Treasury Liquidity and Funding Liquidity: Evidence from Mutual Fund Returns

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This version: March 14, 2012

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I am grateful to Yakov Amihud for helpful suggestions and discussions.

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1. Introduction

There is strong evidence that illiquidity affects asset returns (Amihud and Mendelson (1986, 1989), Amihud (2002)) and that illiquidity is a source of priced systematic risk not captured by traditional factors (Pastor and Stambaugh (2003), and Acharya and Pedersen (2005)). [1] The literature, however, has thus far focused primarily on market liquidity or how easily assets can be traded. This paper extends the exploration of pricing applications of illiquidity and focuses on a different type of liquidity – funding liquidity or availability of trading capital in the economy.

Market liquidity and funding liquidity are related and mutually reinforced with a shock to one propagating into the other and causing a spiral effect (Brunnermeier and Pedersen (2009)). They are, however, driven by different mechanisms. Market liquidity, or the easiness of trading, is asset specific and is influenced by firm-specific and market-wide variables (see Chordia, Roll, and Subrahmanyam, 2001). Funding liquidity is agent specific and depends on borrowing constraints of dealers, hedge funds, investment banks and the availability of arbitrage capital overall (Brunnermeier and Pedersen (2009)). Therefore, funding liquidity may contain information about asset prices beyond what is captured by market liquidity. There are indeed episodes when market crashes are caused by funding liquidity rather than market liquidity (see detailed discussion in Brunnermeier and Pedersen (2009)). Moreover, Brunnermeier and Pedersen (2009) suggest that funding liquidity can be one of the driving forces of market liquidity and can also have applications for risk premiums.

This paper makes two contributions. First, we suggest that Treasury bond illiquidity can capture information about fluctuations in funding liquidity. There are reasons to expect that illiquidity of Treasuries can reflect information other than the easiness of trading in the bond market (Goyenko, Subrahmanyam and Ukhov (2011)). Treasury markets are usually characterized by low noise because of their high liquidity and low credit risk and hence any fluctuations in its illiquidity can contain information. Moreover, Treasuries are usually considered a safe haven during market downturns or periods of high uncertainty. For example, on August 8, 2011, The Wall Street Journal writes:

[1] See also Eleswarapu and Reinganum (1993), Brennan and Subrahmanyam (1996), Jones (2002), among others.

"Treasury bonds proved again Monday that they are still a haven for global investors despite the first credit-rating downgrade on the U.S. in modern history from one of the big three firms. Bond prices rallied broadly as investors fled risky assets including U.S. stocks, with the benchmark 10-year note's yield falling toward the lowest level since October. The two-year note's yield earlier hit a fresh record low of 0.232%, falling below the top end of zero-0.25% range for the Federal Reserve's key policy rate."

WSJ, August 8, 2011, "Treasuries Rally as U.S. Debt Remains Go-To Haven"

Fund inflows into Treasuries suggest higher uncertainty and lower capital availability in the stock market. The scarcity of trading capital in the stock market decreases the ability of arbitragers to provide liquidity and thus increases illiquidity. During these events the illiquidity of both the stock and bond markets increase. However, the illiquidity of the bond market increases less and bonds still remain the most liquid assets in the economy.

The empirical results show that an increase in Treasury bond illiquidity predicts an increase in the Treasury-Eurodollar (TED) spread and the VIX. The TED spread and the VIX are commonly used as measures of speculator's capital availability in the economy (see Teo (2011), Gupta and Subrahmanyam (2000), Boyson, Stahel, and Stulz (2010), Brunnermeier and Pedersen (2009) among others). Stock illiquidity has no significant impact on the TED spread or the VIX. Controlling for monetary policy and stock illiquidity, bond illiquidity is the only variable that predicts changes in both the TED and the VIX. Moreover, bond illiquidity Granger causes the TED spread and the VIX but the reverse is not true. This suggests that bond illiquidity contains information about funding liquidity.

Second, the paper explores the applications of the above findings for domestic mutual fund returns. Garleanu and Pedersen (2011) show that assets with the same cash flows can have different prices if they have different exposures to funding liquidity risk. This difference in prices, a funding liquidity premium, is especially pronounced before and during a funding liquidity shock and is insignificant during normal times. However, for mutual fund managers this risk can be important at all times. While stock returns react to fundamental shocks to the market, mutual fund returns react to both fundamental shocks to the market and fund flows associated with past performance. If, for example, a fund is forced to liquidate in a fire sale (Coval and Stafford (2007)) it will have higher losses in stocks with higher margin requirements since arbitragers' ability to provide liquidity in those stocks is limited (Garleanu and Pedersen (2011)). This will further destroy the fund's value. In contrast, if a financially stable fund holds a high funding liquidity risk portfolio and liquidation is avoided, the fund should earn abnormal returns in excess of the fund's benchmark. Therefore, unlike stocks, mutual funds can be exposed to funding liquidity risk at all times.

This paper shows that after controlling for stock liquidity, mutual funds with a high bond liquidity beta outperform funds with a low liquidity beta by 5.5% per annum. Active equity mutual funds in the high liquidity beta decile portfolio outperform the low beta-decile portfolio by 5.9% per annum, and for corporate bond funds this number amounts to 2.5% per annum. The results also hold across different styles of active equity and corporate bond funds and are robust to different holding periods, up to one year. Other funds (e.g. municipal, financial services, sector funds, commodity funds) do not exhibit significant difference in performance conditioned on lagged bond liquidity beta. Further, for both equity and corporate bond funds, funds sorted into the highest quintile on past alpha and then past bond liquidity beta produce a significant risk-adjusted premium of 3.1% after expenses and management fees. The exposure to bond liquidity risk is also observed across all size, expenses and turnover portfolios.

What do these results imply about liquidity management of fund managers? There are different liquidity considerations pertaining to each trade of mutual funds. Edelen (1999), for example, states that mutual funds provide liquidity services to their investors and liquidity therefore is a major concern for fund managers. Alexander et al (2007) show that liquidity trades occur mostly during fund inflows while fund outflows cause valuation-motivated trades. However, the funds with inflows are less liquidity constrained and can therefore afford to take higher funding liquidity risk. The conditions under which fund managers invest in funding liquidity risk is an empirical question.

We find that for both the lowest and highest fund flow quintiles (outflows and inflows, respectively), funds in the high liquidity beta quintile portfolio outperform funds in the low liquidity beta quintile portfolio by 5% per annum. Therefore, regardless of whether the trade is liquidity motivated or valuation-motivated, fund managers always seem to maintain exposure to funding liquidity risk. However, less financially constrained funds, i.e., funds in the highest fund inflow quintile, and funds in the highest bond liquidity quintile portfolios produce statistically significant next period alpha of 2.1% per year for equity funds, and 2.3% per year for corporate bond funds. For similar portfolios in the outflow quintile these alphas are statistically indistinguishable from zero. Thus, smart-money (high fund inflows) and high bond liquidity beta predict higher future performance.

We identify an investment strategy which produces superior performance. Funds sorted into the highest quintile lagged alpha and highest quintile lagged bond liquidity beta produce a significant premium of 3.1% per year for both active equity and corporate bond funds.

The financial constraints of a fund can be reflected in fund's cash holdings. For example Simutin (2012) finds that managers with higher cash holdings can anticipate better fund outflows and their portfolios suffer less during asset firesales. Since cash holdings contribute to fund's liquidity we hypothesize that funds with higher positive cash holdings can invest more in high funding liquidity risk stocks and therefore have higher abnormal returns. We compare funds with positive cash holdings with funds without cash holdings. For both categories high bond liquidity beta funds significantly outperform low bond liquidity beta funds. However, this superior performance is almost twice or three times higher for positive cash holdings group for active equity or corporate bond funds respectively. Therefore less financially constrained funds invest more in funding liquidity risk and produce superior profits compared to their finically restricted counterparts.

This paper also analyzes the determinants of bond liquidity betas. For the cross-section of active equity funds, older funds (fund's age) and managers with longer tenure have portfolios with higher liquidity betas. The latter is consistent with Chevalier and Ellison's (1999) evidence that younger managers tend to "avoid unsystematic risk" and thus tend to avoid investing in funding liquidity risk. It also suggests that fund's survival (fund's age) and unsystematic bets of fund managers are correlated. Fund flows, size and expenses are also significant determinants of a corporate bond fund's beta. This is consistent with the hypothesis that less financially restricted funds, i.e. those with higher cash inflows and of larger size, can afford to have higher liquidity risk in their portfolios.

The paper proceeds as follows. Section 2 describes the data and liquidity measures. Section 3 links bond illiquidity and funding liquidity. Section 4 presents cross-sectional results for mutual fund portfolios. Section 5 concludes.

2. Data

We use changes in the Fed fund rate (FED) as an indicator of monetary policy stance following Bernanke and Blinder (1992). FED data are obtained from the Federal Reserve Bank of St. Louis. The Treasury–Eurodollar (TED) spread is the difference between the 3-month Eurodollar LIBOR rate and the 3-month Treasury bill rate, where the data are obtained from the Federal Reserve Board’s website. The VIX data are taken from the CBOE’s website. The sample for TED is from 03/1971to 12/2010 and from 03/1990 to 12/2010 for the VIX, based on the historical data availability.

A. Bond Illiquidity

Illiquidity in the US Treasury market is measured using relative quoted spreads. The simple bid-ask spread, based on widely available data, is a standard measure of market illiquidity. Goyenko, Subrahmanyam, and Ukhov (2011) analyze the illiquidity of U.S. Treasuries across all maturities and on-the-run/off-the-run status and find that the illiquidity of off-the-run T-bills with maturities of up to one year best captures the illiquidity of the Treasury market overall. Accordingly, the average percentage bid-ask spread of off-the-run U.S. T-bills with maturities of up to one year is used to proxy for U.S. Treasury bond market illiquidity. The quoted bid and ask prices come from CRSP’s daily Treasury Quotes file. This file includes quotes for Treasury fixed income securities of three and six months, as well as 1, 2, 3, 5, 7, 10, 20, and 30 years to maturity. Under the standard definition, when a new security of a given maturity is issued it is considered to be on-the-run and the older issues of nearby maturity are treated as off-the-run. The paper uses quotes for three-, six-, and 12-month securities. The quoted spread is first computed for each security as the average proportional daily spread for the month and then equally weighted across short-term assets.[2] These data have also been used by Acharya, Amihud, and Bharath (2009), Goyenko and Ukhov (2009), and Baele, Bekaert, and Inghelbrecht (2010). The primary motivation for using the CRSP data is to have a long enough Treasury bond illiquidity time series to be able to study the connection between the economic environment, liquidity conditions, and asset prices. CRSP is the only data source that allows for the use of a sufficiently long period to include a variety of economic events.

B. Stock Illiquidity

An important determinant of the choice of the liquidity measure is the long time period of our study. The high frequency microstructure data that is used to compute effective and quoted spreads are not available for the whole time period of our analysis. To measure illiquidity in the stock market the paper uses Amihud's (2002) illiquidity measure. Amihud (2002), Hasbrouck (2009), and Goyenko et al (2009) argue that Illiquidity is a good measure of the price impact in the stock market.

As defined by Amihud (2002), the illiquidity of stock i in month t is

$$\mathrm{ILLIQ}_t^i = \frac{1}{\mathrm{DAYS}_t^i} \sum_{d=1}^{\mathrm{DAYS}_t^i} \frac{\left|R_{td}^i\right|}{V_{td}^i},$$

where R_{td}^i and V_{td}^i are respectively the return and dollar volume (in millions) on day d in month t, and DAYS_t^i is the number of valid observation days in month t for stock i. This measure has the following intuition. A stock is illiquid (i.e., has a high value of ILLIQ_t^i), if the stock price moves a lot in response to little volume.[3] For convenience, the ratio is multiplied by 10^5.

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[2] The results are similar when non-scaled (raw) quoted spreads are used as an alternative to proportional quoted spreads. This is consistent with Chordia, Sarkar, and Subrahmanyam (2005), who show that the daily correlation between quoted and effective spread changes in the bond market is 0.68 over their nine-year sample period. Thus, quoted spreads are reasonable liquidity proxies.

