Corporate Bond Liquidity: A Revealed Preference Approach*

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Abstract

We propose a novel measure of bond market liquidity that does not depend on transaction data. Capturing how the strength of the relation between mutual fund cash holdings and uncertainty about fund flows varies in the cross section, our measure reflects funds' perceived illiquidity of their portfolio holdings at a given point in time. Speculative grade and smaller bonds are perceived to be significantly less liquid, with the illiquidity of speculative grade bonds in particular deteriorating in the post-crisis period. Our measure can be applied to asset-backed securities, syndicated loans, and municipal securities for which publicly available data on transactions are not available.

JEL classification: G11, G23

Keywords: liquidity, corporate bonds, mutual funds

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1 Introduction

The liquidity of corporate bond markets is crucial to their functioning. Over time, the fraction of corporate bonds held by entities like mutual funds that may need to sell their holdings quickly has increased substantially. According to the Flow of Funds, mutual funds' share of domestic holdings of corporate bonds rose from 9% in 2000Q4 to 23% in 2017Q2. Moreover, the liquidity of corporate bond markets has important implications for financial stability. If some investors are forced to sell bonds into illiquid markets, the price impact of these sales has a greater chance of causing amplification through fire sales channels.

The literature has proposed many measures of the liquidity of individual corporate bonds, including Roll (1984), Lesmond, Ogden, and Trzcinka (1999), Amihud (2002), Bao, Pan, and Wang (2011), Feldhütter (2012), and Dick-Nielsen, Feldhütter, and Lando (2012). These measures differ substantially in their construction and have various pro and cons. One key feature they share, however, is that they rely on the characteristics of trades that actually took place. If funds choose not to trade bonds they perceive as relatively illiquid, existing measures will understate the true illiquidity of the overall market. This issue is much more important for bond markets, where about 40% of outstanding corporate bonds do not trade during a given quarter, than for equity markets.[1] In contrast, the vast majority of securities in equity markets trade every day. Indeed, recent debate about the liquidity of the corporate bond market has centered exactly around this issue. Regulators who allege that liquidity has not declined point to traditional measures of price impact, while market participants who allege that liquidity has declined point to decreased trading volume, particularly among smaller bond issues.

In this paper, we propose a novel measure of the liquidity of corporate bond markets that does not depend directly on quote or transaction data. We take a revealed preference approach based on the cash holdings of mutual funds. The idea is that mutual funds try to minimize the price impact of their trading, and they do so in part by holding cash buffers. Cash buffers allow mutual funds to avoid trading immediately when they get a redemption request from clients, allowing funds to instead trade over time in a way that minimizes price impact. We write down a simple model showing that the optimal size of the cash buffer is directly related to two factors: the illiquidity of the bonds the fund holds and the volatility of flows into and out of the fund. When the fund holds more illiquid bonds, it holds more cash because being forced to trade those bonds is costlier. And when the fund faces more

[1] We look at all bonds in FISD with CDEB bond type, par value of at least $100 million, and valid credit rating at the end of the quarter, and we exclude government and agency issuers (industry codes 41–45). During the 2005-2016 period, the average share of such bonds with at least one transaction in TRACE is 58%.

volatile flows, it holds more cash because of the greater risk of having to liquidate its holdings in order to meet redemption requests. Thus, by examining the cross-sectional relationship between funds' cash holdings and the volatility of the fund flows they face, we can recover how funds perceive the illiquidity of the bonds they own.

We start by providing simulation evidence to establish the feasibility of our procedure. The simulations show that when each mutual fund holds a relatively homogeneous set of bonds, as will be the case if mutual funds have somewhat restrictive mandates, our procedure does a good job of recovering the liquidity of the underlying bonds.

We then implement our regression procedure in data on actively managed bond mutual funds from 2002 to 2016. We start by verifying the basic logic of the procedure, running panel regressions relating a fund's cash holdings to the volatility of its fund flows. We find a strong and significant positive relationship. In our benchmark specification, we run the regression at the security-fund-time level so that we can include security-time fixed effects. Thus, the regression tells us that when comparing two funds that hold the same security at the same time, the fund with higher flow volatility holds more cash. The magnitudes are economically significant. When a mutual fund faces flows that are one percentage point more volatile, its cash-assets ratio increases by 1.2% to 1.4%.

We next show that our measure behaves the way one would expect in the cross section of bonds. Specifically, we run our baseline regression relating fund cash holdings to the volatility of fund flows, but now interact the volatility of fund flows with bond characteristics. Our results are intuitive. We find that the relationship between cash holdings and flow volatility is stronger for bonds with smaller issue sizes, consistent with those bonds being less liquid. Similarly, we find that the relationship between cash holdings and flow volatility is stronger for speculative grade bonds, consistent with those securities being relatively illiquid. In addition, we find that bonds that do not trade are significantly less liquid than bonds that do.

Finally, we use our methodology to examine how the liquidity of the corporate bond market has evolved over time. Our methodology fundamentally only relies on a single cross section. At each point in time, we can measure the cross sectional relationship between fund cash holdings and flow volatility. The time series of the strength of this cross sectional relationship thus allows us to measure the evolution of bond market liquidity over time. We find that bond market liquidity sharply deteriorated during the crisis and then partially recovered after the crisis abated. In contrast to other measures of liquidity, we find that liquidity of speculative grade bonds deteriorated significantly during the post crisis period. We attribute the difference between what we find and what other measures of bond market liquidity imply about the post-crisis period (Adrian et al. (2017), Bessembinder et al. (2017), Trebbi and Xiao (2016), and Anderson and Stulz (2017)) to the fact that our measure takes into account the option of funds to trade bonds less frequently and hold larger cash buffers.

Our paper is related to the very large literature on debt and equity market liquidity, including Roll (1984) Amihud and Mendelson (2001) Chordia, Roll, and Subrahmanyam (2001), Amihud (2002), Pastor and Stambaugh (2003), Acharya and Pedersen (2005), Bao, Pan, and Wang (2011), Dick-Nielsen, Feldhütter, and Lando (2012), Feldhütter (2012), and many others. Our approach differs from most of these papers in that we do not attempt to estimate security-level measures of liquidity. Instead, we take a revealed preference approach that allows us to measure overall market liquidity as perceived by an important group of market participants, mutual fund managers. The main advantage of our approach is that it allows us to estimate liquidity for securities that do not trade very often. This is particularly important in light of debates about bond market liquidity since the financial crisis. While market participants have expressed concern about deteriorating liquidity since the crisis, many standard transaction-based measures of liquidity suggest that liquidity is comparable to the pre crisis period. For instance, Bessembinder et al. (2017) and Trebbi and Xiao (2016) find little evidence of deterioration in average trade execution costs, though they note some deterioration in other measures of liquidity. Adrian et al. (2017) finds little evidence of deterioration in a variety of price-based measures of liquidity, while Bao, O'Hara, and Zhou (2017) find evidence of deterioration around stress events. One possible reconciliation of these differing perspectives may be that liquidity has deteriorated for a subset of bonds that do not trade frequently. Our methodology allows us to assess this possibility, and we find some evidence for it.

2 Empirical Framework

2.1 Model

To help fix ideas and motivate our empirical procedure, we begin by presenting a simple static model linking the liquidity of fund assets to cash holdings. Consider a single mutual fund that faces outflows x that are normally distributed, with mean zero and variance σ^2. The fund may accommodate redemptions in two ways. First, it may choose to hold cash reserves R. These reserves are liquid claims that can be sold costlessly to meet outflows. In practice, these claims are supplied by the traditional banking system or shadow banking system, but, for simplicity, we model them here as existing in elastic supply. Each dollar of cash reserves is associated with carrying cost i. One may think of i as the cost of tracking error for the fund. If it does not have sufficient cash reserves, the fund meets outflows by liquidating some of its illiquid security holdings. When it does so, the fund incurs average cost c per dollar of sales. The fund chooses its cash reserves R to minimize the sum of carry costs and expected liquidation costs:

$$iR + \int_R^\infty c(x - R)dF(x) \tag{1}$$

where F is the cumulative distribution function of x.

2.1.1 Discussion of setup

This setup, though stylized, captures key features of how mutual funds manage their liquidity. The fund aggregates buying and selling across investors, costlessly netting trades between them and only selling the illiquid asset if it faces large net outflows. Individual investors trading for themselves in a market would only achieve this if they traded simultaneously. Outside of the model, the presence of a cash buffer allows funds to perform this kind of netting across longer periods of time. However, when the fund runs out of cash, it has to sell some of its illiquid assets to meet redemptions, which is costly.

