	-0.32	-0.13	-0.09	0.06	0.18	0.50	-0.06
	[-4.00]	[-2.04]	[-1.38]	[0.81]	[1.79]	[3.28]	[-1.47]
4	-0.30	-0.16	-0.12	-0.02	0.14	0.44	-0.09
	[-3.59]	[-2.41]	[-1.92]	[-0.34]	[1.40]	[2.93]	[-2.32]
5	-0.30	-0.18	-0.11	-0.01	0.08	0.44	-0.10
[large]	[-3.76]	[-3.03]	[-1.90]	[-0.16]	[0.77]	[2.56]	[-2.48]
Large - Small	-0.06	-0.07	-0.08	-0.02	-0.15		-0.08
	[-1.12]	[-1.49]	[-0.62]	[-0.38]	[-2.67]		[-2.41]

Table 9

Flows and Liquidity Risk Exposure

Each month mutual funds are first sorted into outflow and inflow funds and then sorted into five portfolios according to liquidity factor betas within the inflow and outflow funds respectively. Fund flow is calculated as the montly percentage difference in the total net assets not atributable to performance (adjusted for fund mergers). The liquidity factor 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 years. The table reports the average monthly excess return (in percent) of the liquidity-beta quintile portfolios and the inflow and the outflow portfolios, as well as of the high-minus-low liquidity-beta and the inflow-minus-outflow portfolios. Alphas are four-factor alphas, where returns are adjusted by Fama-French three factors (MKT, SMB, and HML) and the momentum factor (UMD) of Carhart (1997). T-statistics are reported in square brackets. The sample includes the CRSP mutual-fund universe for the period April 1983 to December 2009.

Flow Sorted Portfolios	Liquidity Beta Portfolios						
	1	2	3	4	5		
	[low]				[high]	High-Low	All
Outflow	-0.25	-0.16	-0.10	0.09	0.12	0.37	-0.06
	[-2.98]	[-2.01]	[-1.36]	[1.10]	[1.31]	[2.83]	[-0.93]
Inflow	-0.26	-0.09	-0.12	0.06	0.36	0.58	0.04
	[-2.95]	[-1.34]	[-1.66]	[0.93]	[3.08]	[3.67]	[0.68]
Inflow - Outflow	-0.02	0.08	-0.02	-0.02	0.25		0.00
	[-0.21]	[1.15]	[-0.30]	[-0.35]	[2.91]		[1.27]

Table 10

The High-Minus-Low Liquidity-Beta Decile Return Spreads Using Alternative Liquidity-Risk Measures

Each month hedge funds are sorted into ten equally weighted portfolios according to historical liquidity beta. The liquidity beta is calculated using a regression of monthly portfolio returns on the market portfolio and a liquidity factor, using the 12 months prior to portfolio formation. The non-traded liquidity-risk factors are Pástor and Stambaugh (2003), the Amihud (2002) measure, and the permanent-variable and transitory-fixed components of price impact in Sadka (2006). The table reports the average monthly return (in percent) and risk-adjusted return (alpha; in percent) of the high-minus-low decile portfolio spread for the entire sample period. Alpha is the return adjusted by Fama-French three factors (MKT, SMB, and HML) and the momentum factor (UMD) of Carhart (1997). T-statistics are reported in square brackets. The sample includes the CRSP mutual-fund universe for the period April 1983 to December 2009.