[3] ILLIQ_t^i is computed for NYSE/AMEX common stocks with at least 5 observations on return and volume during month *t*.

Since both bond and stock illiquidity are persistent we use relative changes of this variable in the VAR analysis presented below. Figure 1 presents graphs of relative changes in bond illiquidity, Panel A, and stock illiquidity, Panel B. Bond illiquidity has one of the highest spikes in February 2009, in the midst of the credit crisis; in October, 1987 which is a reflection of the black Monday market crash on October 19, 1987. Among other spikes are market panics in the end of 1960's, recessions in 1972, and a market panic in 1979.

Stock illiquidity exhibits the highest percentage change in April 2000 which is associated with the NASDAQ technology bubble burst. It has similar extreme values to bond illiquidity. However, since overall stock market liquidity improves over time, the recent 2007-2009 crisis is not reflected with as high values of stock illiquidity as the collapse of the NASDAQ bubble.

Table 1 Panel A presents summary statistics for stock and bond illiquidity and funding liquidity as measured by the TED and the VIX. Bond illiquidity has a low mean and a high standard deviation. The low mean compared to stock illiquidity is attributed to the analysis of short-term Tbills, which have the highest liquidity.

The TED spread achieves its highest value, almost 50 basis points, during the oil crisis in July 1974. The second highest value is 39 basis points reached in October 2008 during the beginning of the credit crisis. It should be noted that these are monthly data for TED spread which are less volatile. The daily data exhibit more extreme values. For example, on September 17, 2008, the TED spread jumped to 300 basis points.

Panel B reports the correlation matrix between liquidity measures and FED. FED is used in the analysis since it can indirectly affect TED via its effect on the 3-month Tbill rate. Moreover, monetary policy is one of the main determinants of bond illiquidity (Goyenko et al 2011). Bond illiquidity has low correlation with TED, and the VIX, 0.09 and 0.036 respectively, and has a higher positive correlation with FED, 0.266. Stock illiquidity also has a positive correlation with the VIX, 0.202. The correlation between stock and bond illiquidity is low, 0.087. While a positive sign indicates commonality between two illiquidity series, the low magnitude of a correlation coefficient suggests that both are quite different. Among other variables, the TED spread has a high and positive correlation with the VIX, 0.551. This is expected since both are a proxy for funding liquidity.

3. Vector Autoregression Analysis

The purpose of this section is to establish the link between bond illiquidity and funding liquidity. Given that there are reasons to expect cross-market effects and bidirectional causalities, we adopt a four-equation vector autoregression specification that incorporates four variables: FED, Stock Illiquidity, Bond Illiquidity and Funding Liquidity, where funding liquidity is either measured by the TED spread or the VIX. Therefore, consider the following system:

(1) $$X_t = \sum_{j=1}^{K} a_{1j} X_{t-j} + \sum_{j=1}^{K} b_{1j} Y_{t-j} + u_t \quad \text{and}$$

(2) $$Y_t = \sum_{j=1}^{K} a_{2j} X_{t-j} + \sum_{j=1}^{K} b_{2j} Y_{t-j} + \upsilon_t ,$$

where X is a vector that represents monetary policy, stock and bond illiquidity, and Y is the vector containing either the TED spread or the VIX as proxies for funding liquidity. The number of lags, K, in equations (1) and (2) is chosen on the basis of the AIC and Schwarz Bayesian Information Criterion. The VAR with 2 lags is identified to be optimal. The TED spread, or the VIX, is set in the end of the VAR ordering since these are the variables of interest.[4] However, we also test the robustness of results for alternative ordering.

Before reporting VAR results, we first provide pairwise Granger-causality test results in Table 2. The null hypothesis is that the row variable does not Granger cause the column variable. Bond illiquidity Granger causes stock illiquidity and there is also reverse causality from bond illiquidity to stock illiquidity. Stock illiquidity has no Granger causality effect for the TED spread or the VIX while Bond illiquidity Granger-causes both. Moreover there is no reverse causality from the TED spread or the VIX to

[4] Since TED spread and VIX are proxy for funding liquidity we do not use them in the same VAR. We run two sets of VAR, first with TED spread and then with VIX in the end of ordering.

bond illiquidity. This provides first evidence that bond illiquidity contains information about funding liquidity and also highlights the fundamental difference between stock and bond illiquidity. All variables of interest, except stock illiquidity, also Granger-cause FED suggesting that FED policy responds to worsening liquidity conditions in the markets. FED also has a reverse causality effect across liquidity measures. This implies that monetary policy actions do affect market liquidity which is consistent with the findings in Goyenko et al (2011).

Note that the Granger causality results are based on the analysis of the coefficients from a single equation, and do not account for the joint dynamics implied by the VAR system. A clearer picture can potentially emerge by the use of impulse response functions (IRFs). The IRF traces the impact of a one-time, unit standard deviation, positive shock to one variable on the current and future values of the endogenous variables. Since innovations are correlated, they need to be orthogonalized. They are computed using standard Cholesky decompositions of the VAR residuals.

Figure 2, Panel A, illustrates the response of the TED spread to a unit standard deviation change in a particular variable, traced forward over a period of 10 moths. The 95% confidence intervals are obtained via 1,000 Monte-Carlo simulations. A positive shock to FED increases the TED spread and this impact is quite persistent. Stock illiquidity has no significant impact on the TED spread while a positive shock to bond illiquidity predicts an increase in the TED spread, i.e. a worsening of funding liquidity. This effect is persistent and is independent of monetary policy.

Panel B further describes the differences between stock and bond illiquidity. While a positive shock to TED increases stock illiquidity it has no significant impact on bond illiquidity. Therefore, bond illiquidity predicts changes in the TED spread controlling for other variables and the reverse is not true. It supports the Granger causality results in Table 2 and suggests that bond illiquidity is one of the drivers of funding liquidity.

A positive shock to stock illiquidity decreases bond illiquidity and this effect is significant only in the third lag. This is consistent with the results of Goyenko and Ukohov (2009) and supports the evidence of flight-to-liquidity episodes: when the stock market is illiquid, i.e. a positive shock to stock illiquidity, funds flow into the Treasury market and improve Treasury bond liquidity.

A positive shock to bond illiquidity increases stock illiquidity and this effect persists for two lags. Thus, while bond illiquidity contains information about changes in funding liquidity (TED spread) it also transmits this information into stock market illiquidity. This is consistent with Brunnermeier and Pedersen (2009) who suggest that funding liquidity at times can be a main driver of market (stock) liquidity. The above results are also robust to VAR ordering.

Figure 3, Panel A, presents impulse response functions of the same VAR(2) system as above where funding liquidity is now proxied by VIX. A positive shock to bond illiquidity predicts an increase in the VIX and this effect persists for two lags. FED or Stock illiquidity only marginally affects the VIX in the first lag. However, the results for FED and Stock ILLIQ are not robust to VAR ordering. When VIX is in the beginning of the VAR ordering, the effect of stock illiquidity and FED on the VIX is no longer significant while the effect of bond illiquidity remains highly significant for two lags (these results are not reported for brevity). Therefore, bond illiquidity is the only variable that predicts changes in VIX.

Panel B shows that Bond illiquidity increases in the second lag in response to a positive shock to FED, and decreases in the third lag with response to a positive shock to stock illiquidity. The latter is consistent with flight to liquidity episodes when stock liquidity tightens, funds are moved to bond markets and thus improve bond market liquidity. However, there is no significant impact of VIX on bond illiquidity. Therefore the effect of bond illiquidity on VIX in Panel A is independent from factors driving fluctuations in VIX.

Among other variables, a positive shock to VIX increases stock illiquidity. The impact of bond illiquidity on stock illiquidity is no longer significant and is now dominated by VIX. However, once VIX is not in the system, bond illiquidity regains significant impact on stock illiquidity.

We therefore find that bond illiquidity is one of the main drivers of funding liquidity proxied by the TED and the VIX. Below we explore applications of bond illiquidity as funding liquidity for mutual fund returns.

4. Mutual Funds and Funding Liquidity

It is not obvious why fund managers should invest in stocks with high liquidity risk. For example Edelen (1999) states that mutual funds primary service is to provide liquidity to their investors and fund managers therefore engage in a fair deal of uninformed liquidity motivated trading. Buying illiquid stocks would contradict the liquidity priorities of mutual funds. Analyzing fund trades by flows Alexander et al (2007) show that liquidity trades occur mostly during fund inflows while outflows are accompanied primarily by valuation-motivated trades. Nevertheless there is evidence in the literature that hedge fund managers have significant exposure to stock liquidity risk in their portfolios (Sadka, 2010) and that mutual fund managers also invest in stocks with high stock market liquidity risk (Dong, Feng, and Sadka 2011). Therefore, the relationship between funding liquidity risk (or bond liquidity beta) and mutual fund returns is an empirical question.

Funding liquidity can be an important source of risk to control for mutual fund managers. Although most mutual funds are not allowed to short-sale and borrow on margin they can hold stocks with high trading constraints. If there is a shock to the market the margins will increase and arbitrageurs will have limited ability to provide liquidity in these stocks. Therefore, the price of these stocks will be lower compared to similar stocks with the same cash flows (Garleanu and Pedersen (2011)). If a fund needs to liquidate in asset fire sales (Coval and Stafford, 2007) it will experience further losses and decrease in the fund’s value overall. However, if a fund attracts low liquidity need investors and the rate of withdrawals is low, this fund would have higher abnormal returns (Nanda, Narayanan and Warther (2000)). Therefore, the hypothesis here is that funds with higher bond liquidity beta should have higher alphas.

4.1 Mutual Fund Data and Evidence from Portfolio Sorting

The paper uses the CRSP Survivorship Bias Free Mutual Fund Database with the CDA/Spectrum holdings database and merges the two databases using Mutual Fund Links tables available at CRSP. The monthly mutual fund data are from January 1991 to

December 2010 and include net returns after fees, expenses, and brokerage commissions but before any front-end or back-end loads, total net assets, the fund's turnover ratio, expense ratio, investment objective, and other fund characteristics. The CRSP database identifies each shareclass separately, whereas the CDA database lists only the underlying funds. The Mutual Fund Links tables assign each shareclass to the underlying fund. Whenever a fund has multiple shareclasses at the CRSP database, the weighted CRSP net returns, expenses, turnover ratio and other characteristics are computed for each fund. The weight is based on the most recent total net assets of that shareclass. The analysis first employs all domestic mutual funds. We exclude money-market funds, index funds, and funds investing in foreign assets. Subsequently the funds are categorized into active equity funds, corporate funds and others.

Active equity funds are funds with investment objective codes from Weisenberg and Lipper to be aggressive growth, growth, growth and income, equity income, growth with current income, income, long-term growth, maximum capital gains, small capitalization growth, micro-cap, mid-cap, unclassified, or missing. When both the Weisenberg and the Lipper codes are missing, Strategic Insight Objective Code to identify the style is applied, and if Weisenberg, Lipper and Strategic Insight Objective Code are missing, investment objective codes from Spectrum, if available, are used to identify the fund's style. If no code is available for a fund and a fund has a past month/s with the style identified, that fund month is assigned the style of the previously identified style-month/s. If the fund style cannot be identified, it is not included in the sample. Overall there are nine style categories: (i) Aggressive Growth, (ii) Equity Income, (iii) Growth, (iv) Long term growth, (v) Growth and Income, (vi) Mid-Cap, (vii) Micro-Cap funds, (viii) Small cap, and (ix) Maximum Capital Gains. Index funds are eliminated by deleting those whose name includes the word "index" or the abbreviation ind, S&P, DOW, Wilshire and Russell. Also funds that hold less than 70% in common stocks are excluded. Small funds with total net assets of less than $15 million at the end of the period preceding the test period are also eliminated. Addressing Evans's (2004) comment on incubation bias, observations before the reported starting year by CRSP are eliminated. And, following Cremers and Petajisto (2009), funds with a missing name in CRSP are deleted. Overall there are 2,820 active equity funds included in the sample. Their summary statistics are presented in Table 3, Panel A. We also report fund characteristics which commonly appear in studies of fund performance. For example, Cremers and Petajisto (2009) use Total Net Assets, *TNA*, ($mm); *Expense*, the expense ratio of the most recently completed fiscal year; *Turnover*, defined as the minimum of aggregated sales or aggregated purchases of securities divided by the average 12-month *TNA* of the fund; *Fund Age* computed as the difference in years between current date and the date the fund was first offered; and *Manager Tenure*, the difference in years between the current date and the date when the current manager took control.[5]

We also include corporate bond funds with identified investment styles. The styles are: Corporate Debt A Rated, Corporate Debt BBB-Rated, Intermediate Investment Grade Debt, Short-Term Investment Grade Debt and Short-Intermediate Investment Grade Debt, High Current Yield, Balanced, General Bond, Income (including flexible and multi-sector) , and Flexible Portfolio. As before we require that *TNA* > $15 million. We also require corporate bond funds to be invested at least 35% in common equity. This accommodates balanced funds and other corporate bond funds which have pretty flexible strategies and can switch between asset classes.