The model could be generalized in two ways. First, we could more carefully model net inflows. As structured, the model is set up to consider how the fund manages outflows, but the fund faces a similar problem when it has inflows. On one hand, the fund increases its tracking error if it holds the inflows as cash. But on the other hand, holding cash reduces the price impact the fund generates in buying the illiquid asset. Thus, the logic of the model suggests that cash is useful for managing both inflows and outflows.

A second generalization would be to endogenize the volatility of investor flows. Presumably, the fact that investors do not directly face the costs of liquidation that they generate for the fund means that they are more willing to trade fund shares than they would be if they bore their own liquidation costs. This means that gross flows in the model are higher than gross trade would be in a setting where investors traded the illiquid asset themselves.

2.1.2 Optimal cash reserves for a single fund

We now solve for the fund's optimal holdings of cash reserves R. Proposition 1 characterizes the optimal reserve holdings R^*.

Proposition 1 *Assuming $i \leq \frac{c}{2}$, optimal cash holdings R^* satisfy the first order condition $F(R^*) = 1 - \frac{i}{c}$. Because x is normally distributed, we have $R^* = k\sigma$, where $k = \Phi^{-1}\left(1 - \frac{i}{c}\right)$, and Φ is the standard normal cumulative distribution function.*

Intuitively, the fund trades off the carrying costs of cash reserves against the expected liquidation costs. The fund always pays the carrying cost i, while if it carries zero cash, it pays liquidation costs only half of the time—when it has outflows. Thus, we need $i \leq \frac{c}{2}$ for the fund to hold any cash.

When $i < \frac{c}{2}$, the fund uses cash holdings to further reduce its expected liquidation costs. These costs depend on expected total outflows, which are determined by the volatility of outflows.

It follows from the fund's trade off that optimal cash reserves are increasing in the fund's expected liquidation costs, which depend on the liquidity of the fund's non-cash assets. Intuitively, if the fund chooses to hold more cash, it is choosing to pay higher carrying costs. This is optimal only if the fund faces higher expected liquidation costs.

Proposition 2 *Assuming $i \leq \frac{c}{2}$, optimal cash holdings R^* and optimal cash-to-assets ratio r^* satisfy the following comparative statics:*

- $\frac{\partial r^*}{\partial c} > 0$*: The optimal cash-to-assets ratio increases with asset illiquidity.*
- $\frac{\partial r^*}{\partial \sigma} > 0$*: The optimal cash-to-assets ratio increases with the volatility of fund flows.*
- $\frac{\partial^2 r^*}{\partial c \partial \sigma} > 0$*: The relationship between cash-to-assets ratios and fund flow volatility is stronger for funds with more illiquid assets.*

The three comparative statics describe optimal cash holdings. Cash holdings are driven by the intersection of investor behavior and asset illiquidity. If the fund faces more volatile flows, it will incur greater liquidation costs on average and is therefore willing to hold more cash. Similarly, if the fund's assets are more illiquid, it will incur greater liquidation costs. These two effects interact: the more illiquid the assets, the stronger the relation between the cash-to-assets ratio and flow volatility.

2.2 Methodology

Following the intuition of Proposition 2, suppose that funds set their cash-to-assets ratio according to

$$\left(\frac{Cash}{TNA}\right)_{f,t} = \left[\sum_{b} w_{b,f,t} \times Illiq_{b,t}\right] \sigma_{f,t} \tag{2}$$

where the term in the square brackets represents the weighted average illiquidity of bonds in the portfolio. We assume that the measure of bond illiquidity is appropriately scaled, and we omit the constant term assuming that a fund with zero flow volatility will not hold any precautionary cash. Given data on F funds over T periods, Equation 2 represents a system of $F \times T$ equations in $B \times T$ unknown values of $Illiq_{b,t}$. With about 25,000 unique bonds, close to 1,000 funds, and 56 quarters, the system is not identified. One way to make progress on identification is to assume that each bond has constant illiquidity

$$Illiq_{b,t} = Illiq_b \text{ for all } t$$

Equation 2 then reduces to $F \times T$ equations in B unknowns. Even though we have just about enough fund-date observations to identify constant bond-specific illiquidity, assuming time-invariant liquidity is rather unrealistic.

A more fruitful approach to the identification challenge is to assume that all bonds within a given category, say BBB-rated bonds with 3–5 years to maturity and par value of less than $500 million have the same illiquidity:

$$Illiq_{b,t} = Illiq_{k,t} \text{ for all } b \in k$$

Equation 2 then reduces to $K \times T$ unknowns where K is the number of bond categories for which we want to estimate liquidity. As long as the number of categories K is smaller than the number of funds in the data, F, Equation 2 is identified. In this sense, our methodology is most appropriate for estimating market-level illiquidity for bonds, where we can define up to K markets.

To bring this to the data, we could calculate the share of each fund's portfolio invested in different categories and estimate a regression of fund cash-to-assets ratio on the portfolio shares interacted with flow volatility

$$\left(\frac{Cash}{TNA}\right)_{f,t} = \beta_{1,t} \cdot w_{1,f,t} \times \sigma_{f,t} + \cdots \beta_{K,t} \cdot w_{K,f,t} \times \sigma_{f,t} + \varepsilon_{f,t} \tag{3}$$

where $w_{k,f,t}$ is the share of the portfolio invested in category k bonds. The coefficients $\beta_1, \ldots, \beta_K$ would then capture the (time-varying) illiquidity of different categories.

One potentially challenge however with estimating Equation 3 is the endogeneity of security choice—funds with volatile fund flows may choose to hold more liquid securities, requiring smaller cash buffers.

To help address this concern we will estimate position-level regression

$$\left(\frac{Cash}{TNA}\right)_{b,f,t} = \alpha_{b,t} + \beta_{1,t} \cdot I(1)_{b,t} \times \sigma_{f,t} + \cdots + \beta_{K,t} \cdot I(K)_{b,t} \times \sigma_{f,t} + \varepsilon_{b,f,t} \tag{4}$$

where $I(k)_{b,t}$ is an indicator variable for bond b belonging to category k at time t. With the inclusion of bond-date fixed effects, we can look at how cash holdings vary with flow volatility across funds holding the same bond. Because our explanatory variable is calculated at the fund level, for proper statistical inference, we will need to adjust the standard errors for clustering by fund-time.

2.3 Simulation

To validate our methodology we run a simulation showing that the coefficients β_k in regression Equation 4 can indeed recover the average illiquidity of bonds in different categories. The simulation procedure is as follows:

1. Initialize a sample of 1,000 bonds.
   - Assign each bond to one of 5 categories. Bonds in different categories will vary in their average illiquidity.
   - For each bond in category $k \in \{1, 2, 3, 4, 5\}$, randomly draw its illiquidity from the log-normal distribution with $\mu = 0.25k$ and $\sigma = 0.05$. This specification is meant to capture the idea that bonds in different categories vary in average liquidity but that the distribution of illiquidity across categories overlaps.
2. Initialize a sample of 250 funds.
   - Assign each fund to one of 5 objectives corresponding to different bond categories. Funds in objective k will invest only in category k bonds, consistent with most bond funds having restricted mandates.
   - Randomly sample each fund's portfolio from bonds that belong to fund's objective.
3. Calculate portfolio illiquidity as the mean bond level illiquidity.
4. Draw each fund's flow volatility, σ_f, from the lognormal distribution with mean of 0.045 and standard deviation of 0.059. These are set to match the empirical moments of the distribution of flow volatility in our data.
5. Set fund's cash-to-assets ratio according to

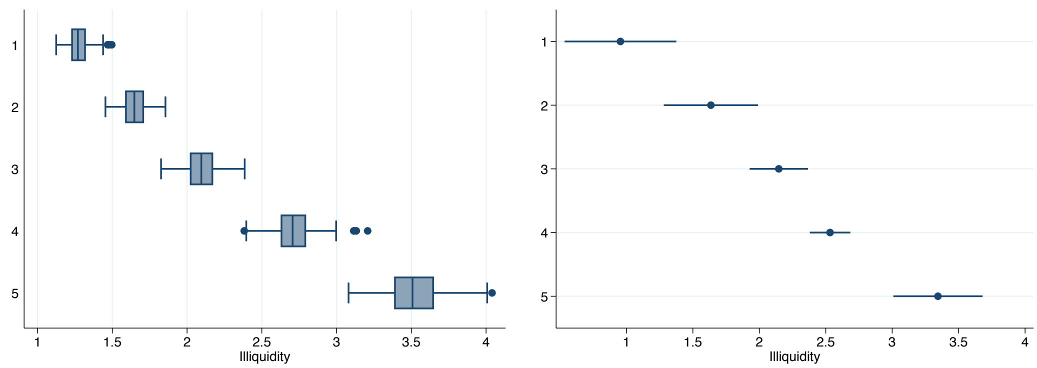
$$\left(\frac{Cash}{TNA}\right)_f = Illiquidity_f \times \sigma_f + 0.05 \times \varepsilon_f \tag{5}$$

   where ε is standard normal.