Liquidity Risk Measure							
Pástor-Stambaugh		Amihud		Permanent-Variable		Transitory-Fixed	
Return	Alpha	Return	Alpha	Return	Alpha	Return	Alpha
0.00	0.12	0.07	0.00	0.42	0.51	0.16	0.16
[-0.01]	[0.61]	[0.38]	[0.68]	[2.65]	[3.21]	[0.92]	[0.94]

Table 11

Longer Holding and Ranking Periods

Liquidity portfolios with different holding or ranking periods are reported. In Panel A, each month mutual funds are first sorted into ten equally weighted portfolios according to historical liquidity beta. The monthly returns of longer holding-period strategies are calculated from an equal weighted average of a series of liquidity beta sorted portfolios. For example, the return of Decile 1 of the 3-month holding period strategy on January is an equal weighted average of the January returns of the Decile 1 portfolios sorted in December, November, and October of the previous year. 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 April 1984, using funds with at least 11 months of returns during the prior years. In Panel B, each month mutual funds are sorted into ten equally weighted portfolios according to the historical Sadka liquidity factor beta. The factor beta is calculated using a regression of monthly portfolio returns on the market portfolio and the factor, using the 12, 24, 36, 48, 60 months prior to portfolio formation respectively. Portfolio returns begin from April 1984, April 1985, April 1986, April 1987, and April 1988, respectively, using funds with at least 11, 18, 24, 36, and 48 months of returns during the prior years.The table reports the monthly returns (in percent) for the decile portfolios, as well as the returns and alphas (returns adjusted by Fama-French three factors (MKT, SMB, and HML) and the momentum factor (UMD) of Carhart (1997)) for the high-minus-low portfolio. T-statistics are reported in square brackets. The sample includes the CRSP mutual-fund universe for the period April 1983 to December 2009.

Panel A.

Holding Period	Liquidity Beta Deciles (12-month Ranking Period)			
	1 [low]	10 [high]	10-1 Return	10-1 Alpha
1 month	0.15	0.57	0.42	0.51
	[0.59]	[2.37]	[2.65]	[3.21]
3 months	0.19	0.58	0.39	0.48
	[0.73]	[2.49]	[2.63]	[3.16]
6 months	0.22	0.58	0.36	0.42
	[0.87]	[2.54]	[2.46]	[2.93]
12 months	0.27	0.50	0.23	0.25
	[1.08]	[2.17]	[1.85]	[2.05]
24 months	0.32	0.46	0.14	0.14
	[1.34]	[1.96]	[1.59]	[1.59]
36 months	0.34	0.43	0.10	0.07
	[1.47]	[1.84]	[1.41]	[0.97]
48 months	0.35	0.43	0.08	0.04
	[1.53]	[1.82]	[1.39]	[0.62]
60 months	0.37	0.40	0.04	0.01
	[1.61]	[1.72]	[0.75]	[0.28]

Panel B.

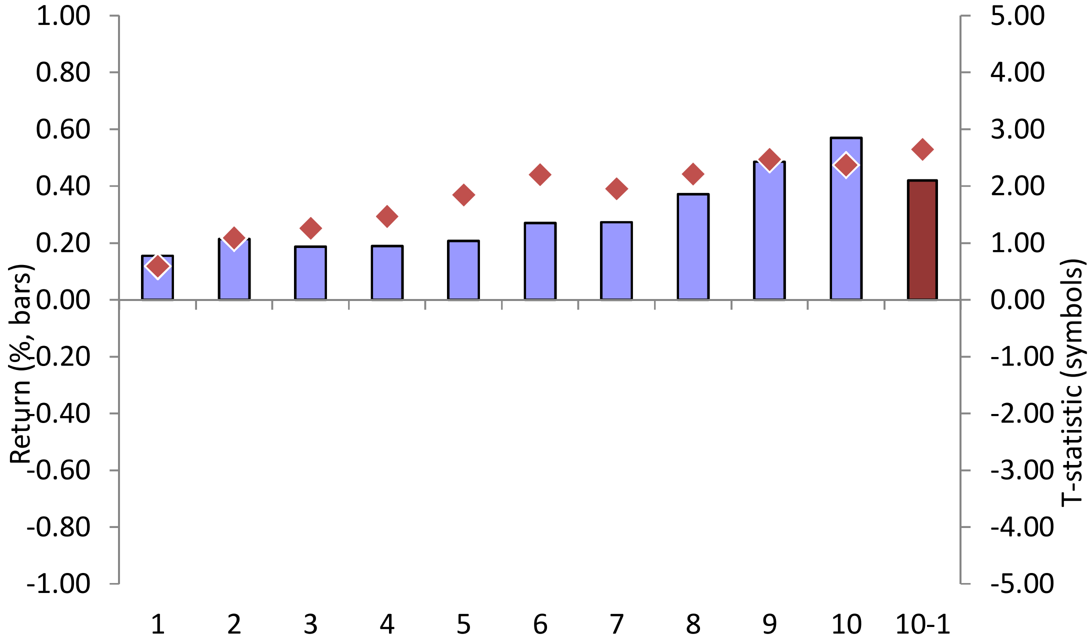
Ranking Period	Liquidity Beta Deciles (One-month Holding Period)			
	1 [low]	10 [high]	10-1 Return	10-1 Alpha
12 months	0.15	0.57	0.42	0.51
	[0.59]	[2.37]	[2.65]	[3.21]
24 months	0.20	0.52	0.32	0.40
	[0.83]	[2.08]	[2.03]	[2.51]
36 months	0.27	0.52	0.25	0.25
	[1.13]	[2.07]	[1.65]	[1.58]
48 months	0.36	0.53	0.18	0.05
	[1.54]	[1.98]	[1.30]	[0.40]
60 months	0.15	0.36	0.20	0.14
	[0.66]	[1.35]	[1.63]	[1.15]