The remaining funds are real estate, commodity, multi-sector, sector, multi-strategy and utility funds. We also require them to hold at least 35% in common equity and have *TNA* > $15 million to be included in the sample. Panels B and C report summary statistics of corporate bond funds and other funds respectively. The corporate bond funds are not as numerous as equity funds. Only 654 funds satisfy our data requirements. However, these funds on average are bigger than equity funds with slightly lower average turnover and higher average fund age. The rest of the eligible funds, 3,244 funds, have very similar fund characteristics to the active equity funds.

Mutual fund bond liquidity betas are estimated using the model

$$r_{i,t} = \beta_i^0 + \beta_i^{BLiq} BondLIQ_t + \beta_i^{SLiq} StockLIQ_t + \beta_i^M MKT_t + \varepsilon_{i,t} \tag{3}$$

where $r_{i,t}$ denotes fund *i*'s excess return. Bond illiquidity beta in month *t-1* is estimated by using return data from month *t-24* to *t-1*. In contrast to stocks, the shorter window of 24 months is used for the mutual fund sample. This is consistent with previous

[5] The manager can be an institution with a long tenure.

work that advocates estimating fund risk exposures over a short period (Brown, Harlow and Starks (1996), Chevalier and Ellison (1997), (1999)). A shorter estimation window also decreases the survivorship bias and allows us to capture the most recent mutual fund strategies. Bond liquidity and stock liquidity are the same as in the previous section with the only exception that instead of relative changes we now use AR(2) residuals estimated from the illiquidity levels over the shorter mutual fund sample, from January 1991 to December 2010. The residuals are multiplied by -1 to have a series of liquidity, rather than illiquidity, shocks. This is similar to the approach of Pastor and Stambaugh (2003), who use a second order autoregression to calculate unexpected innovations of liquidity. The shorter sample is due to data availability since monthly TNA values are available starting January 1991. Since there is evidence of stock liquidity risk in mutual fund returns (Dong, Feng, and Sadka 2011) we use an estimation model that controls for stock liquidity.

All funds in month *t* are sorted into decile portfolios based on bond liquidity beta estimated from model (3) in month *t-2*. We thus skip one month between portfolio ranking and portfolio formation. Table 4 presents risk adjusted returns (alphas) of these portfolios and their Newey-West adjusted t-statistics. We use the standard Fama-French-Carhart model (FFC) to estimate alphas for equity funds, and similar to Bessembinder et al. (2008), we augment the FFC model with Term and Default spreads (FFCTD model) to estimate alphas for corporate bond and other funds. Default (DEF) is the difference between the return on BAA-rated bonds and AAA-rated bonds, and TERM is the difference between the return on the 30-year Treasury bonds and the 3-month Treasury bill rate. Bond return data are from the Lehman\Barclays series, obtained from Datastream.

The first Panel of Table 4 reports portfolio alphas when all funds are included in the sample. The alpha monotonically increases with bond liquidity beta. The difference between the high beta and low beta portfolios is 0.455% per month (or 5.5% per year) regardless of the benchmark model specification. Therefore, on average, high beta funds outperform low beta funds by 5.5% per year, controlling for stock market liquidity. This number varies across fund categories. It is the highest for active equity funds, where high beta funds outperform low beta funds by 0.49% per month (or 5.9% per year), and it is the lowest for corporate bond funds, 0.206% per month (2.5% per year). For Other funds, the High minus Low spread is statistically insignificant. This suggests that liquidity concerns for the real estate, multi-sector, utility, commodities and multi-strategy funds are not of primary importance. In subsequent analysis we therefore consider only active equity and corporate bond funds.

4.2 Style Analysis and Longer Holding Periods

In this section we explore whether our results are driven by a small sub-sample of funds associated with certain styles or it is observed across all styles. The styles are grouped into the following categories. Active equity style categories (Panel A) are Growth, Income and Other. Growth category includes Aggressive Growth, Growth and Long Term Growth styles. The Income category consists of Income, Income and Growth styles, while Other includes Micro-Cap, Small Cap, Mid-cap, Maximum Capital Gains and Capital Appreciation funds. Bond funds (Panel B) are categorized into Balanced which include only balanced funds because they have the highest representation in our sample, and Other. Other includes Corporate Debt A Rated, Corporate Debt BBB-Rated, Intermediate Investment Grade Debt, Short-Term Investment Grade Debt and Short-Intermediate Investment Grade Debt, High Current Yield, General Bond, Flexible Income and Flexible Portfolio.

As before, the funds are sorted into bond liquidity beta decile portfolios in month *t-2* and the portfolio average return is computed in month *t*. The portfolio alphas are then estimated using either the FFC or FFCTD benchmark model. Table 5 presents alphas in percent and their Newey-West adjusted t-statistics. For both active equity and corporate bond funds, portfolio alpha increases with bond liquidity beta. The spread between High and Low beta portfolios is the highest for Growth equity funds, 0.445% per month (5.3% per year), followed by Other equity category, 0.371% per month (4.5% per year), and then followed by Income equity funds, 0.283% per month (3.4% per year) (Panel A). Therefore, Growth funds on average are more aggressive about taking funding liquidity risk and Income funds are more conservative in their approach to liquidity risk. Nevertheless the High-Low spread is higher for equity funds across all categories compared to corporate bond funds (Panel B). Here the spread is 0.20% and 0.21% (2.4% and 2.5% per year) for Balanced and Other funds respectively.

Therefore, the evidence of funding liquidity risk is observed across all fund categories and is not style specific.

We also test the robustness of our findings for different holding periods. Table 6 presents results where the performance of bond liquidity beta sorted mutual fund portfolios is analyzed for 3, 6 and 12 month holding periods. Specifically, in this table, similar to Jegadeesh and Titman (1993) we rebalance fund portfolios every 3, 6 and 12 months respectively. For the first half-year for active equity funds (Panel A) and corporate bond funds (Panel B) High minus Low portfolio has almost the same performance as for the one month holding period in Table 4. For example, the High-Low risk-adjusted spread for equity (bond) funds after 3 months of holding is 0.477% (0.218%) per month compared to 0.49% (0.206%) in Table 4. High beta funds continue to outperform low beta funds for the 6 month holding period by almost the same magnitude as for the 3 month period. The High minus Low spread for equity funds insignificantly decreases to 0.421% per month, and for bond funds it remains at almost the same level, 0.204%.

After 12 months of holding, high beta funds continue to outperform low beta funds but the High-Low spread decreases by nearly half for both active equity (0.273% per month) and corporate bond funds (0.116% per month), and remains significant at the 10% level. For longer than 12 month holding periods the High-Low spread is statistically insignificant from zero. Therefore, the results are robust to holding periods of up to one year and are especially strong for the first half-year.

4.3 Mutual Fund Characteristics and Funding Liquidity Risk

In this section we analyze the relationship between fund size, expenses, turnover and bond liquidity risk. Holding illiquid stocks can be risky, costly and might involve high turnover in the case when financially constrained funds need to liquidate costly positions during market liquidity shocks.

Berk and Green (2004) provide the theoretical rational that as a fund grows its performance deteriorates due to the decreasing return to scale of a manager's actions. Therefore, smaller funds should be investing more in bond/funding liquidity risk compared to the larger funds due to their higher flexibility in investment decisions. However, if high funding liquidity risk stocks are suitable for diversification we also can observe the same effect for larger funds. Further, since funding liquidity can deteriorate market liquidity (Brunnermeier and Pedersen (2009)) trading in high funding liquidity risk stocks can be expensive. Thus, higher bond liquidity betas should be associated with higher expenses unless mutual funds choose to buy and hold those stocks. Buy and hold strategies would also imply lower turnover for high bond liquidity beta portfolios. Otherwise, if funds rebalance frequently in high funding liquidity risk stocks the turnover should be high. Therefore, the relationship between fund size, expenses, turnover and bond liquidity beta remains an empirical question.

Table 7 presents the results of portfolios first sorted into quintiles based on either size, or fund's expenses, or turnover and then each quintile is sorted into bond liquidity beta portfolios for both active equity and corporate bond funds. As before, the bond liquidity beta is estimated with model (3) using a 24 month rolling window. We omit one moth between portfolio ranking and portfolio formation. The portfolio Alphas are presented in percent after adjusting average excess returns with either the FFC model for active equity funds or the FFCTD model for corporate bond funds, and Newey West adjusted t-statistics are in parentheses.

Panel A presents results for 25 size/bond liquidity beta sorted portfolios. For each size quintile Alphas are monotonically increasing with liquidity beta. It holds for both, active equity and corporate bond funds. Bond liquidity beta portfolios produce a positive and significant spread for all size quintile portfolios for equity funds, and for four size portfolios for bond funds. Therefore, the exposure to bond liquidity risk is observed across all size categories. Interestingly, for equity funds, the High-Low bond beta spread is higher for lager funds. Specifically, High-Low spread of the fourth size portfolio is almost 0.5% per month compared to 0.38% for the small size portfolio. The highest spread is observed not in the extreme size portfolios but rather in the medium size portfolios for equity funds. Thus, exposure to funding liquidity risk is not specific to a fund's size. High-Low spreads by beta portfolio are also very close in magnitude across all size quintiles for bond funds with the exception of the fourth quintile where it is insignificant.

Panel B presents expenses-bond beta sorted portfolios. High-Low spread by beta portfolio is slightly higher for the last four expense quintiles but not significantly different across all expense quintiles. For example, for equity funds, High-Low spread is 0.39% per month for the lowest expenses quintile and 0.42% per month for the highest expenses quintile, which is almost the same order of magnitude. For bond funds these numbers are 0.13% and 0.17%, respectively. This supports the idea that trading strategies associated with managing funding liquidity risk do not significantly change a fund's expense ratio. This is probably due to the fact that funds do not rebalance frequently stocks with high trading constraints.

Turning to the frequency of rebalancing, Panel C presents portfolio results for funds first sorted into turnover quintiles and then each quintile is sorted into five bond liquidity beta portfolios. For both, equity and bond funds, High-Low beta spread for the last turnover quintile (the highest turnover) is insignificant. This is consistent with the hypothesis that high funding liquidity risk stocks are not the most frequently traded ones. For equity funds, the fourth turnover quintile has a slightly higher High-Low spread, 0.503%, compared to the first turnover quintile, 0.383%. However, a portfolio with Low Turnover/High Liquidity Beta produces significant at the 10% level alpha of 0.178% per month (2.13% per year) while the similar portfolio in the fourth turnover quintile produces an alpha statistically insignificant from zero. Therefore, low turnover and high funding liquidity risk seem to benefit mutual fund performance. The results are qualitatively similar for bond funds. Here, however, the corner portfolio, Low Turnover/High Beta portfolio and two adjacent portfolios produce statistically significant positive alphas.

We conclude that funds do manage their funding liquidity risk exposure across all size categories. It is only marginally reflected in their expense ratios, and it does not cause high turnover. Higher exposure to funding liquidity risk and low frequency of portfolio rebalancing produces superior returns. The latter is consistent with the theoretical predictions of Nanda, Narayanan and Warther (2000) who suggest that funds attracting low liquidity-need investors, which means lower withdrawal rates and lower turnover, will have higher abnormal returns.