Figure 1
Simulation Results

This figure reports the results of a simulation of our empirical methodology. Simulation setup is described in text. Panel (a) plots the distribution of illiquidity across different bond categories (1–5). Panel (b) plots the estimated coefficients from the regression 6. Estimated coefficients do a fairly good job of approximating average illiquidity in each one of the five bond categories.

(a) Distribution of illiquidity　　**(b)** Estimated coefficients



6. In the simulated holdings data, estimate the regression

$$\left(\frac{Cash}{TNA}\right)_{b,f} = \alpha_b + \beta_1 \cdot (1)_b \times \sigma_f + \cdots + \beta_5 \cdot I(5)_b \times \sigma_f + \nu_{b,f} \tag{6}$$

adjusting the standard errors for clustering by fund.

Figure 1 presents the results of this simulation exercise. Figure 1a is a box plot of the distribution of bond liquidity for bonds within each of five categories. Figure 1b plots the coefficients and the corresponding 95% confidence intervals. The figures show that our methodology does a good job of uncovering the average liquidity of funds in each category.

3 Data

Our data come from three main sources: Morningstar, CRSP Mutual Fund Database, and Mergent FISD. We obtain holdings of bond mutual funds from Morningstar, fund TNA and flows from CSRP, and bond characteristics from FISD.

3.1 Cash holdings

We measure cash holdings as the sum of a fund's long positions in cash, certificates of deposit, commercial paper, repurchase agreements, money market funds, and Treasury and Agency securities with original maturity of less than one year. While most of these can be identified based on the security code in Morningstar, this classification is imperfect and we make a number of adjustments.

First, some holdings of money market funds are classified by Morningstar as generic open-end mutual funds (security code `FO`) or as 'Equity - Unidentified' (code `EQ`) rather than as 'Mutual Fund - Money Market' (code `FM`).[2] We use a list of CUSIPs that correspond to money market funds in CRSP Mutual Fund Database (based on CRSP objective code starting with 'IM') to identify positions misclassified by Morningstar.

Second, Morningstar classifies many commercial paper issues as 'Unidentified Holding' (code `Q`).[3] We use the CP institution type variable from the CUSIP Master File to identify six-character issuer CUSIPs that correspond to commercial paper programs.

Third, Morningstar does not differentiate between short- and long-maturity Treasury and Agency securities. Using offering date and maturity information from FISD, we include Treasury and Agency securities with original maturities of less than one year in our definition of cash.

Fourth, because Morningstar's classification is not always consistent within a given CUSIP, we identify as cash any CUSIP that is classified as such more than 50% of the time.[4]

As previously mentioned, in calculating the level of cash holdings we include only long positions. Negative values of Morningstar security code `C` appear to correspond to short positions in CDS and other derivatives.[5] We used N-CSR and N-Q filings to measure the cash-to-assets ratio for a random sample of 363 observations. For this sample, the correlation between the true value of cash and equivalents and the Morningstar measure is 0.61 when only long positions are included and 0.06 when both long and short positions are included.

Figure 2a shows the distribution of the cash-to-assets ratio over time. Except for the

[2] About 3% of all holdings of money market funds is misclassified this way.

[3] About 43% of CP holdings is classified as 'Unidentified Holding' (Q), another 13% is classified as 'Bond - Corporate Bond' (B).

[4] CUSIP 85799G001 which corresponds to Euro Time Deposits with State Street is one example. Most of the security codes associated with this CUSIP get tagged as cash, but for some funds' positions, Morningstar assigns security codes `B` or `Q`. We calculate the average of the raw cash dummy across funds and time. If this average is greater than 50%, all positions with that CUSIP are considered to be cash.

[5] Nuveen High Yield Bond Fund in June 2008 is one example.

beginning of the sample period in 2002, the percentiles are relatively stable. The median fund holds about 4% of its portfolio in cash and equivalents.

3.2 Flow volatility

Following the mutual fund literature, we estimate monthly fund flows as

$$Flow_{f,t} = \frac{TNA_{f,t} - (1 + r_{f,t}) \times TNA_{t-1}}{TNA_{f,t-1}}$$

Flow volatility is then calculated as the standard deviation of fund-level flows over the previous twelve months, requiring there to be at least nine observations. To mitigate the effects of outliers, we exclude observations with lagged TNA of less than $10 million and observations that correspond to fund mergers.[6]

Figure 2b shows the distribution of flow volatility over time. Over the full sample period, the interquartile range is between 1.2% and 3.6%. There is a pronounced spike in flow volatility during the financial crisis, as well as smaller spikes in the 75th percentile in the years after the crisis.

3.3 Final sample

Our final sample consists of long positions in corporate bonds held by actively managed mutual funds that invest primarily in corporate bonds. Specifically, we restrict the sample of funds to Lipper objective codes A, BBB, EMD, GB, GLI, HY, I, IID, MSI, and SII and funds for which corporate bonds make up more than 25% of portfolio holdings. We apply a number of additional screens to guard against errors in linking CRSP and Morningstar data bases and potential biases. First, we require the ratio of the net market value of securities from Morningstar to fund TNA from CRSP to be in the [0.5, 1.5] interval. Such filters are common in the mutual funds literature (Coval and Stafford, 2007). Second, since the relation between flow volatility and cash holdings may not be informative of the portfolio holdings liquidity during a fund's incubation period, we exclude funds that are less than two years old (Evans, 2010). Finally, we exclude funds with less than $10 million in TNA.

The sample of corporate bonds is identified based on corporate debenture (CDEB) type in FISD. We exclude a small number of observations that correspond to government issuers according to the SIC in FISD or that are reported later than the bond's original maturity.

[6] We also screen the data for likely data errors, which we define as situations where fund assets fall by more than 80% and increase by at least 500% the following month, and conversely where fund assets first increase by more than 500% and then decline by more than 80%.

The sample period is 2002Q2–2016Q2.

3.4 Summary statistics

Table 1 reports summary statistics for funds (Panel A) and bonds (Panel B) in our data. The median fund has TNA of \$340 million, cash-to-assets ratio of 3.15%, and monthly flow volatility of 2.28%. Most funds take only long positions: the 75th percentile of the gross to net value of portfolio securities is 1.02. Mutual fund ownership captures the fraction of a fund's shares owned by other mutual funds. The distribution is highly skewed: while the 75th percentile is 20 basis points, the mean is 543 basis points. For most funds, holdings of equities and ETFs, which could be potentially liquidated first to meet redemption requests, are very small. About 23% of all fund-date observations impose redemption fees.

Panel B reports summary statistics for bonds. The median bond has a par value of \$400 million. Credit ratings are encoded so that $AAA = 0, AA+ = 1$, etc. Thus the 25th, 50th, and 75th percentiles of the distribution correspond to A-, BBB-, and B+ credit ratings. During a given quarter, the median bond is held by 6 funds in the final sample.

Table 1
Summary Statistics

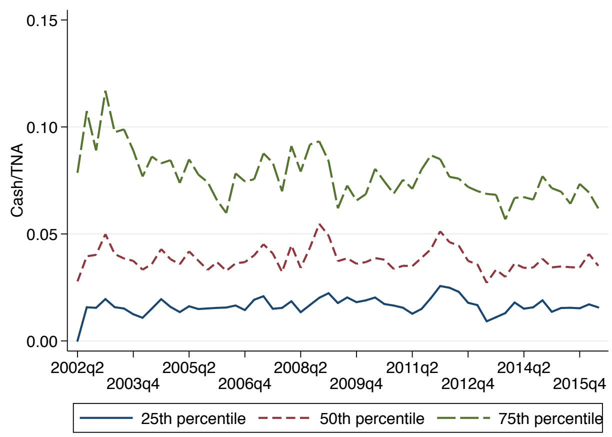
Panel A reports summary statistics for fund-date observations, while Panel B reports summary statistics for bond-date observations. The sample consists of funds that are at least 2 years old, have TNA of at least \$10 million (in 2009 dollars), and invest at least 25% of their portfolio in corporate bonds. The sample period is 2002Q2–2016Q2.