Table 12

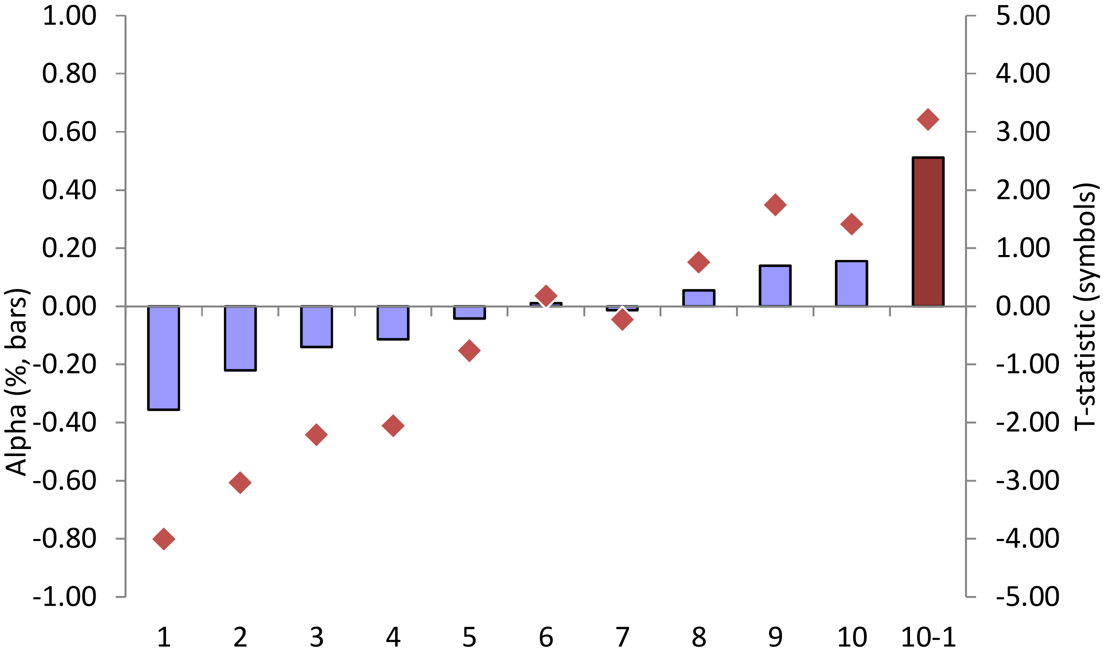
Liquidity-Beta Portfolios: Subperiod Analysis