4.4 Past Performance and Bond Liquidity Beta

The literature uses different ways to analyze past performance of mutual funds. The first is smart-money or fund flows. It is based on the idea that investors are chasing good performance and fund inflows or outflows will reflect this (Sirri and Tufano, 1998). Moreover, fund flows are interesting for another reason. Alexander et al (2007) find that fund inflows force fund manager to make liquidity trades, and fund outflows are accompanied by valuation-based trade. We would therefore expect that fund inflows are accompanied with low funding liquidity risk trades. Alternatively, funds with higher inflows can have lower financial constraints and can afford higher liquidity risk.

Similar to the previous literature, we compute fund flows as

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

where $TNA_{i,t}$ is measured in the end of month *t*, and $R_{i,t}$ is the fund's return for month *t*.

Second, performance is measured by a fund's alpha. It is computed as the intercept from regressing mutual fund excess monthly returns on either FFC factors for equity funds, or FFCTD factors for bond funds and using the preceding 24 months of historical data. Bond liquidity betas are estimated as before using model (3) and a 24 month rolling window. All funds are first sorted in quintiles based on lagged fund flows (or alphas) and then each quintile is sorted into five bond beta portfolios. Table 8 presents risk-adjusted returns of these portfolios.

Panel A provides sorting results by fund flows and liquidity beta. Funds in the first Flow quintile always have negative flows (outflows) and funds in the last quintile always have positive flows (inflows). For both, equity and bond funds, High Flow and High beta portfolio always produce positive and significant alpha of similar magnitudes (0.18% per month for equity funds and 0.19% per month for bond funds, or 2.16% and 2.28% per annum, respectively). Therefore, funds with lower financial constraints can afford higher funding liquidity risk and are rewarded with higher abnormal returns.

However, high beta funds outperform low beta funds in the outflow quintile by the same magnitude as in the inflow quintile. For equity funds, High-Low spread by bond beta portfolio is 0.42% per month for both the first and fifth flow portfolios. Given the results of Alexander et al (2007), funds invest in funding liquidity risk regardless of whether the trade is liquidity or valuation-based.

Sorting on past alphas and then on bond liquidity betas provides similar results (Panel B). High Alpha quintile and High bond beta portfolio produces next period alpha of 0.258% per month (3.1% per year) for equity funds and it is also positive and significant for two adjacent portfolios. Moreover, across all alpha portfolios bond liquidity beta always produces positive and significant High-Low spread. This means that regardless of what a fund's alpha is a manger can always benefit from investing in high funding liquidity risk stocks.

4.5 Cash Holdings and Funding Liquidity Risk

The above analysis relies on the fact that all inflows into a fund will be invested. However, fund managers might keep certain percentage of their portfolios invested in cash. Holding cash allows higher flexibility in managing fund's liquidity. Moreover, funds which hold cash are found to do better during asset firesales compared to those without cash holdings (Simutin, 2012). Our hypothesis in this section is that less liquidity constrained funds, or funds with higher cash holdings, can invest in higher funding liquidity risk and have superior performance. These funds typically have a better ability to anticipate outflows (Simutin, 2012) and forced liquidations related to funding liquidity shocks will be less costly for them. This also implies that managers of these funds might keep cash to cover unexpected losses on their funding liquidity risk positions.

Funds do not normally keep high proportion of their portfolios invested in cash. The average portfolio holding in cash for our sample of active equity funds is 4.5% with the median of 3%. For corporate bond funds these numbers are 6.1% and 4% respectively. We split funds in two groups, the first is without cash holdings and the second is with positive cash holdings. Each group is then sorted into bond liquidity beta quintiles estimated as before with model (3) and using a rolling window of 24 months. One month is omitted between portfolio ranking and portfolio formation. Table 9 presents portfolio FFC-risk adjusted returns for equity funds, Panel A, and FFCTD-adjusted returns for corporate bond funds, Panel B. For each cash holdings group portfolio alpha increases with portfolio bond liquidity beta and high beta portfolios always outperform low beta portfolios by significant magnitude. However, the High minus Low spread is almost twice higher for equity funds in positive cash holdings group, Panel A, compared to no cash holdings group. This difference is even higher for corporate bond funds, Panel B. While funds in the high beta quintile outperform funds in the low beta quintile by 0.15% per months in the no cash holdings group, this number increases to 0.40% per month for cash holdings group.

Therefore, funds with lower liquidity constraints, i.e. positive cash holdings, and higher funding liquidity risk exhibit better performance.

4.6 Determinant of Bond liquidity Beta

Table 10 presents monthly cross-sectional Fama-MacBeth regression results of fund bond liquidity beta on characteristics variables reported in Table 3 and the measures of past performance, $Alpha_{t-1}$ and Fund $Flows_{t-1}$. All regressions include style dummies and t-statistics are based on Newey-West adjusted standard errors.

Higher expenses are associated with lower bond liquidity betas for both equity and bond funds, as seen in columns (1) and (4), respectively. This is consistent with portfolio sorting results which show that the highest expenses do not necessarily produce a high performance difference between high and low bond beta portfolios. Moreover, for bond funds, the highest difference is obtained for the second to the lowest expense quintile portfolio (Table 7, Panel B). This effect is not robust to the inclusion of other fund characteristics for equity funds but it holds across all specifications for bond funds. Therefore, higher expenses lead to lower bond liquidity beta for the cross-section of corporate bond funds. Fund size does not seem to be important for equity fund bond liquidity betas but it is always significant for corporate bond funds.

Turnover, fund's age, and manager's tenure are significant determinants of bond liquidity betas for equity funds (columns (2) and (3)). Higher turnover suggests lower beta which means that higher funding liquidity risk is not associated with higher frequency of portfolio rebalancing. Fund's Age and Manager's tenure lead to higher liquidity beta. The later in consistent with Chevalier and Ellison (1999) who argue that younger fund managers, because of their career concerns, avoid taking unsystematic risk and will be more systematic in their investment strategies. The former suggests that the longevity of a fund in the business is to some extent attributed to the fund's ability to take on unsystematic bets.

Fund flows increase bond liquidity beta of corporate bond funds (column (5)). This is consistent with the hypothesis that less financially constrained funds can allow for higher funding liquidity risk in their portfolios. However, we do no observe the same effect for equity funds.

The regression R-square for equity funds is between 0.26-0.29 suggesting that about one third of the cross-sectional variations in fund liquidity betas is explained by fund characteristics. The regression R-square for bond funds is lower (0.09-0.12).

5. Conclusion

This paper links Treasury bond liquidity and funding liquidity. It is shown that Treasury bond illiquidity predicts changes in the Treasury-Eurodollar (TED) spread and the VIX, which are commonly used as proxies for funding liquidity. Stock market illiquidity is lacking these properties. We therefore suggest that bond illiquidity contains information about funding liquidity.

Unlike stocks that can be exposed to funding liquidity risk only before and during fundamental shocks to the market (Garleanu and Pedersen (2011)), mutual fund returns can be exposed to this risk at all times. Mutual fund portfolio returns are sensitive not only to market shocks but also to fund inflows and outflows. The latter can cause liquidity constrained funds to limit their exposure to funding liquidity risk.

We find that mutual fund portfolios exhibit substantial exposure to funding liquidity risk. Both equity and corporate bond funds in the high bond liquidity beta decile significantly outperform funds in the low beta decile. This result holds across different style categories and different holding periods.

Moreover, bond liquidity risk exposure is observed across all fund size categories. It is accompanied by low to medium turnover suggesting infrequent rebalancing for high bond liquidity beta portfolios and an insignificant effect of these strategies on funds' expense ratios.

Sorting funds on past flows or alphas and bond liquidity betas allows one to identify portfolios with highly significant and positive subsequent period alphas. Low financial constraints of a fund and high bond liquidity risk predict better future performance.

References

Acharya, V, Amihud, Y., and S. Bharath, 2009, Liquidity risk of corporate bond returns, NYU working paper.

Acharya, V. and L. Pedersen, (2005) Asset Pricing with Liquidity Risk, *Journal of Financial Economics*, 77, 375-410

Alexander, Gordon, Gjergji Cici, and Scott Gibson, 2007, Does Motivation Matter When Assessing Trade Performance? An Analysis of Mutual Funds. *Review of Financial Studies* 12, 1, 125-150

Amihud, Y., and H. Mendelson. (1986) "Asset Pricing and the Bid-Ask Spread." *Journal of Financial Economics*, 17, 223-249.

Amihud, Y., and H. Mendelson. (1989) "The Effect of Beta, Bid-Ask Spread, Residual Risk, and Size on Stock Returns." *Journal of Finance*, 2, 479-486

Amihud, Y. (2002) "Illiquidity and Stock Returns: Cross-Section and Time-Series Effects." *Journal of Financial Markets*, 5, 31-56

Baele, L., G. Bekaert, and K. Inghelbrecht, 2010, The determinants of stock and bond return comovements, *Review of Financial Studies* 23, 2374-2428.

Berk, J.B. and R. Green, 2004, Mutual Fund Flows and Performance in Rational Markets. *Journal of Political Economy* 112, 1269-1295.

Bernanke, B., and A. Blinder, 1992, The federal funds rate and the channels of monetary transmission, *American Economic Review* 82, 901-921

Boyson, N. M., Stahel, C.W. and R. Stulz, 2010, "Hedge Fund Contagion and Liquidity Shocks." *Journal of Finance* 65,1789–1816

Brown, Keith C., Van Harlow, and Laura T. Starks, 1996, Of Tournaments and Temptations: An Analysis of Managerial Incentives in the Mutual Fund Industry, *Journal of Finance* 51, 85-110.

Brunnermeier, M. and L. Pedersen, 2009. "Market Liquidity and Funding Liquidity" *Review of Financial Studies* 22, 2201-2238

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

Chevalier, Judith, and Glenn Ellison, 1997, Risk Taking by Mutual Funds as a Response to Incentives, *Journal of Political Economy* 105, 1167-2000.

Chevalier, J.A. and G. Ellison, 1999, Career Concerns of Mutual Fund Managers, *Quarterly Journal of Economics* 114, 389-432.

Chordia, T.; R. Roll; and A. Subrahmanyam. "Market Liquidity and Trading Activity." *Journal of Finance*, 56 (2001), 501–-530.

Chordia, T., Sarkar A., and A. Subrahmanyam. 2005. "An Empirical Analysis of Stock and Bond Market Liquidity." *Review of Financial Studies*, 18, 85-129

Coval, J. and E. Stafford, 2007, Asset Fire Sales (and Purchases) in Stock Markets. *Journal of Financial Economics* 86,479–512.

Dong, X, Feng, S. and R. Sadka, 2011, Liquidity Risk and Mutual Fund Returns, Working paper

Edelen, R., 1999, Investor flows and the assessed performance of open-end fund managers, *Journal of Financial Economics* 53, 439-466

Fama, E. and MacBeth, J. (1973), Risk, Return, and Equilibrium: Empirical Tests, *Journal of Political Economy*, 71, 607-636

Garleanu N., and L. Pedersen, 2011, Margin-Based Asset Pricing and Deviations from the Law of One Price, *Review of Financial Studies*, 24(6), 1980-2022

Goyenko, R., C. Holden, and C. Trzcinka, 2009, Do liquidity measures measure liquidity? *Journal of Financial Economics* 92, 153-181.

