NBER WORKING PAPER SERIES

MEASURING THE PERCEIVED LIQUIDITY OF THE CORPORATE BOND MARKET

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Working Paper 27092
http://www.nber.org/papers/w27092

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
May 2020

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NBER Working Paper No. 27092
May 2020
JEL No. G12,G23

ABSTRACT

We propose a novel measure of bond market liquidity that does not depend on transaction data: the strength of the cross-sectional relationship between mutual fund cash holdings and fund flow volatility. Our measure captures how liquid funds perceive their portfolio holdings to be at a given point in time. The perceived liquidity of speculative grade and Rule 144A bonds is significantly lower than investment grade bonds in the cross section and deteriorated significantly following the 2008-9 financial crisis. Our measure can be applied in settings where either transaction data are not available or transactions are rare, including the markets for asset-backed securities, syndicated loans, and municipal bonds.

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1 Introduction

The liquidity of corporate bond markets is crucial to their functioning. If investors are forced to sell bonds into an illiquid market, the price impact of these sales can be amplified through fire sales channels, threatening financial stability and real economic activity (e.g., Shleifer and Vishny (1992), Coval and Stafford (2007), Ellul, Jotikasthira, and Lundblad (2011), and Stein (2012)). As the share of corporate bonds held by investors like mutual funds who may need to sell their holdings quickly has grown,[1] so have concerns about liquidity and the potential for fire sales.[2] These developments make it important to understand investors' perceptions of corporate bond market liquidity and to develop measures of market liquidity that are forward looking and capture the risk that liquidity suddenly evaporates.

The literature has proposed many measures of the liquidity of individual corporate bonds, including Roll (1984), Amihud (2002), Chen, Lesmond, and Wei (2007), Bao, Pan, and Wang (2011), Jankowitsch, Nashikkar, and Subrahmanyam (2011), Corwin and Schultz (2012), Feldhütter (2012), and Dick-Nielsen, Feldhütter, and Lando (2012). These measures differ substantially in their construction and have various strengths and weaknesses. One key feature they share, however, is that they do not fully capture how liquid bond traders perceive the market to be. In particular, most existing measures rely on the characteristics of trades that actually took place. If investors choose not to trade bonds that they perceive to be relatively illiquid, existing measures will understate the true illiquidity of the overall market. Similarly, if investors care about the risk that liquidity will substantially deteriorate in (as yet unobserved) states of the world where they need to sell, these concerns will not be captured by the existing measures. Recent debate about the liquidity of the corporate bond market has centered exactly around these issues. Regulators who allege that liquidity has not declined point to the traditional measures of price impact among trades that occur. In contrast, market participants who allege that liquidity has declined point to changes in the set of trades that occur; for instance, declines in the trading volume of smaller bonds[3].

[1] According to the Financial Accounts of the United States, also known as the Flow of Funds, mutual funds' share of domestic holdings of corporate bonds tripled from 9.2% in 2000 to 28.3% in 2019.

[2] In 2014, the Financial Stability Oversight Council issued a notice seeking public comments on the financial stability risks posed by the asset management industry. Comments are available at https://www.regulations.gov/docketBrowser?D=FSOC-2014-0001. In October 2016, the Securities and Exchange Commission adopted new rules to strengthen the liquidity management practices of open-end mutual funds.

[3] See, for instance, "For Bond Investors, Bigger is Better", Wall Street Journal (2012). Consistent with a decline in the liquidity of small bonds, the Barclays US Corporate index raised its liquidity constraint on bond size from $250m to $300m in 2017.