Each month mutual funds are sorted into ten equally weighted portfolios according to the historical Sadka liquidity factor beta. The factor beta is calculated using a regression of monthly portfolio returns on the market portfolio and the 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 years. The table reports the average monthly excess return (in percent) of the decile portfolios, as well as of the high-minus-low portfolio. Alphas are returns adjusted by Fama-French three factors (MKT, SMB, and HML) and the momentum factor (UMD) of Carhart (1997). T-statistics are reported in square brackets. The sample includes the CRSP mutual-fund universe for the period April 1983 to December 2009.

Liquidity Beta Deciles										Decile Spread 10-1	
1 [low]	2	3	4	5	6	7	8	9	10 [high]	Return	Alpha
Panel A. 1984-1996											
0.27	0.44	0.41	0.33	0.30	0.36	0.34	0.38	0.49	0.61	0.34	0.68
[0.89]	[1.75]	[1.98]	[1.77]	[2.23]	[2.40]	[2.13]	[2.03]	[2.25]	[2.28]	[1.66]	[3.21]
Panel B. 1997-2009											
-0.07	-0.07	-0.06	0.02	0.07	0.17	0.17	0.30	0.43	0.51	0.59	0.61
[-0.16]	[-0.21]	[-0.28]	[0.09]	[0.38]	[0.80]	[0.68]	[1.01]	[1.24]	[1.22]	[2.29]	[2.43]