Goyenko, R. and A. Ukhov, 2009, "Stock and Bond Market Liquidity: A Long-Run Empirical Analysis." *Journal of Financial and Quantitative Analysis*, 44 (2009), 189-212

Goyenko, R., Subrahmanyam, A. and A. Ukhov, 2011, "The Term Structure of Bond Market Liquidity and Its Implications for Expected Bond Returns" *Journal of Financial and Quantitative Analysis,* 46 (2011), 111-139

Gupta, A. and M. G. Subrahmanyam, 2000, "An Empirical Investigation of the Convexity Bias in the Pricing of Interest Rate Swaps." *Journal of Financial Economics* 55,239–279

Hasbrouck, J., 2009, Trading costs and returns for US equities: Estimating effective costs from daily data, *Journal of Finance* 64, 1445-1477

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

Nanda, V., M. Narayanan, and V. Warther, 2000, ‘‘Liquidity, Investment Ability, and Mutual Fund Structure,’’ *Journal of Financial Economics*, 57, 417–443

Pastor, L. and R. Stambaugh. 2003. “Liquidity Risk and Expected Stock Returns.” *Journal of Political Economy*, 113, 642-685

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

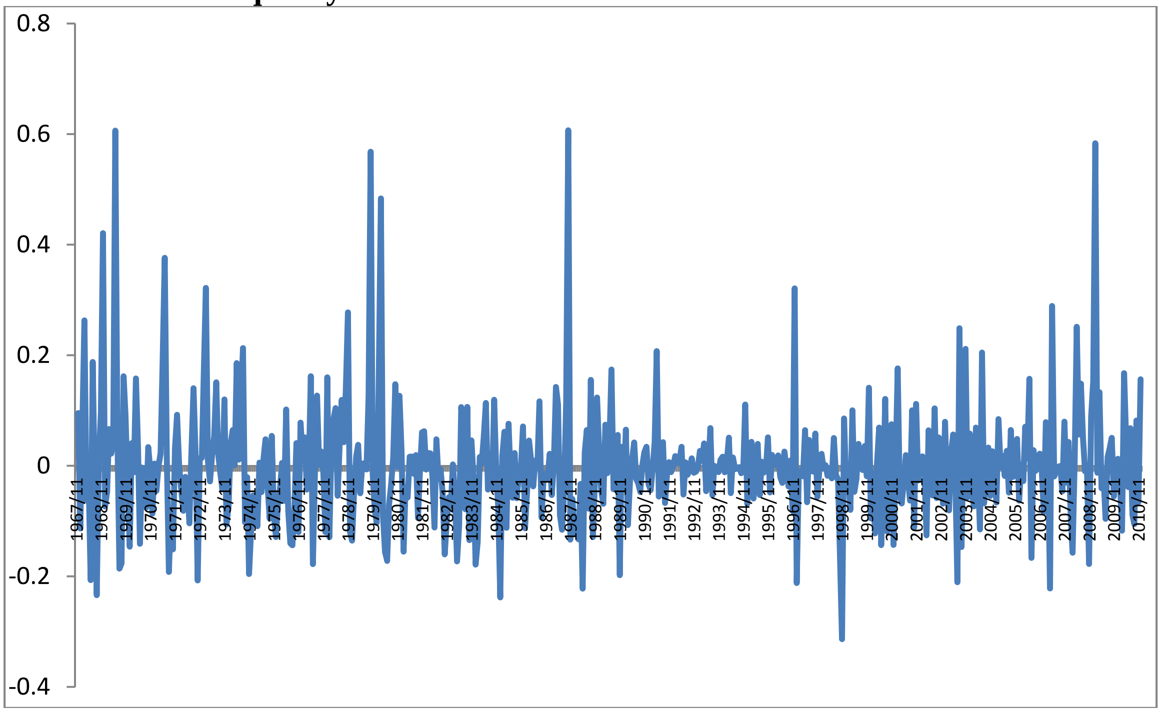
Simutin, M., 2012, Excess Cash and Mutual Fund Performance, Working paper, University of Toronto

Sirri, E. R., and P. Tufano, 1998, ‘‘Costly Search and Mutual Fund Flows,’’ *Review of Financial Studies*, 53, 1589–1622.

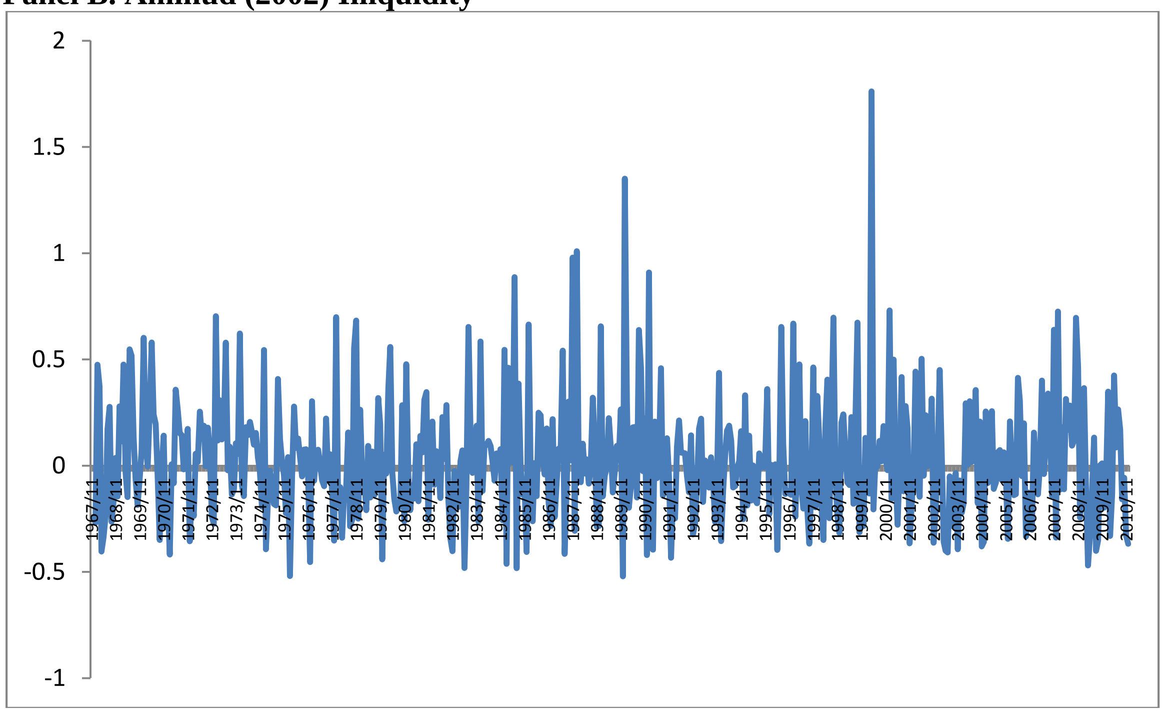
Teo, M., 2011, The Liquidity Risk of Liquid Hedge Funds, Journal of Financial Economics, 100, 24-44

Figure 1

Panel A. Bond Illiquidity



Panel B. Amihud (2002) Illiquidity

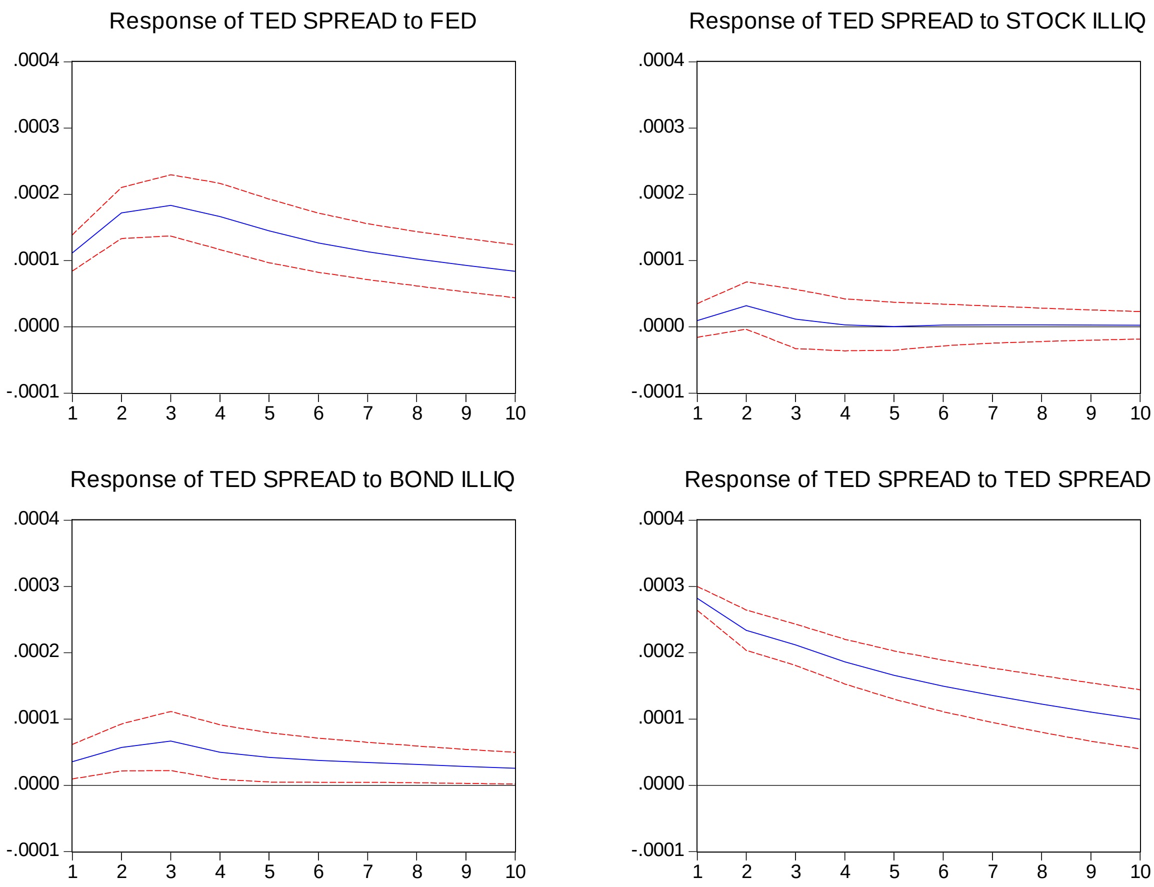


The graphs present relative changes in Treasury bond and stock illiquidity for the period 1967/11 to 2010/12. Bond illiquidity is computed using end of day relative bid-ask spreads and stock illiquidity is Amihud's (2002) Illiquidity ratio

Figure 2.

Panel A. Response of TED spread to endogenous variables

Response to Cholesky one standard deviation. Dashed lines represent 95% confidence bands derived via 1,000 Monte-Carlo simulations.



Panel B. Response of Stock and Bond ILLIQ to endogenous variables

Response to Cholesky one standard deviation. Dashed lines represent 95% confidence bands derived via 1,000 Monte-Carlo simulations.