				Percentile		
	N	Mean	SD	25	50	75
Panel A: Funds						
TNA	16,695	1291.00	2974.00	106.00	340.00	1082.00
$\frac{Cash}{TNA}$(%)	16,695	4.88	6.11	1.35	3.15	6.01
$\sigma(Flows)$ (%)	16,695	3.39	3.65	1.26	2.28	4.07
Fund age	16,695	15.59	11.48	7.51	13.25	20.48
$\frac{Goss}{Net}$	16,695	1.10	0.37	1.00	1.00	1.02
Mutual fund ownership (%)	16,695	5.43	19.12	0.00	0.00	0.20
ETF portfolio share (%)	16,695	0.07	0.66	0.00	0.00	0.00
Equities portfolio share (%)	16,695	0.67	2.28	0.00	0.00	0.22
Redemption fee	16,695	0.23	0.42	0.00	0.00	0.00
Panel B: Bonds						
Issue size (million \$)	445,204	572.02	1730.73	250.00	400.00	700.00
Rating	425,597	9.34	4.10	6.00	9.00	13.00
Num. funds	445,204	10.31	11.75	2.00	6.00	14.00

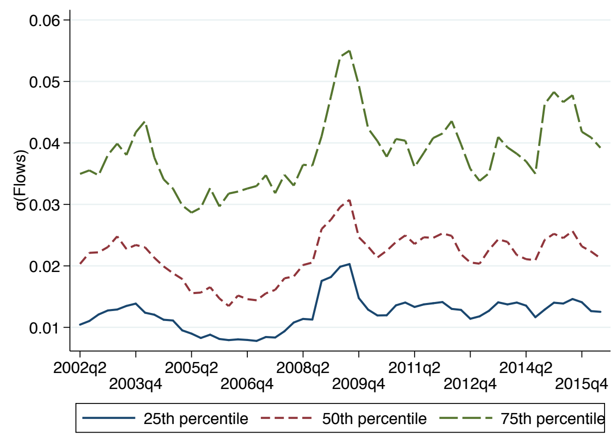
Figure 2
Distribution of Cash/Assets and $\sigma(Flows)$

This figure shows the distribution of the cash-to-assets ratio and $\sigma(Flows)$ over time for funds in the sample.

(a) Cash/Assets



(b) $\sigma(Flows)$



4 Results

We start by presenting baseline results on the relation between fund flow volatility and cash-to-assets ratio. We then show in subsection 4.2 that, consistent with theory, the coefficient on fund flow volatility is larger for bonds that are likely to be less liquid: bonds with speculative grade credit ratings and smaller bonds. These cross-sectional results validate the idea of using the coefficient on fund flow volatility as a measure of funds' perceived illiquidity of portfolio holdings. Finally, subsection 4.4 presents our results on the time series changes in perceived illiquidity.

4.1 Baseline results

Table 2 presents results of regressions of the cash-to-assets ratio on fund flow volatility

$$\left(\frac{Cash}{TNA}\right)_{b,f,t} = \alpha_{b,t} + \delta_{obj(f),t} + \beta \cdot \sigma_{f,t} + \gamma' X_{f,t} + \varepsilon_{b,f,t}. \tag{7}$$

Columns 1–4 present equal-weighted results, while columns 5–8 weight observations by their portfolio share. Standard errors are adjusted for clustering by fund-date.

In column 1, the coefficient on flow volatility is 0.118 and is highly statistically significant. The interpretation is that a one standard deviation increase in monthly flow volatility of 3.65% is associated with 43 basis points higher cash-to-assets ratio. Relative to the median

Table 2
Cash-to-Assets Ratio and Fund Flow Volatility

This table reports results of regressions of the cash-to-assets ratio on fund flow volatility

$$\left(\frac{Cash}{TNA}\right)_{b,f,t} = \alpha_{b,t} + \delta_{obj(f),t} + \beta \cdot \sigma_{f,t} + \gamma' X_{f,t} + \varepsilon_{b,f,t},$$

where b indexes bonds, f indexes funds, and t indexes time. The number of observations is 3,043,430. σ is the standard deviation of monthly fund flows, scaled by lagged TNA, over the previous twelve months. At least nine monthly observations are required. σ is winsorized at the 95th percentile of its distribution within each quarter. Standard errors are adjusted for clustering by fund-date. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

	Equal-weighted				Portfolio share-weighted			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\sigma_{f,t}$	0.118***	0.145***	0.118***	0.149***	0.142***	0.140***	0.135***	0.148***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.014)	(0.014)	(0.013)	(0.013)
$Ln(TNA)_{f,t}$	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Gross/Net_{f,t}$	0.017***	0.016***	0.017***	0.016***	0.018***	0.016***	0.018***	0.017***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$Redemption\ fee_{f,t}$	−0.002**	0.000	−0.003***	−0.000	0.006***	0.006***	0.003***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$TBA\ share_{f,t}$	0.306***	0.297***	0.298***	0.289***	0.299***	0.309***	0.315***	0.308***
	(0.020)	(0.019)	(0.020)	(0.019)	(0.017)	(0.017)	(0.018)	(0.017)
$ETF\ share_{f,t}$	−0.063	−0.063	−0.052	−0.042	0.025	0.003	0.006	0.014
	(0.041)	(0.043)	(0.045)	(0.045)	(0.049)	(0.048)	(0.042)	(0.041)
$Equity\ share_{f,t}$	0.011	0.026	−0.016	0.009	0.093***	0.087***	0.065***	0.071***
	(0.015)	(0.017)	(0.013)	(0.016)	(0.017)	(0.018)	(0.016)	(0.017)
$Mutual\ fund\ ownership_{f,t}$	0.002	0.001	0.002	0.000	0.001	−0.001	−0.000	−0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Adjusted R^2	0.11	0.24	0.19	0.26	0.08	0.18	0.24	0.29
Bond-date FEs		✓		✓		✓		✓
Objective-date FEs			✓	✓			✓	✓

cash-to-assets ratio of 315 basis points, this is a sizable effect.

The coefficient on fund size is statistically and economically insignificant. Although larger funds may enjoy certain economies of scale, they are also more likely to trade derivatives or to short securities, both of which would require funds to hold cash collateral. Consistent with this idea, the coefficient on the ratio of the gross and net values of portfolio securities is positive, indicating that funds that short sell securities and for which the gross value of positions exceeds the net value, have higher cash-to-assets ratios. The coefficient on the portfolio share of to be announced (TBA) agency mortgage-backed securities is large and positive: funds that commit to purchasing such securities in the future set aside cash to cover such purchases. The coefficients on the other controls, including redemption fees, ETF share, equity share, and mutual fund ownership are small and insignificant.

One concern with the simple OLS regression in column 1 is that funds with highly volatile fund flows may choose to hold more liquid securities, which require smaller precautionary cash buffers. This would bias the coefficient on flow volatility towards zero. To address this concern, column 2 adds bond-date fixed effects. This regression therefore asks whether among funds that hold a given bond at a particular point in time, the ones with more volatile fund flows hold more cash. The coefficient on flow volatility increases by more than one-third from 0.118 to 0.145.

Column 3 adds objective-date fixed effects, while column 4 controls for both bond-date and objective-date fixed effects. The results here are similar to column 2.

Columns 5–8 report the results of value-weighted regressions that give more weight to observations that make up a larger share of a fund's portfolio and that therefore contribute more to the overall liquidity of a fund's portfolio. We get broadly similar results.

4.2 Cross-sectional results

We next show that our measure of perceived illiquidity, the coefficient on fund flow volatility, is larger for speculative grade and smaller bonds. Speculative grade bonds are likely to be less liquid because of greater scope for asymmetric information and because the set of investors who can hold speculative grade bonds is smaller. Smaller bonds are likely to be issued by smaller and more opaque firms that are also subject to greater asymmetric information. They are also likely to be less widely held, resulting in higher costs of searching for potential counterparties (Duffie, Gârleanu, and Pedersen, 2007). Finally, only bonds with outstanding amount greater than $250 million are included in popular bond indexes such as the Barclays U.S. Corporate Index.

Table 3 and Figure 3 present the results of our analysis of perceived illiquidity by credit rating. Column 1 reports the results of equal-weighted regressions where we interact flow volatility with an indicator variable for different credit ratings. Except for BB vs B rated bonds, the coefficient on flow volatility increases monotonically with lower ratings. The pattern of coefficients suggests that most of the difference in illiquidity happens at the investment grade boundary. The coefficient on flow volatility jumps from 0.083 for BBB rated bonds to 0.181 for BB rated bonds. In column 2 we replace individual credit ratings with dummies for investment and speculative grade and find a very large difference between the two. The perceived illiquidity of speculative grade bonds is over twice as large as the illiquidity of investment grade bonds.