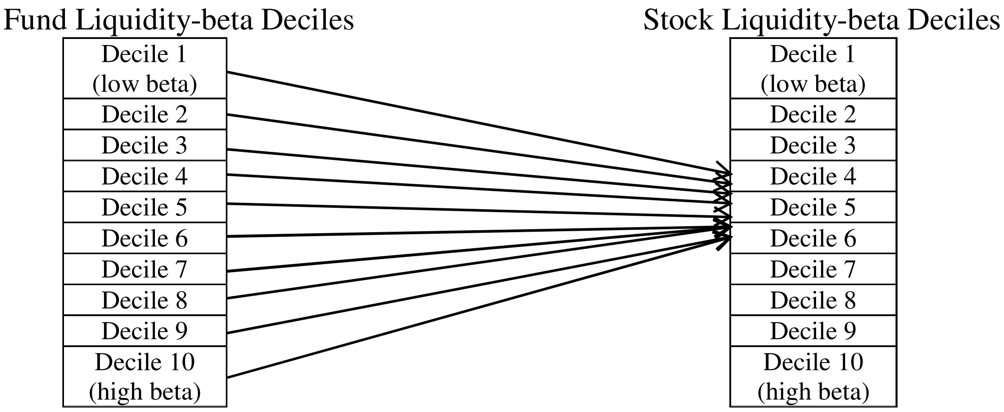


Panel A. Monthly Returns of Liquidity Beta Portfolios

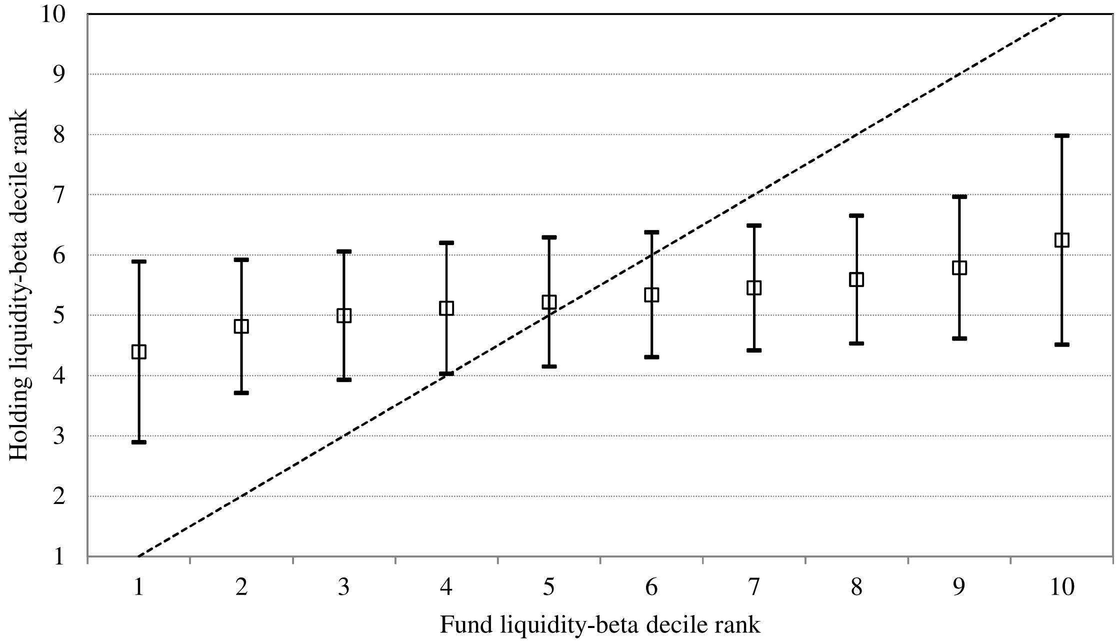


Panel B. Monthly Alphas of Liquidity Beta Portfolios

Figure 1. The figure plots the monthly returns (Panel A) and four-factor alphas (Panel B) of liquidity risk sorted portfolios as well as the high-minus-low portfolio. Each month mutual funds are first sorted into ten equally 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 Sadka factor, using the 12 months prior to portfolio formation. Alphas are the returns adjusted by four factors (i.e., MKT, SMB, HML, and UMD). Portfolio returns begin April 1984, using funds with at least 11 months of returns during the prior years. The sample includes the mutual-fund universe for the period April 1983 to December 2009.



Panel A. Liquidity-Beta Decile Ranking of Funds in the Fund Universe vs. that of Stocks in the Stock Universe



Panel B. Fund Liquidity Beta vs. Holding Liquidity Beta

Figure 2. In Panel A, on the left hand side, all mutual funds in the sample are sorted into decile portfolios based on the ranking of the liquidity-beta of each fund in the fund universe. On the right hand side, all common stocks in the CRSP stock universe are sorted into decile portfolios based on the liquidity-beta ranking of each stock in the stock universe. The arrow that connects a fund decile and a stock decile indicates the average decile rank of the fund-decile stock holdings in the stock universe. Panel B plots the average liquidity-beta decile ranking of fund stock holdings in the stock universe for each fund liquidity-beta decile. X axis reports the fund decile portfolios sorted on fund liquidity beta. Y axis reports the average decile rank of the fund-decile stock holdings in the CRSP stock universe (the cubic) for each liquidity-beta fund decile. The range of minus and plus two standard deviation away from the average (the bars around the cubic) is the cross-sectional standard deviation of the average decile rankings of the stock holdings across individual funds in each fund liquidity-beta decile in each month averaged over all months. The sample includes the mutual-fund universe for the period April 1983 to December 2009.