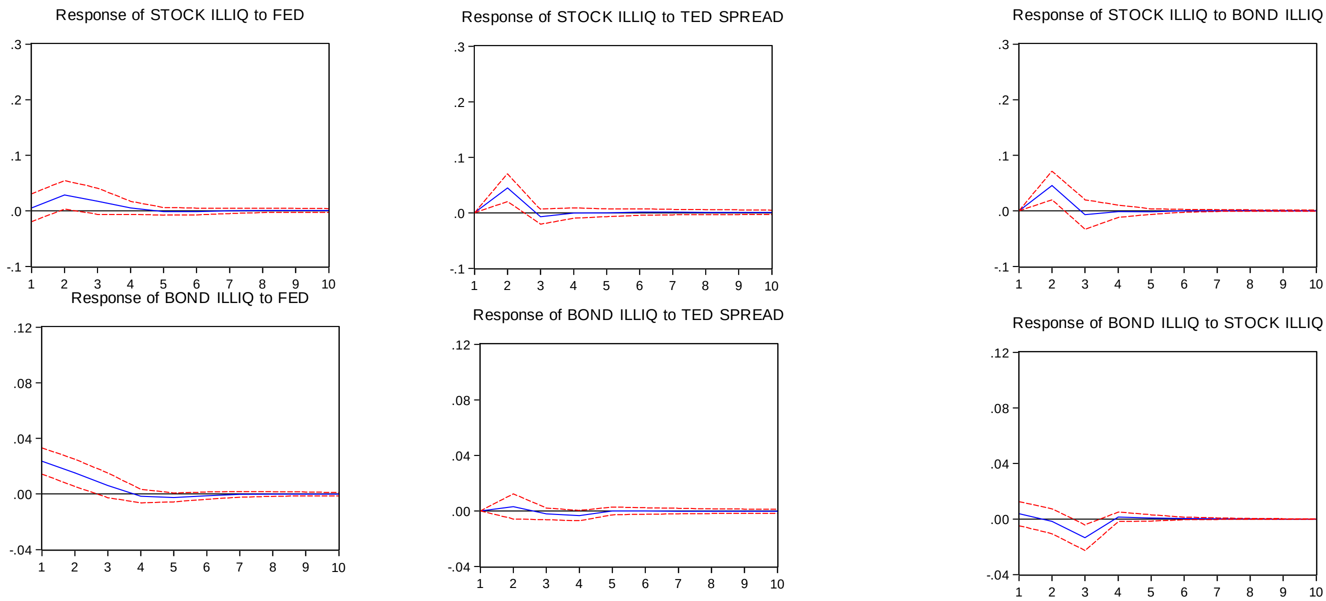
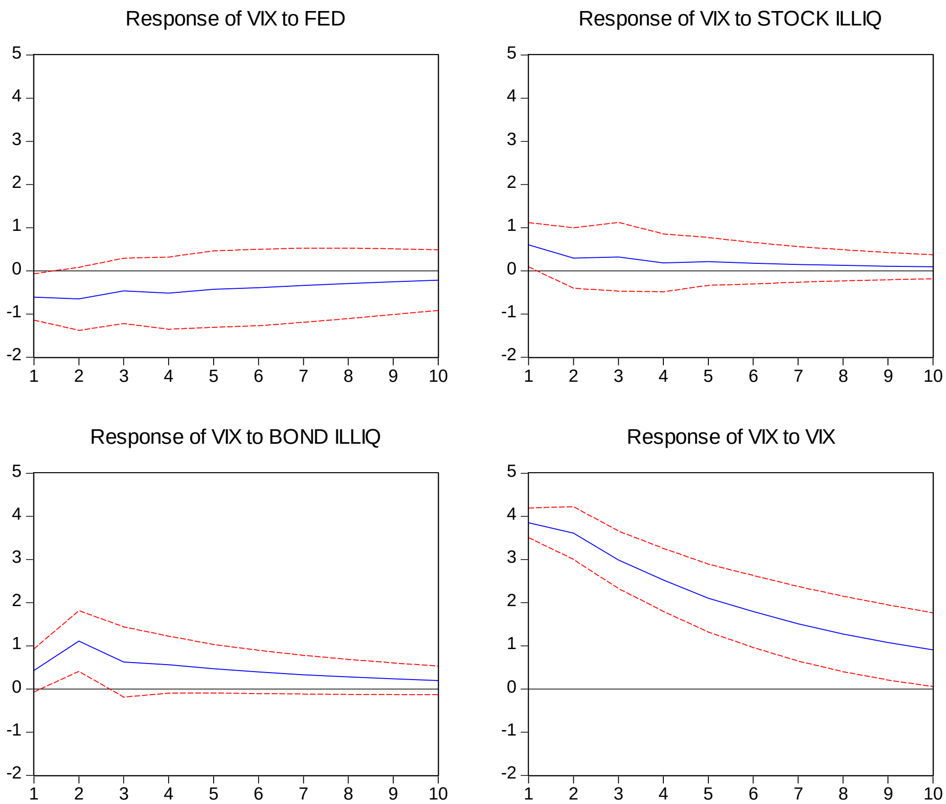


Figure 3.

Panel A. Response of VIX to endogenous variables

Response to Cholesky one standard deviation. Dashed lines represent 95% confidence bands derived via 1,000 Monte-Carlo simulations.



Panel B. Response of Stock and Bond ILLIQ to endogenous variables

Response to Cholesky one standard deviation. Dashed lines represent 95% confidence bands derived via 1,000 Monte-Carlo simulations.

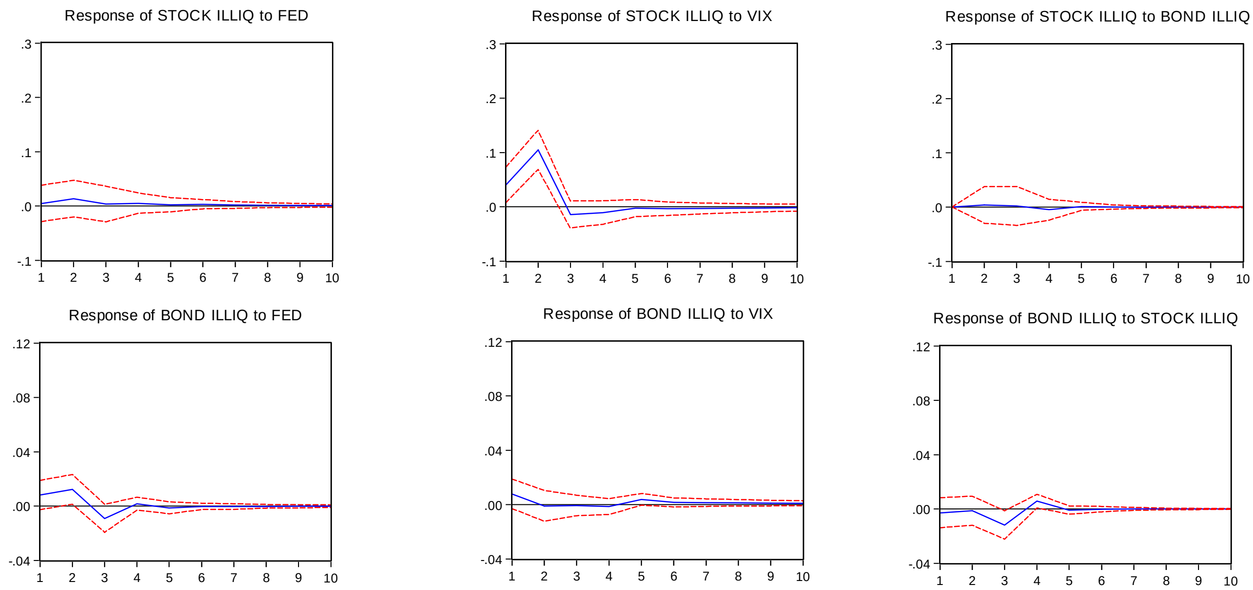


Table 1. Summary Statistics: Liquidity Measures.

Panel A presents summary statistics of stock illiquidity (Stock ILLIQ), bond illiquidity (Bond ILLIQ), TED (Treasury-Eurodollar spread) and VIX (implied volatility of S&P500 index). TED and VIX are proxies for funding liquidity. Stock ILLIQ and Bond ILLIQ are in relative changes. TED Spread is in percent. Panel B presents correlation matrix of liquidity measures and changes in Fed fund rates (FED). The data for Stock ILLIQ, Bond ILLIQ and FED are from 11/1967 to 12/2010. The sample for TED is from 03/1971to 12/2010 and from 03/1990 to 12/2010 for VIX, based on the historical data availability.

Panel A. Liquidity Variables

	Bond ILLIQ	Stock-ILLIQ	TED Spread	VIX
mean	0.002	0.033	0.086	20.395
min	-0.313	-0.520	0.007	10.420
max	0.607	1.762	0.498	59.890
stdev	0.107	0.283	0.076	7.870

Panel B. Correlation Matrix

	Bond ILLIQ	*Stock ILLIQ*	*FED*	*TED Spread*	*VIX*
Bond ILLIQ	1				
Stock ILLIQ	0.087	1			
FED	0.266	0.054	1		
TED Spread	0.090	0.099	0.009	1	
VIX	0.036	0.202	-0.361	0.551	1

Table 2. Granger Causality Tests.

The table presents chi-square statistics and p-values (in parentheses) of pair-wise Granger Causality tests between endogenous VAR variables. The endogenous variables are the Federal Funds rate (FED as indicator of the monetary policy stance), stock illiquidity (Stock ILLIQ), bond illiquidity (Bond ILLIQ), TED (Treasury-Eurodollar spread) and VIX (implied volatility of S&P500 index options). TED and VIX are proxies for funding liquidity. The null hypothesis is that the row variable does not Granger-cause the column variable. The sample is from 03/1971to 12/2010 for TED Spread and from 03/1990 to 12/2010 for VIX. Numbers is bold are significant on either 1% or 5% level.

	FED	Stock ILLIQ	Bond ILLIQ	TED Spread	VIX
FED		**9.200**	**19.563**	**31.557**	0.312
		(0.01)	**(0.00)**	**(0.00)**	(0.86)
Stock ILLIQ	5.631		**10.965**	5.687	1.369
	(0.06)		**(0.00)**	(0.60)	(0.50)
Bond ILLIQ	**1.677**	**21.741**		**11.358**	**10.378**
	(0.43)	**(0.00)**		**(0.00)**	**(0.01)**
TED Spread	**18.449**	**23.608**	3.543		**6.873**
	(0.00)	**(0.00)**	(0.17)		**(0.03)**
VIX	**9.015**	**40.631**	0.345	**9.368**	
	(0.01)	**(0.00)**	(0.84)	**(0.01)**	

Table 3. Summary Statistics: Mutual Fund Sample

The table presents summary statistics of actively managed mutual funds included in the sample. The Total Net Assets (*TNA*) in $mm, *Expenses* and *Turnover* are as of the end of the month. *Age* is fund age, the number of years since the fund was first offered. *Tenure* is the tenure of the manager, the number of years since the current manager took control. Included are Active Equity funds, Panel A, with at least 70% of assets invested into common stocks. Corporate Bond funds, Panel B, and Other funds, Panel C, are funds with at least 35% invested in common stocks. Other funds include real estate, commodity, sector, multi-strategy and utility funds. The sample is from January 1991 to December 2010.

Panel A. Active Equity Funds

	Mean	Median	Minimum	Maximum
Total number of funds: 2,820				
TNA (total net assets, in $millions)	1,453.70	279.20	15.00	202,305.8
Fund Age (years)	12.96	9.08	0.08	86.42
Expenses (%)	1.22	1.20	0.01	6.42
Turnover (%)	86.75	65.00	0.02	4,550
Manager Tenure (years)	6.94	5.67	0.01	63.83

Panel B. Corporate Bond Funds

	Mean	Median	Minimum	Maximum
Total number of funds: 654				
TNA (total net assets, in $millions)	1,855.19	260.21	15.00	113,664.8
Fund Age (years)	16.68	10.01	0.08	81.92
Expenses (%)	1.11	1.10	0.01	4.03
Turnover (%)	79.65	60.00	0.02	3,065
Manager Tenure (years)	7.47	5.92	0.01	71.17

Panel C. Other Funds

	Mean	Median	Minimum	Maximum
Total number of funds: 3,244				
TNA (total net assets, in $millions)	1,478.65	271.70	15.00	202,305.80
Fund Age (years)	13.21	9.12	0.08	86.42
Expenses (%)	1.21	1.19	0.01	6.42
Turnover (%)	87.43	65.00	0.00	4,550
Manager Tenure (years)	7.02	5.70	0.01	71.17

Table 4. Bond Liquidity Beta Sorted Portfolios

Each month mutual funds are sorted into decile portfolios based on bond liquidity beta. Bond liquidity beta is estimated from regressing mutual fund excess monthly returns on market factor, MKT, stock liquidity and bond liquidity and using preceding 24 months of historical data. One month is omitted between portfolio ranking and portfolio formation. Portfolio Alpha is computed after regressing each portfolio return on Fama-French and Carhart four factors (FFC) or Fama-French-Carhart model augmented with Term Premium and Default Premium (FFCTD) similar to Bessembinder et al. (2008) model. Newey-West adjusted t-statistics are reported below in parentheses. The sample period, including pre-estimation period, is from 1991/1 to 2010/12.