In columns 3–4 we weight observations by the extent to which a given fund's portfolio is homogeneous across ratings. The idea here is that cash holdings of funds that invest

Table 3
Perceived Illiquidity By Credit Rating

This table reports results of regressions of the cash-to-assets ratio on fund flow volatility interacted with each bond's credit rating

$$\left(\frac{Cash}{TNA}\right)_{b,f,t} = \alpha_{b,t} + \delta_{obj(f),t} + \beta \cdot \sigma_{f,t} \times Rating_b + \varepsilon_{b,f,t},$$

where b indexes bonds, f indexes funds, and t indexes time. σ is the standard deviation of monthly fund flows, scaled by lagged TNA, over the previous twelve months. At least nine monthly observations are required. σ is winsorized at the 95th percentile of its distribution within each quarter. Standard errors are adjusted for clustering by fund-date. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

	Equal-weighted		Portfolio share-weighted	
	(1)	(2)	(3)	(4)
$\sigma_{f,t} \times I(AAAorAA)_b$	0.060**		0.064***	
	(0.028)		(0.022)	
$\sigma_{f,t} \times I(A)_b$	0.086***		0.095***	
	(0.027)		(0.020)	
$\sigma_{f,t} \times I(BBB)_b$	0.083***		0.100***	
	(0.025)		(0.018)	
$\sigma_{f,t} \times I(BB)_b$	0.181***		0.185***	
	(0.019)		(0.016)	
$\sigma_{f,t} \times I(B)_b$	0.180***		0.162***	
	(0.020)		(0.017)	
$\sigma_{f,t} \times I(CCC)_b$	0.198***		0.189***	
	(0.022)		(0.018)	
$\sigma_{f,t} \times Investment\ grade_b$		0.082***		0.096***
		(0.024)		(0.017)
$\sigma_{f,t} \times Speculative\ grade_b$		0.183***		0.174***
		(0.019)		(0.016)
$Ln(TNA)_{f,t}$	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
$Gross/Net_{f,t}$	0.016***	0.016***	0.017***	0.017***
	(0.002)	(0.002)	(0.002)	(0.002)
$TBA\ share_{f,t}$	0.292***	0.292***	0.309***	0.309***
	(0.019)	(0.019)	(0.017)	(0.017)
$ETF\ share_{f,t}$	−0.044	−0.044	0.013	0.013
	(0.046)	(0.045)	(0.041)	(0.041)
$Equity\ share_{f,t}$	0.014	0.014	0.076***	0.076***
	(0.017)	(0.017)	(0.017)	(0.017)
$Mutual\ fund\ ownership_{f,t}$	0.000	0.000	−0.001	−0.001
	(0.002)	(0.002)	(0.001)	(0.001)
$Redemption\ fee_{f,t}$	0.000	0.000	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
N	2,943,838	2,943,838	2,943,838	2,943,838
Adjusted R^2	0.27	0.27	0.29	0.29

primarily in bonds with a given rating, say BB, are likely to be more informative about the illiquidity of bonds with that rating than cash holdings of funds that invest in bonds with very different credit ratings. To implement this idea, we start by calculating the share of each fund's portfolio invested in bonds with different credit ratings. We then use these shares to calculate the fund's Herfindahl-Hirschman Index (HHI). The results in columns 3–4 indicate similar differences in perceived liquidity between investment and speculative grade bonds.

Figure 3 offers a visual representation of estimated illiquidity by credit rating; specifically it reports the coefficients and 95% confidence intervals from column 3 of Table 3.

Figure 3
Perceived Illiquidity by Credit Rating

This figure reports the coefficient estimates and 95% confidence intervals from the regression in column 3 of Table 3.

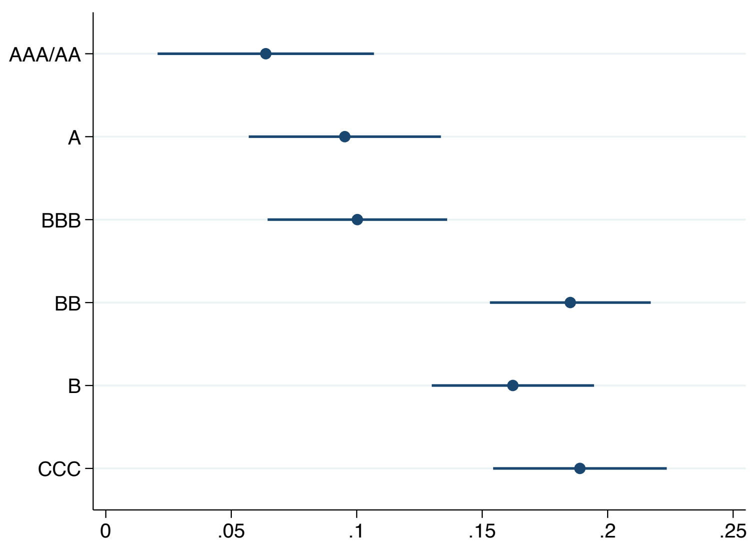


Table 4 presents the results of our analysis of perceived illiquidity by bond size. Columns 1 and 2 report the results of equal-weighted regressions. In column 1, we interact flow volatility with the natural log of bond's size. While the coefficient on the interaction term is negative, it is not statistically significant. In column 2, we interact flow volatility with indicator variable for bonds falling into different size buckets. Once again the differences are not statistically significant.

Following the logic in Table 3, in columns 3 and 4, we weight observations by whether a fund invests mostly in bonds of similar size. Specifically, we calculate HHI across the following size buckets: [0, 250), [250, 500), [500, 1000), and greater than 1,000 million. Differences in the sensitivity of cash to flow volatility remain insignificant. As we will see below, this reflects evolution in the distribution of bond sizes over time. As Appendix Figure A1 shows, the fraction of observations with par value of less than $500 million shrinks dramatically over our sample period from more than 60% in 2002 to less than 30% in 2016.

In Table 5, we use our methodology to examine the illiquidity of bonds that do not trade frequently. A key advantage of our methodology, relative to other procedures for measuring bond liquidity that rely on transactions, is that it does not require trade data. Thus, with our methodology, we can assess whether bonds that do not trade are indeed much less liquid than bonds that do trade frequently. Because we need TRACE data to assess whether a bond has traded or not, the sample in this table is restricted to 2005Q1-2016Q2 because before 2005Q1 most high yield bond trades were not disseminated through TRACE.

Column 1 of Table 5 reports the results of equal-weighted regressions where we interact flow volatility with a dummy variable indicating that the bond has not traded in quarter t. The coefficient on the interaction term is 0.038, compared to a baseline coefficient on flow volatility of 0.143. Thus, bonds that do not trade are about 27% more illiquid than bonds that do trade. In columns 2 and 3, we split the sample into investment grade and speculative grade bonds. The effect of not trading is concentrated in speculative grade bonds, as one would expect.

Columns 4–6 report the results of value-weighted regressions that give more weight to observations that make up a larger share of a fund's portfolio and that therefore contribute more to the overall liquidity of a fund's portfolio. We get broadly similar results.

4.3 Is illiquidity priced?

We next turn to the question of whether our measure of illiquidity is priced. Since our procedure does not recover bond-level measures of illiquidity, we must take an indirect approach. We simply ask whether bonds that in general have high spreads also have high levels of illiquidity according to our measure. Specifically, we run our baseline regressions interacting flow volatility with the bond's spread. We calculate spread in two ways. The raw spread is the yield of the bond at issuance minus the yield on a Treasury of comparable maturity at the time. The adjusted spread is to the raw spread demeaned by the spreads on comparable bonds: bonds issued during the same quarter with the same letter notched rating, similar maturity, and similar offering size. In calculating the adjusted spread we require at least 5 such comparable bonds.

Column 1 of Table 6 reports the results of equal-weighted regressions where we interact flow volatility with the raw spread. The interaction term is positive and significant, indicating that bonds with high spreads are more illiquid. In other words, illiquidity by our measure does appear to be priced. Column 2 of the table shows similar results when we use the adjusted spread. Columns 3 and 4 report the results of value-weighted regressions that give more weight to observations that make up a larger share of a fund's portfolio and that therefore contribute more to the overall liquidity of a fund's portfolio. We get broadly similar results.

4.4 Time series results

Having shown that our measure of perceived liquidity behaves sensibly in the cross section of corporate bonds, we turn to examining the time series behavior of liquidity. Market participants have expressed concern about deteriorating liquidity since the financial crisis, ascribing it in part to the Volcker Rule and bank's reluctance to use their balance sheet to intermediate in the corporate bond market. However, standard measures of liquidity that are based on transactions suggest that liquidity is comparable to the pre crisis period.[7] An important limitation of standard measures however is that because they are based on transactions that do take place, they cannot speak to the perceived illiquidity of bonds that do not trade. Our holdings-based measure can therefore help shed light on whether an important subset of investors in the corporate bond market does indeed perceive bond liquidity to be worse than before the crisis.