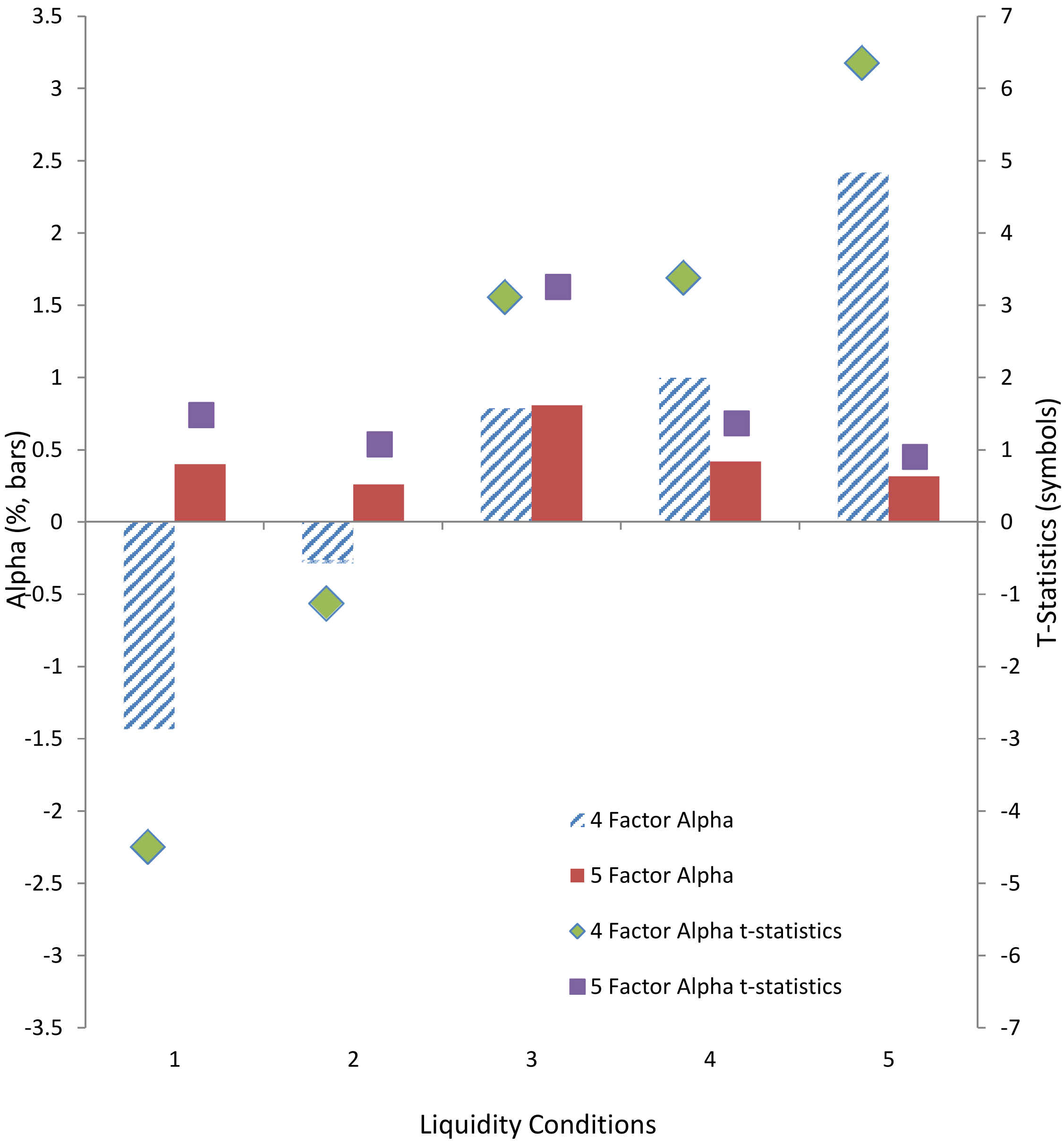


Figure 3. The liquidity conditions of the market in the sample period are divided into five quintiles based the traded liquidity factor realizations in each month. Quintile 5 includes the months with the highest 20% of the factor realizations (good liquidity state). Quintile 1 includes the months with the lowest 20% of the factor realizations (bad liquidity state). Other quintiles are in-between. The figure plots the four-factor alpha of the high-minus-low liquidity-beta fund decile return spread, where four factors are MKT, SMB, HML, and UMD, and the five-factor alpha, whether the additional factor is the traded liquidity risk factor alpha. The sample includes the mutual-fund universe for the period April 1983 to December 2009.