	1 [Low]	2	3	4	5	6	7	8	9	10 [High]	High-Low
	All Funds										
FFC-Alpha	-0.242	-0.316	-0.193	-0.133	-0.075	-0.057	-0.029	0.031	0.097	0.213	0.455
	(1.93)	(3.40)	(2.52)	(2.49)	(1.51)	(1.30)	(0.55)	(0.44)	(1.19)	(1.62)	(2.23)
FFCTD-Alpha	-0.242	-0.315	-0.191	-0.132	-0.075	-0.057	-0.030	0.030	0.094	0.212	0.454
	(1.91)	(3.42)	(2.55)	(2.56)	(1.53)	(1.29)	(0.57)	(0.42)	(1.15)	(1.61)	(2.21)
	Active Equity Funds										
FFC-Alpha	-0.333	-0.324	-0.182	-0.144	-0.103	-0.053	-0.044	0.034	0.079	0.157	0.490
	(2.71)	(3.42)	(2.36)	(2.28)	(1.96)	(1.07)	(0.76)	(0.44)	(0.87)	(1.22)	(2.28)
	Corporate Bond Funds										
FFCTD-Alpha	-0.069	-0.033	-0.015	0.014	-0.008	0.000	0.029	0.036	0.090	0.138	0.206
	(0.90)	(0.57)	(0.30)	(0.31)	(0.15)	(0.00)	(0.57)	(0.81)	(1.83)	(2.36)	(2.55)
	Other Funds										
FFCTD-Alpha	-0.073	-0.151	-0.293	-0.193	-0.087	-0.084	0.005	0.007	0.150	0.267	0.341
	(0.26)	(0.77)	(1.86)	(1.52)	(0.70)	(0.66)	(0.04)	(0.05)	(1.04)	(1.24)	(1.10)

Table 5. Bond Liquidity-Beta Sorted Portfolios: Style Analysis

Each month mutual funds are sorted into decile portfolios based on bond liquidity beta. Bond liquidity beta is estimated from regressing mutual fund excess monthly returns on market factor, MKT, stock liquidity and bond liquidity and using preceding 24 months of historical data. One month is omitted between portfolio ranking and portfolio formation. Portfolio Alpha is computed after regressing each portfolio return on Fama-French and Carhart four factors (FFC) or Fama-French-Carhart model augmented with Term Premium and Default Premium (FFCTD) similar to Bessembinder et al. (2008). Newey-West adjusted t-statistics are reported below in parentheses. The funds are grouped by style categories. The equity styles are Growth which includes Aggressive Growth, Growth, Long Term Growth; Income: Income, Income and Growth, and Other: Micro-Cap, Small Cap, Mid-cap, Maximum Capital Gains and Capital Appreciation funds. The bond funds are Balanced and Other, the latter includes Corporate Debt A Rated, Corporate Debt BBB-Rated, Intermediate Investment Grade Debt, Short-Term Investment Grade Debt and Short-Intermediate Investment Grade Debt, High Current Yield, General Bond, Income (including flexible and multi-sector), and Flexible Portfolio. The sample period, including pre-estimation period, is from 1991/1 to 2010/12.

Panel A. Active Equity Funds

	1 [Low]	2	3	4	5	6	7	8	9	10 [High]	High-Low
					FFC Alpha						
Growth	-0.325	-0.188	-0.202	-0.172	-0.143	-0.140	-0.106	-0.030	0.012	0.120	0.445
	(2.93)	(2.55)	(3.59)	(3.44)	(3.26)	(3.38)	(2.44)	(0.54)	(0.17)	(1.10)	(2.38)
Income	-0.232	-0.094	-0.113	-0.069	-0.102	-0.099	-0.002	0.014	-0.003	0.052	0.283
	(3.48)	(2.10)	(2.69)	(1.47)	(2.02)	(1.93)	(0.03)	(0.25)	(0.04)	(0.66)	(2.61)
Other	-0.281	-0.263	-0.227	-0.223	-0.138	-0.093	-0.039	0.018	0.098	0.090	0.371
	(2.05)	(2.32)	(2.21)	(2.27)	(1.40)	(0.96)	(0.37)	(0.16)	(0.75)	(0.61)	(1.90)

Panel B. Corporate Bond Funds

	1 [Low]	2	3	4	5	6	7	8	9	10 [High]	High-Low
					FFCTD Alpha						
Balanced	-0.097	-0.068	-0.046	0.021	0.008	0.002	0.015	-0.030	0.007	0.102	0.199
	(1.80)	(1.24)	(0.93)	(0.49)	(0.17)	(0.05)	(0.31)	(0.67)	(0.16)	(1.74)	(2.56)
Other	-0.062	-0.045	0.000	-0.001	-0.029	-0.009	0.005	0.088	0.132	0.145	0.207
	(0.60)	(0.66)	(0.01)	(0.01)	(0.58)	(0.17)	(0.08)	(1.67)	(2.29)	(2.11)	(2.01)

Table 6. Bond Liquidity-Beta Sorted Portfolios: Longer Holding Periods

Depending on holding period, every 3, 6 or 12 months mutual funds are sorted into decile portfolios based on bond liquidity beta. Bond liquidity beta is estimated from regressing mutual fund excess monthly returns on market factor, MKT, stock liquidity and bond liquidity and using preceding 24 months of historical data. One month is omitted between portfolio ranking and portfolio formation. Portfolio Alpha is computed after regressing each portfolio return on Fama-French and Carhart four factors (FFC) or Fama-French-Carhart model augmented with Term Premium and Default Premium (FFCTD) similar to Bessembinder et al. (2008). Newey-West adjusted t-statistics are reported below in parentheses. The sample period, including pre-estimation period, is from 1991/1 to 2010/12.

Panel A. Active Equity Funds

	1 [Low]	2	3	4	5	6	7	8	9	10 [High]	High-Low
					FFC Alpha						
3 months	-0.336	-0.304	-0.192	-0.134	-0.081	-0.026	-0.058	0.032	0.051	0.141	0.477
	(2.86)	(3.47)	(2.59)	(2.26)	(1.49)	(0.52)	(1.05)	(0.41)	(0.58)	(1.12)	(2.35)
6 months	-0.311	-0.269	-0.201	-0.128	-0.097	-0.030	-0.044	0.021	0.046	0.110	0.421
	(2.69)	(3.06)	(2.84)	(2.12)	(1.69)	(0.61)	(0.81)	(0.29)	(0.56)	(0.96)	(2.22)
12 months	-0.229	-0.216	-0.153	-0.120	-0.085	-0.085	-0.074	0.005	0.004	0.044	0.273
	(2.17)	(2.66)	(2.44)	(2.34)	(2.02)	(2.24)	(1.61)	(0.08)	(0.06)	(0.47)	(1.72)

Panel B. Corporate Bond Funds

	1 [Low]	2	3	4	5	6	7	8	9	10 [High]	High-Low
					FFCTD Alpha						
3 months	-0.064	-0.008	-0.027	-0.012	-0.012	-0.003	0.050	0.047	0.069	0.154	0.218
	(0.83)	(0.15)	(0.56)	(0.27)	(0.26)	(0.05)	(1.00)	(0.99)	(1.46)	(2.68)	(2.78)
6 months	-0.050	-0.001	-0.030	-0.045	0.021	0.008	0.018	0.040	0.061	0.154	0.204
	(0.64)	(0.02)	(0.62)	(1.00)	(0.44)	(0.16)	(0.38)	(0.87)	(1.25)	(2.73)	(2.64)
12 months	-0.015	-0.042	0.000	-0.042	0.035	0.004	0.051	0.015	0.078	0.100	0.116
	(0.26)	(0.88)	(0.00)	(0.98)	(0.86)	(0.10)	(1.27)	(0.33)	(1.84)	(1.90)	(1.90)

Table 7. Fund Size, Expenses, Turnover and Bond Liquidity Beta Portfolios

The table present portfolio sorting results. The fund are first sorted into five portfolios based on fund size (measured by fund's TNA) (Panel A), expenses (Panel B) and turnover (Panel C), and then each quintile portfolio is sorted into five bond liquidity beta portfolios. Bond liquidity beta is estimated from regressing mutual fund excess monthly returns on market factor, MKT, stock liquidity and bond liquidity and using preceding 24 months of historical data. One month is omitted between portfolio ranking and portfolio formation. Portfolio Alpha is computed after regressing each portfolio return on on Fama-French and Carhart four factors (FFC) for equity funds or Fama-French-Carhart model augmented with Term Premium and Default Premium (FFCTD) similar to Bessembinder et al. (2008) for corporate bond funds. Newey-West adjusted t-statistics are reported below in parentheses. The sample period, including pre-estimation period, is from 1991/1 to 2010/12.

Panel A. Fund Size and Bond Liquidity Beta Portfolios

	Active Equity Funds, FFC Alpha						***Corporate Bond Funds, FFCTD Alpha***					
	Size 1 [Small]	2	3	4	Size 5 [Big]	Small-Big	Size 1 [Small]	2	3	4	Size 5 [Big]	Small-Big
Beta 1 [Low]	-0.264	-0.319	-0.372	-0.378	-0.291	0.027	-0.066	-0.066	-0.087	-0.015	0.041	0.108
	(2.63)	(3.14)	(3.16)	(3.11)	(2.79)	(0.40)	(0.89)	(1.05)	(1.21)	(0.21)	(0.46)	(1.59)
2	-0.132	-0.188	-0.222	-0.195	-0.138	0.005	-0.045	-0.051	-0.010	-0.003	0.002	0.047
	(1.59)	(2.50)	(2.72)	(2.51)	(2.58)	(0.08)	(0.80)	(1.15)	(0.21)	(0.06)	(0.03)	(1.01)
3	-0.057	-0.079	-0.039	-0.116	-0.073	0.016	-0.004	0.007	-0.012	-0.021	0.069	0.073
	(1.01)	(1.45)	(0.63)	(2.00)	(1.87)	(0.36)	(0.08)	(0.14)	(0.23)	(0.37)	(1.13)	(2.06)
4	0.005	0.060	0.017	-0.036	-0.077	0.082	0.043	0.059	0.000	0.032	0.034	-0.008
	(0.07)	(0.76)	(0.21)	(0.54)	(1.43)	(1.96)	(0.80)	(1.22)	(0.01)	(0.56)	(0.52)	(0.17)
Beta 5 [High]	0.118	0.149	0.088	0.121	0.103	0.015	0.119	0.077	0.065	0.074	0.197	0.078
	(1.11)	(1.26)	(0.75)	(1.04)	(1.05)	(0.28)	(2.12)	(1.41)	(1.31)	(1.25)	(2.71)	(1.27)
High-Low	0.382	0.467	0.459	0.499	0.394		0.185	0.143	0.153	0.089	0.156	
	(2.35)	(2.52)	(2.24)	(2.45)	(2.22)		(2.33)	(2.02)	(2.09)	(1.25)	(1.99)	

Panel B. Fund Expenses and Bond Liquidity Beta Portfolios

	Active Equity Funds, FFC Alpha						*Corporate Bond Funds, FFCTD Alpha*					
	Exp 1 [Low]	2	3	4	Exp 5 [High]	High-Low	Exp 1 [Low]	2	3	4	Exp 5 [High]	High-Low
Beta 1 [Low]	-0.251	-0.319	-0.324	-0.339	-0.327	-0.076	0.094	-0.076	-0.042	-0.027	-0.098	-0.192
	(3.24)	(3.07)	(2.93)	(2.92)	(2.87)	(1.07)	(1.30)	(1.06)	(0.64)	(0.42)	(1.16)	(2.94)
2	-0.057	-0.162	-0.158	-0.197	-0.279	-0.222	0.115	0.025	-0.041	-0.106	-0.057	-0.171
	(1.22)	(2.56)	(2.43)	(2.29)	(2.93)	(2.74)	(2.43)	(0.39)	(0.74)	(1.71)	(1.04)	(4.21)
3	-0.038	-0.070	-0.058	-0.096	-0.151	-0.113	0.015	-0.015	0.035	-0.040	-0.054	-0.069
	(0.94)	(1.40)	(0.99)	(1.59)	(2.12)	(1.61)	(0.25)	(0.32)	(0.69)	(0.77)	(0.93)	(1.33)
4	0.034	0.006	0.006	-0.050	-0.035	-0.069	0.090	0.048	0.053	-0.020	-0.032	-0.123
	(0.58)	(0.10)	(0.08)	(0.69)	(0.46)	(1.19)	(1.76)	(0.93)	(0.83)	(0.40)	(0.66)	(2.63)
Beta 5 [High]	0.137	0.128	0.095	0.127	0.093	-0.043	0.222	0.127	0.123	0.046	0.075	-0.147
	(1.44)	(1.20)	(0.87)	(1.08)	(0.78)	(0.61)	(3.57)	(2.11)	(2.09)	(0.92)	(1.14)	(2.47)
High-Low	0.388	0.447	0.419	0.466	0.420		0.128	0.203	0.164	0.073	0.173	
	(2.51)	(2.49)	(2.28)	(2.35)	(2.27)		(2.02)	(2.79)	(2.16)	(1.05)	(1.85)	