Table 7 reports our basic results. We estimate regression Equation 7 interacting flow volatility with indicator variable for various subperiods. The *Pre* period is June 2002–August 2008. We define the *Crisis* period as September 2008–June 2009. Finally, the *Post crisis* period is July l 2009–June 2016.

Table 7 presents both equal- and portfolio share-weighted results. Our estimates in columns 1 and 6 suggest that mutual funds perceived liquidity to be worse during the crisis than during the pre-crisis period. Our estimates likely understate perceived illiquidity during the crisis because the model assumes that funds are at their target cash-to-assets ratio, while funds may have temporarily drawn down their cash buffers to satisfy redemption requests.

As for the post crisis period, columns 1 and 6 suggest that since the crisis liquidity has recovered, but not fully to its precrisis levels. One concern that may arise with these estimates is that the nature of fund flows may have changed over time. In particular, our methodology relies on the idea that realized flow volatility is a good proxy for future expected flow volatility. If the relationship between future flow volatility and past flow volatility has changed over time, then differences in our estimates may be driven by differences in

[7] Bessembinder et al. (2017) and Trebbi and Xiao (2016) find little evidence of deterioration in average trade execution costs, though they note some deterioration in other measures of liquidity. Adrian et al. (2017) find little evidence of deterioration in a variety of price-based measures of liquidity. Bao, O'Hara, and Zhou (2017) find evidence of deterioration around stress events.

Table 4
Perceived Illiquidity by Bond Size

This table reports the results of regressions of the cash-to-assets ratio on fund flow volatility interacted with bond size

$$\left(\frac{Cash}{TNA}\right)_{b,f,t} = \alpha_{b,t} + \delta_{obj(f),t} + \beta_0 \cdot \sigma_{f,t} + \beta_1 \cdot \sigma_{f,t} \times Bond\ size_b + \varepsilon_{b,f,t},$$

where b indexes bonds, f indexes funds, and t indexes time. In columns 3–4, observations are weighted by the concentration of the fund's portfolio across four buckets of bond size. Thus a fund that holds bonds that all fall in the same bucket will be weighted more heavily than a fund that holds bonds of very different sizes. Standard errors are adjusted for clustering by fund-date. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

	Equal-weighted		Portfolio share weighted	
	(1)	(2)	(3)	(4)
$\sigma_{f,t}$	0.179***		0.081*	
	(0.053)		(0.048)	
$\sigma_{f,t} \times Bond\ size_b$	−0.005		0.011	
	(0.009)		(0.007)	
$\sigma_{f,t} \times I(Bond\ size_b \in [0, 250))$		0.146***		0.129***
		(0.020)		(0.019)
$\sigma_{f,t} \times I(Bond\ size_b \in [250, 500))$		0.157***		0.144***
		(0.018)		(0.014)
$\sigma_{f,t} \times I(Bond\ size_b \in [500, 1,000))$		0.151***		0.153***
		(0.019)		(0.014)
$\sigma_{f,t} \times I(Bond\ size_b > 1,000)$		0.138***		0.156***
$Ln(TNA)_{f,t}$	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
$Gross/Net_{f,t}$	0.016***	0.016***	0.017***	0.017***
	(0.002)	(0.002)	(0.002)	(0.002)
$Redemption\ fee_{f,t}$	−0.000	−0.000	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
$TBA\ share_{f,t}$	0.289***	0.289***	0.308***	0.308***
	(0.019)	(0.019)	(0.017)	(0.017)
$ETF\ share_{f,t}$	−0.042	−0.042	0.014	0.014
	(0.045)	(0.045)	(0.041)	(0.041)
$Equity\ share_{f,t}$	0.009	0.009	0.071***	0.071***
	(0.016)	(0.016)	(0.017)	(0.017)
$Mutual\ fund\ ownership_{f,t}$	0.000	0.000	−0.002	−0.002
	(0.002)	(0.002)	(0.001)	(0.001)
		(0.022)		(0.015)
N	3,043,430	3,043,430	3,043,430	3,043,430
Adjusted R^2	0.26	0.26	0.29	0.29
Bond-date FEs	✓	✓	✓	✓
Objective-date FEs	✓	✓	✓	✓

Table 5
Perceived Illiquidity of Bonds that Do Not Trade

This table reports the results of regressions of the cash-to-assets ratio on fund flow volatility interacted with a dummy variable for bonds that do not have any trades in TRACE

$$\left(\frac{Cash}{TNA}\right)_{b,f,t} = \alpha_{b,t} + \delta_{obj(f),t} + \beta_0 \cdot \sigma_{f,t} + \beta_1 \cdot \sigma_{f,t} \times No\ Trades_{b,t} + \varepsilon_{b,f,t},$$

where b indexes bonds, f indexes funds, and t indexes time. The sample period is restricted to March 2005–June 2016, the period during which transactions in both investment- and speculative-grade securities are disseminated through TRACE. Standard errors are adjusted for clustering by fund-date. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

	Equal-weighted			Portfolio share weighted		
		by Grade			by Grade	
	All	Inv.	Spec.	All	Inv.	Spec.
	(1)	(2)	(3)	(6)	(7)	(8)
$\sigma_{f,t}$	0.143***	0.043	0.209***	0.148***	0.091***	0.180***
	(0.020)	(0.027)	(0.022)	(0.015)	(0.020)	(0.019)
$\sigma_{f,t} \times No\ Trades_{b,t}$	0.038***	−0.014	0.028***	0.027***	−0.006	0.019*
	(0.010)	(0.013)	(0.010)	(0.010)	(0.012)	(0.011)
$Ln(TNA)_{f,t}$	−0.000	−0.002***	0.001***	0.000	−0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Gross/Net_{f,t}$	0.016***	0.019***	0.012***	0.017***	0.017***	0.016***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
$Redemption\ fee_{f,t}$	−0.000	−0.004**	0.000	0.004***	0.001	0.005***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
$TBA\ share_{f,t}$	0.219***	0.180***	0.287***	0.252***	0.220***	0.316***
	(0.024)	(0.018)	(0.033)	(0.024)	(0.020)	(0.037)
$ETF\ share_{f,t}$	−0.037	0.221***	−0.100**	0.021	0.202***	−0.036
	(0.047)	(0.066)	(0.041)	(0.042)	(0.057)	(0.046)
$Equity\ share_{f,t}$	−0.026*	0.023	−0.039**	0.019	0.072***	0.009
	(0.016)	(0.024)	(0.016)	(0.015)	(0.021)	(0.016)
$Mutual\ fund\ ownership_{f,t}$	0.000	0.008***	−0.004**	−0.001	0.005**	−0.005***
	(0.002)	(0.003)	(0.002)	(0.001)	(0.002)	(0.002)
N	2,539,903	957,521	1,579,834	2,539,903	957,521	1,579,834
Adjusted R^2	0.24	0.25	0.23	0.28	0.30	0.26
Bond-date FEs	✓	✓	✓	✓	✓	✓
Objective-date FEs	✓	✓	✓	✓	✓	✓

Table 6
Is Perceived Illiquidity Priced?

This table reports the results of regressions of the cash-to-assets ratio on fund flow volatility interacted with the bond's at-issue yield spread

$$\left(\frac{Cash}{TNA}\right)_{b,f,t} = \alpha_{b,t} + \delta_{obj(f),t} + \beta_0 \cdot \sigma_{f,t} + \beta_1 \cdot \sigma_{f,t} \times Spread_b + \varepsilon_{b,f,t},$$

where b indexes bonds, f indexes funds, and t indexes time. In columns 1 and 3, *Spread* is the at-issue yield spread relative to a Treasury security with comparable maturity. In columns 2 and 4, *Adjusted Spread* is demeaned relative to bonds with the same letter notched rating, similar maturity and offering size, and issued during the same quarter. Maturity bins (in years) are $[0, 5)$, $[5, 10)$, and $[10, .)$. Offering size bins (in million \$) are $[0, 500)$, $[500, 1000)$, and $[1000, .)$. We require at least 5 comparable bonds to calculate the *Adjusted Spread* and winsorize the *Adjusted Spread* at the 1st and 99th percentiles, setting extreme values of adjusted spread to missing. The sample of bonds consists of fixed rate corporate debentures (FISD bond type `CDEB`), excluding bonds with IPO clawback provisions. Standard errors are adjusted for clustering by fund-date. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