Panel C. Fund Turnover and Bond Liquidity Beta Portfolios

	Active Equity Funds, FFC Alpha						*Corporate Bond Funds, FFCTD Alpha*					
	Turn 1 [Low]	2	3	4	Turn 5 [High]	High-Low	Turn 1 [Low]	2	3	4	Turn 5 [High]	High-Low
Beta 1 [Low]	-0.206	-0.294	-0.296	-0.400	-0.228	-0.023	0.004	-0.083	-0.018	-0.045	-0.032	-0.036
	(2.81)	(3.43)	(2.78)	(3.37)	(1.65)	(0.18)	(0.05)	(1.14)	(0.23)	(0.60)	(0.42)	(0.45)
2	-0.126	-0.168	-0.153	-0.221	-0.248	-0.122	0.067	-0.011	-0.023	-0.066	-0.078	-0.145
	(2.31)	(2.50)	(2.05)	(2.46)	(2.57)	(1.26)	(1.19)	(0.17)	(0.39)	(1.13)	(1.62)	(2.60)
3	-0.054	-0.099	-0.084	-0.148	-0.120	-0.065	-0.013	0.048	0.057	-0.030	-0.034	-0.020
	(1.17)	(1.91)	(1.54)	(2.27)	(1.41)	(0.66)	(0.19)	(0.92)	(1.07)	(0.59)	(0.71)	(0.35)
4	0.054	0.007	-0.006	-0.028	0.000	-0.054	0.124	0.053	-0.013	0.019	0.023	-0.101
	(0.89)	(0.11)	(0.09)	(0.39)	(0.00)	(0.73)	(2.17)	(0.92)	(0.25)	(0.39)	(0.50)	(1.81)
Beta 5 [High]	0.178	0.096	0.098	0.103	0.060	-0.117	0.151	0.130	0.082	0.105	0.035	-0.116
	(1.77)	(1.03)	(0.90)	(0.88)	(0.46)	(1.31)	(2.87)	(2.42)	(1.18)	(1.44)	(0.65)	(1.90)
High-Low	0.383	0.389	0.395	0.503	0.289		0.148	0.213	0.099	0.150	0.067	
	(2.71)	(2.58)	(2.22)	(2.55)	(1.49)		(1.97)	(2.96)	(1.18)	(1.78)	(0.73)	

Table 8. Fund Flows, Alpha and Bond Liquidity Beta Portfolios

The table presents portfolio sorting results. The fund are first sorted into five portfolios based on lagged fund Flows (computed as in Sirri and Tufano (1998)) (Panel A), and lagged alpha expenses (Panel B), and then each quintile portfolio is sorted into five bond liquidity beta portfolios. Bond liquidity beta is estimated from regressing mutual fund excess monthly returns on market factor, MKT, stock liquidity and bond liquidity and using preceding 24 months of historical data. One month is omitted between portfolio ranking and portfolio formation. Portfolio Alpha is computed after regressing each portfolio return on on Fama-French and Carhart four factors (FFC) for equity funds or Fama-French-Carhart model augmented with Term Premium and Default Premium (FFCTD) similar to Bessembinder et al. (2008) for corporate bond funds. Lagged Alpha is estimated as the intercept from regressing mutual fund excess monthly returns on either FFC factors for equity funds, or FFCTD factors for bond funds and using preceding 24 months of historical data. Newey-West adjusted t-statistics are reported below in parentheses. The sample period, including pre-estimation period, is from 1991/1 to 2010/12.

Panel A. Fund Flows and Bond Liquidity Beta Portfolios

	Active Equity Funds, FFC Alpha						*Corporate Bond Funds, FFCTD Alpha*					
	Flow 1 [Out]	2	3	4	Flow 5 [Inflow]	5-1	Flow 1 [Out]	2	3	4	Flow 5 [Inflow]	5-1
Beta 1 [Low]	-0.288	-0.292	-0.293	-0.337	-0.245	0.044	-0.099	-0.082	0.015	-0.004	-0.057	0.042
	(2.58)	(3.03)	(2.94)	(3.04)	(2.00)	(0.38)	(1.28)	(1.07)	(0.23)	(0.05)	(0.75)	(0.59)
2	-0.175	-0.138	-0.152	-0.154	-0.209	-0.034	0.009	-0.065	0.035	0.020	0.034	0.025
	(1.68)	(1.90)	(2.26)	(2.03)	(2.18)	(0.26)	(0.14)	(1.22)	(0.72)	(0.33)	(0.59)	(0.42)
3	-0.075	-0.070	-0.076	-0.056	-0.055	0.020	-0.028	-0.002	-0.011	0.035	0.029	0.057
	(0.82)	(1.22)	(1.53)	(1.22)	(0.79)	(0.17)	(0.47)	(0.04)	(0.20)	(0.76)	(0.55)	(1.18)
4	-0.023	0.003	-0.070	-0.027	0.013	0.036	-0.002	-0.035	0.008	0.062	0.060	0.062
	(0.25)	(0.05)	(1.16)	(0.47)	(0.21)	(0.42)	(0.03)	(0.69)	(0.15)	(1.27)	(0.98)	(1.11)
Beta 5 [High]	0.128	0.076	0.079	0.123	0.175	0.047	0.076	0.054	0.159	0.050	0.191	0.115
	(0.99)	(0.69)	(0.82)	(1.19)	(1.72)	(0.55)	(1.07)	(1.06)	(2.81)	(0.89)	(2.84)	(1.64)
High-Low	0.416	0.368	0.372	0.460	0.420		0.175	0.136	0.143	0.054	0.248	
	(2.45)	(2.14)	(2.30)	(2.55)	(2.29)		(2.41)	(1.93)	(2.12)	(0.77)	(2.92)	

Panel B. Fund Alpha and Bond Liquidity Beta Portfolios

	Active Equity Funds, FFC Alpha						*Corporate Bond Funds, FFCTD Alpha*					
	Alpha 1 [Low]	2	3	4	Alpha 5 [High]	High-Low	Alpha 1 [Low]	2	3	4	Alpha 5 [High]	High-Low
Beta 1 [Low]	-0.407	-0.265	-0.322	-0.304	-0.184	0.223	-0.118	-0.106	-0.055	0.025	0.038	0.156
	(3.59)	(2.77)	(3.36)	(3.04)	(1.32)	(2.00)	(1.58)	(1.54)	(0.76)	(0.35)	(0.45)	(1.84)
2	-0.289	-0.187	-0.148	-0.137	-0.098	0.190	-0.087	-0.042	0.030	0.020	0.080	0.167
	(2.94)	(2.85)	(2.95)	(2.28)	(0.97)	(1.65)	(1.48)	(0.76)	(0.62)	(0.40)	(1.11)	(2.80)
3	-0.209	-0.141	-0.071	-0.012	0.008	0.217	-0.076	-0.043	-0.048	-0.006	0.153	0.228
	(2.48)	(2.67)	(1.78)	(0.22)	(0.10)	(2.01)	(1.31)	(0.83)	(0.87)	(0.09)	(2.43)	(4.17)
4	-0.140	-0.038	-0.005	0.039	0.170	0.310	-0.024	-0.021	0.005	0.104	0.078	0.101
	(1.65)	(0.58)	(0.08)	(0.57)	(1.94)	(3.28)	(0.52)	(0.38)	(0.11)	(1.95)	(1.27)	(1.76)
Beta 5 [High]	0.006	0.035	0.111	0.185	0.258	0.251	0.086	0.038	0.054	0.111	0.260	0.174
	(0.06)	(0.35)	(1.17)	(1.77)	(2.07)	(3.22)	(1.34)	(0.73)	(1.09)	(2.06)	(3.17)	(2.44)
High-Low	0.414	0.300	0.434	0.488	0.441		0.204	0.144	0.109	0.086	0.222	
	(2.41)	(1.90)	(2.67)	(2.72)	(2.14)		(2.61)	(2.04)	(1.55)	(1.24)	(2.21)	

Table 9. Cash Holdings and Bond Liquidity Risk.

The table presents portfolio sorting results. The fund are first sorted into two portfolios based on lagged percent of cash holdings (percent of portfolio TNA invested in cash), and then each portfolio is sorted into five bond liquidity beta portfolios. Bond liquidity beta is estimated from regressing mutual fund excess monthly returns on market factor, MKT, stock liquidity and bond liquidity and using preceding 24 months of historical data. One month is omitted between portfolio ranking and portfolio formation. Portfolio Alpha is computed after regressing each portfolio return on on Fama-French and Carhart four factors (FFC) for equity funds, Panel A, or Fama-French-Carhart model augmented with Term Premium and Default Premium (FFCTD) similar to Bessembinder et al. (2008) for corporate bond funds, Panel B. Newey-West adjusted t-statistics are reported below in parentheses. The sample period, including pre-estimation period, is from 1991/1 to 2010/12.

Panel A. Active Equity Funds

	No Cash	**Positive Cash**
Beta 1	-0.317	-0.548
	(2.98)	(4.01)
2	-0.160	-0.151
	(2.30)	(1.78)
3	-0.074	-0.088
	(1.54)	(1.44)
4	-0.009	0.029
	(0.13)	(0.38)
Beta 5	0.120	0.156
	(1.10)	(1.58)
High-Low	0.437	0.704
	(2.35)	(3.40)

Panel B. Corporate Bond Funds

	No Cash	**Positive Cash**
Beta 1	-0.032	-0.231
	(0.50)	(2.08)
2	-0.005	0.035
	(0.12)	(0.47)
3	-0.008	0.070
	(0.17)	(0.97)
4	0.037	0.108
	(0.82)	(1.48)
Beta 5	0.116	0.164
	(2.22)	(2.09)
High-Low	0.148	0.395
	(2.48)	(3.04)

Table 10. Determinants of Bond Liquidity Betas

The table presents the determinants of mutual fund bond liquidity betas. Bond Liquidity Beta is obtained from regression of monthly fund excess returns on the returns of the markt factor *MKT*, stock liquidity and bond liquidity using the latest 24 months of data. The Total Net Assets (*TNA*) in $mm, *Expenses* and *Turnover* are as of the end of the month t-1. *Fund Age* is the number of years since the fund was first offered. *Manager Tenure* is the number of years since the current manager took control. Lagged Alpha and Fund Flows are the same as in Table 8. The estimation is done using Fama-MacBeth method and style dummies are include in each regression specification. The Newey-West adjusted *t*-statistics are reported in parentheses. The sample period, including pre-estimation period, is from 1991/1 to 2010/12.

	Active Equity Funds			***Corporate Bond Funds***		
	(1)	(2)	(3)	(4)	(5)	(6)
$Expenses_{t-1}$	-0.661	-0.351	-0.340	-0.610	-0.625	-0.721
	(1.91)	(1.06)	(1.06)	(3.91)	(5.48)	(5.09)
$Log(TNA)_{t-1}$	-0.011	0.387	0.094	0.339	0.568	0.437
	(0.04)	(1.03)	(0.35)	(1.61)	(3.08)	(2.31)
$Log(TNA)^2_{t-1}$	-0.016	-0.053	-0.031	-0.045	-0.071	-0.061
	(0.64)	(1.61)	(1.20)	(2.33)	(3.89)	(3.52)
$Turnover_{t-1}$		-0.005	-0.005		-0.004	-0.005
		(2.03)	(2.33)		(2.05)	(2.92)
$Log(Age)_{t-1}$		0.436	0.364		0.402	0.428
		(2.24)	(1.93)		(3.43)	(3.80)
$Log(Tenure)_{t-1}$		0.249	0.224		0.113	0.064
		(2.31)	(2.39)		(1.00)	(0.55)
$Alpha_{t-1}$	0.051		0.071	-0.014		-0.011
	(0.60)		(0.81)	(0.22)		(0.17)
$Fund\ Flows_{t-1}$		1.030			4.815	
		(0.69)			(2.26)	
R-sqr	0.28	0.26	0.29	0.09	0.09	0.12