	Equal-weighted		Portfolio share-weighted	
	(1)	(2)	(3)	(4)
$\sigma_{f,t}$	0.049*	0.074***	0.082***	0.109***
	(0.026)	(0.022)	(0.019)	(0.016)
$\sigma_{f,t} \times Spread_b$	0.015***		0.014***	
	(0.004)		(0.004)	
$\sigma_{f,t} \times Adjusted\ Spread_b$		0.011*		0.015**
		(0.007)		(0.006)
$Ln(TNA)_{f,t}$	−0.001***	−0.001***	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
$Gross/Net_{f,t}$	0.017***	0.017***	0.017***	0.017***
	(0.002)	(0.002)	(0.002)	(0.002)
$Redemption\ fee_{f,t}$	−0.002	−0.002	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
$TBA\ share_{f,t}$	0.313***	0.304***	0.318***	0.307***
	(0.017)	(0.018)	(0.016)	(0.017)
$ETF\ share_{f,t}$	0.076	0.134**	0.120***	0.160***
	(0.053)	(0.055)	(0.044)	(0.049)
$Equity\ share_{f,t}$	0.006	0.020	0.064***	0.080***
	(0.017)	(0.018)	(0.016)	(0.017)
$Mutual\ fund\ ownership_{f,t}$	0.004*	0.005**	0.003	0.004
	(0.002)	(0.002)	(0.002)	(0.002)
N	1,245,961	887,888	1,245,961	887,888
Adjusted R^2	0.28	0.27	0.30	0.30

Table 7
Time Series of Perceived Liquidity

This table reports the results of regressions of the cash-to-assets ratio on fund flow volatility interacted with dummies for different periods

$$\left(\frac{Cash}{TNA}\right)_{b,f,t} = \alpha_{b,t} + \delta_{obj(f),t} + \beta \cdot \sigma(Flows)_{f,t} \times SubPeriod_t + \varepsilon_{b,f,t},$$

where b indexes bonds, f indexes funds, and t indexes time. *Pre* is June 2002–August 2008. *Crisis* is September 2008–June 2009. *Post* is July 2009–June 2016. Standard errors are adjusted for clustering by fund-date. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

	Equal-weighted					Portfolio share-weighted				
		By Grade		By Bond Size			By Grade		By Bond Size	
	All	Inv.	Spec.	Small	Large	All	Inv.	Spec.	Small	Large
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\sigma_{f,t} \times Pre_t$	0.086***	0.006	0.122***	0.105***	0.066**	0.095***	0.051	0.111***	0.098***	0.086***
	(0.025)	(0.042)	(0.026)	(0.026)	(0.027)	(0.021)	(0.032)	(0.024)	(0.023)	(0.022)
$\sigma_{f,t} \times Crisis_t$	0.248***	0.201***	0.284***	0.284***	0.225***	0.274***	0.229***	0.300***	0.293***	0.263***
	(0.056)	(0.075)	(0.071)	(0.063)	(0.058)	(0.049)	(0.052)	(0.066)	(0.059)	(0.047)
$\sigma_{f,t} \times Post_t$	0.165***	0.026	0.250***	0.197***	0.148***	0.158***	0.071***	0.208***	0.145***	0.166***
	(0.025)	(0.032)	(0.027)	(0.024)	(0.026)	(0.017)	(0.024)	(0.020)	(0.018)	(0.018)
$Ln(TNA)_{f,t}$	−0.000	−0.002***	0.001**	0.000	−0.000	−0.000	−0.000	0.000	−0.001***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Gross/Net_{f,t}$	0.015***	0.018***	0.013***	0.013***	0.016***	0.016***	0.017***	0.016***	0.015***	0.017***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
$Redemption\ fee_{f,t}$	−0.000	−0.005***	0.001	0.002**	−0.002*	0.004***	0.001	0.005***	0.007***	0.002***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$TBA\ share_{f,t}$	0.289***	0.310***	0.284***	0.279***	0.298***	0.308***	0.312***	0.307***	0.310***	0.307***
	(0.019)	(0.018)	(0.029)	(0.024)	(0.018)	(0.017)	(0.017)	(0.028)	(0.021)	(0.017)
$ETF\ share_{f,t}$	−0.047	0.185***	−0.112***	−0.073	−0.035	0.011	0.180***	−0.053	−0.040	0.035
	(0.045)	(0.063)	(0.041)	(0.044)	(0.048)	(0.041)	(0.053)	(0.045)	(0.043)	(0.042)
$Equity\ share_{f,t}$	0.008	0.027	0.006	0.041**	−0.024	0.070***	0.081***	0.075***	0.133***	0.020
	(0.016)	(0.023)	(0.017)	(0.019)	(0.016)	(0.017)	(0.021)	(0.019)	(0.023)	(0.014)
$Mutual\ fund\ ownership_{f,t}$	−0.000	0.007**	−0.004**	−0.002	0.001	−0.002	0.005*	−0.005***	−0.004***	−0.001
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Adjusted R^2	0.26	0.28	0.25	0.29	0.25	0.29	0.31	0.26	0.33	0.27
Bond-date FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Objective-date FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

the behavior of flow volatility rather than changes in bond market liquidity. In Appendix Figure A3, we show that the autocorrelation of flow volatility has remained quite stable over time, ruling out this alternative explanation for our results.

Columns 2–5 and 7–10 of Table 7 examine changes in the cross section of liquidity, splitting the results in columns 1 and 6 by whether bonds are investment versus speculative grade and whether bonds are small versus large. We define small bonds to be the ones with par values of less than $500 million.

According to columns 2 and 6, the liquidity of investment grade bonds deteriorated during the crisis, but recovered to nearly its precrisis levels. In contrast, for speculative grade bonds, very little of the deterioration of liquidity that occurred during the crisis has been reversed. In column 3 the coefficient on flow volatility interacted with the post crisis period is 0.250 compared to 0.122 during the pre crisis period. This difference is statistically significant at 1%. Portfolio share weighted regressions in column 8 deliver similar message: the coefficient on flow volatility increases by more than 88% from 0.111 to 0.208. The difference is statistically significant at 3%.

Comparing the estimates in columns 4 versus 5, we can see that small bonds are less liquid than large bonds in each time period. The liquidity of both types of bonds deteriorated in the crisis, and has recovered partially but not fully since the crisis. As noted above, Appendix Figure A1 shows, the fraction of observations with par value of less than $500 million shrinks dramatically over our sample period from more than 60% in 2002 to less than 30% in 2016. Because open-end mutual funds may be investing in the most liquid among the smaller size bonds, our estimates may be understating the decline in liquidity for small bonds.

5 Conclusion

This paper proposes a novel measure of bond market liquidity that is based on portfolio holdings instead of transaction data. Because investors may choose to trade only the more liquid bonds and because many bonds do not trade much, transaction-based measures may not accurately reflect the liquidity of the bonds that do not trade. Our measure is based on the intuition that facing uncertain redemption requests, open-end mutual funds will optimally choose to hold larger cash buffers if their portfolio securities are less liquid. Our measure is therefore captured by the coefficient on fund flow volatility in the regression of cash-to-assets ratios.

We find greater illiquidity for speculative grade and to some extent smaller bonds. Consistent with prior literature (Bao, Pan, and Wang (2011), Dick-Nielsen, Feldhütter, and Lando (2012)), our measure indicates greater illiquidity during the financial crisis. While aggregate liquidity has recovered since the crisis, it has not returned to pre-crisis levels. We find a particularly significant deterioration in the liquidity of speculative-grade bonds.

Our measure can be applied to asset-backed securities, syndicated loans, and municipal securities for which publicly available data on transactions are not available.

References

Acharya, V. V., and L. H. Pedersen. 2005. Asset pricing with liquidity risk. *Journal of Financial Economics* 77:375–410. doi:10.1016/j.jfineco.2004.06.007.

Adrian, T., M. Fleming, O. Shachar, and E. Vogt. 2017. Market liquidity after the fiinancial crisis. *Annual Review of Financial Economics* 43–83.

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

Amihud, Y., and H. Mendelson. 2001. Asset pricing and the bid-ask spread. *Journal of Financial Economics* 17:223–49.

Anderson, M., and R. M. Stulz. 2017. Is post-crisis bond liquidity lower? Dice Center Working Paper 2017-09.

Bao, J., M. O'Hara, and X. Zhou. 2017. The Volcker Rule and corporate bond market-making in times of stress. *Journal of Financial Economics* forthcoming.

Bao, J., J. Pan, and J. Wang. 2011. The illiquidity of corporate bonds. *Journal of Finance* 66:911–46.

Bessembinder, H., S. Jacobsen, W. Maxwell, and K. Venkataraman. 2017. Capital commitment and illiquidity in corporate bonds. *Journal of Finance* forthcoming.

Chordia, T., R. Roll, and A. Subrahmanyam. 2001. Market liquidity and trading activity. *Journal of Finance* 56:501–30. doi:10.1111/0022-1082.00335.

Coval, J., and E. Stafford. 2007. Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics* 86:479–512.

Dick-Nielsen, J., P. Feldhütter, and D. Lando. 2012. Corporate bond liquidity before and after the onset of the subprime crisis. *Journal of Financial Economics* 103:471–92.

Duffie, D., N. Gârleanu, and L. H. Pedersen. 2007. Valuation in over-the-counter markets. *Review of Financial Studies* 20:1865–900.

Evans, R. B. 2010. Mutual fund incubation. *Journal of Finance* 65:1581–611.

Feldhütter, P. 2012. The same bond at different prices: Identifying search frictions and selling pressures. *Review of Financial Studies* 25:1155–206.

Lesmond, D., J. Ogden, and C. Trzcinka. 1999. A New Estimate of Transaction Costs. *Review of Financial Studies* 12:1113–41.

Pastor, L., and R. F. Stambaugh. 2003. Liquidity risk and expected stock returns. *Journal of Political Economy* 111:642–85.

Roll, R. 1984. A simple implicit measure of the effective bid-ask spread in an efficient market. *Journal of Finance* 39:1127–39.

Trebbi, F., and K. Xiao. 2016. Regulation and market liquidity.

Appendix

Table A1
Variable definitions

Variable	**Definition**
Bond size	Offering amount in millions from Mergent FISD.
$\frac{Cash}{TNA}$	The level of cash is long positions in cash (C), currency (CH), certificates of deposit (CD), commercial paper (CP), repurchase agreements (CR), money market mutual funds (FM), stable value funds (SV), and Treasury and Agency securities (BD, BG, and BT) with original maturities of less than one year.
Credit Rating	Credit rating from FISD is set in the following order: Moody's, S&P, Fitch.
Equity portfolio share	The net value of all equity (E) positions divided by TNA.
ETF portfolio share	The net value of fund's holdings of ETF divided by TNA. ETFs are CUSIPs with CRSP share code equatl to 73.
$\frac{Gross}{Net}$	Gross value of all positions divided by their net value.
Mutual fund ownership	Fraction of a given fund owned by other mutual funds. Holdings by other mutual funds are from CRSP Mutual Fund Database.
Redemption fee	Binary variable equal to one if any one of the fund's share classes imposes redemption fees. Redemption fee information is from CRSP Mutual Fund Database.
σ	Standard deviation of monthly fund flows over the last twelve months. Fund flows are calculated as $\frac{TNA_{f,t}-(1+r_{f,t})\times TNA_{f,t-1}}{TNA_{f,t-1}}$. Observations with lagged TNA of less than \$10 million as well as observations that correspond to fund mergers are excluded from the calculation. At least nine monthly observations are required. Flow volatility is winsorized each quarter at the 99th percentile.
TBA portfolio share	The value of TBA securities divided by the net value of all portfolio securities. We consider long positions in Morningstar data to be a TBA agency MBS if a) its security type is BG and b) it does not have a CUSIP.

Figure A1
Share of Observations by Bond Size Bucket

This figure reports the share of observations in the data by bond size bucket.

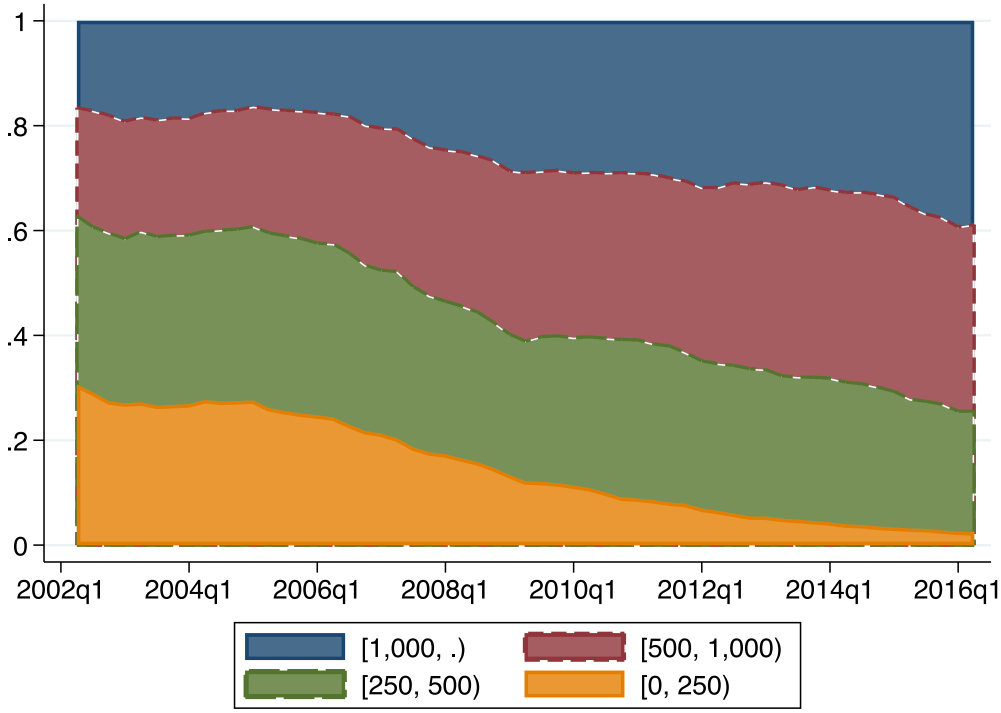


Figure A2
Mutual Fund Holdings of Corporate Bonds with No Trades in TRACE

This figure reports the share corporate bond positions in the data that do not report any trades in TRACE during a given quarter.

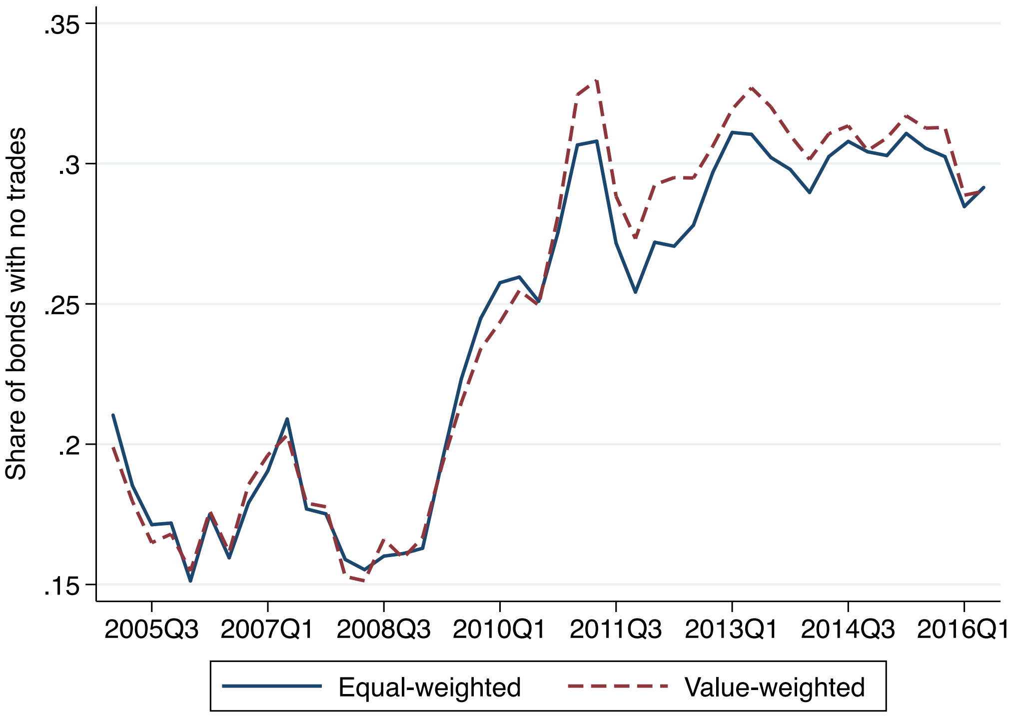


Figure A3
Autocorrelation in Flow Volatility (σ)

This figure shows that there is no time trend in the autocorrelation in flow volatility and that changes in autocorrelation are unlikely to drive changes in the sensitivity of the cash-to-assets ratio to flow volatility, estimated using lagged fund flows. Each quarter we estimate the correlation between between current and lagged values of σ.