In this paper, we propose a novel measure of the perceived liquidity of corporate bond markets that does not depend on quote or transaction data. We take a revealed preference approach based on the cash holdings of open-end 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 funds to meet redemption requests from their clients without trading immediately, instead trading over time in a way that minimizes price impact. Such buffers are particularly valuable when a fund holds relatively illiquid assets. To formalize this intuition, we write down a simple model showing that the optimal size of a fund's cash buffer is related to two factors: the illiquidity of its portfolio securities and the volatility of its inflows and outflows. When a fund holds more illiquid bonds, it holds more cash because being forced to trade those bonds is costlier. Similarly, when a fund faces more volatile flows, it holds more cash because it faces a greater risk of having to liquidate its holdings in order to meet redemption requests. Thus, by examining the cross-sectional relationship between fund cash holdings and flow volatility, we can measure how illiquid funds perceive their portfolio holdings to be. Crucially, our measure is forward looking. It captures funds' perceptions of future liquidity and of the risk that liquidity deteriorates.

We start by providing simulation evidence to establish the feasibility of our procedure. While our simple model is static to highlight the basic intuition, our simulations follow Connor and Leland (1995) and consider the dynamic problem of a fund that holds both cash and an illiquid asset while facing stochastic flows. In our simulations, we consider different funds that vary in terms of the illiquidity of the illiquid asset they hold. We simulate flows and cash holdings assuming these funds follow the optimal policy in Connor and Leland (1995). We then regress simulated fund cash holdings on the estimated volatility of the fund's flows, computed in sample using realized flows. The simulations show that in a realistic dynamic setting, 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 open-end corporate bond mutual funds from July 2009 to June 2016. In our benchmark specifications, we expand the panel to the security-fund-time level. This serves two purposes. First, it allows us to include security-time fixed effects. Thus, the regressions tell us how cash holdings vary with flow volatility, comparing two funds that hold the same security at the same time. This allows us control for funds' endogenous selection of securities, something that is missing from our basic model and simulations, where flow volatility and illiquidity are independent. In particular, one might expect funds facing higher flow volatility to hold more liquid securities, thereby biasing towards zero the cross-sectional relationship between cash and flow volatility. Second, expanding the panel to the security-fund-time level allows us to interact the fund's flow volatility with bond characteristics, so that we can measure how perceptions of liquidity vary with characteristics.

We first verify the basic logic of the procedure, running panel regressions relating a fund's cash holdings to the volatility of its fund flows and including security-time fixed effects. We find a strong positive relationship that is both economically and statistically significant. A one-standard deviation increase in flow volatility is associated with a 46 basis point higher cash-to-assets ratio, relative to a median ratio of 320 basis points.

Having verified the basic logic of the procedure, we examine perceived illiquidity 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. We find that the relationship between cash holdings and flow volatility is stronger for speculative grade and unrated bonds, consistent with these securities being perceived as significantly less liquid. In addition, we find that Rule 144A bonds and secured bonds are perceived to be less liquid, consistent with there being a smaller investor base eligible to buy these bonds.

We next examine whether perceived illiquidity is priced. Since our procedure does not produce a measure of illiquidity bond-by-bond, we take an indirect approach. We ask whether bonds that have high spreads also have high levels of perceived illiquidity according to our measure. Specifically, we estimate our baseline regressions adding interactions of flow volatility with the bond's spread. We find that bonds with higher spreads are perceived to be less liquid, even controlling for a variety of other characteristics, including credit ratings. This result is consistent with perceived illiquidity commanding a premium in the cross section.

We then conduct three empirical exercises that demonstrate the advantages of our methodology relative to existing measures. First, we show that our procedure can be used to make consistent comparisons of perceived illiquidity across different asset classes that have different market microstructures and different degrees of data availability. We separately estimate the perceived illiquidity of domestic equities, foreign equities, corporate bonds, and municipal bonds using our procedure. Specifically, we create security-fund-time panels of mutual fund holdings for each asset class. We then regress fund cash holdings on flow volatility within each asset class and compare the coefficients across asset classes. We find that foreign equities are perceived to be less liquid than domestic equities. Corporate bonds are perceived to be significantly less liquid than equities and significantly more liquid than municipal bonds.

Second, we demonstrate that our procedure can be used to measure the perceived illiquidity of securities that do not trade, or that trade too infrequently to construct reliable transaction-based measures of liquidity. Specifically, we examine the cross section of perceived liquidity for municipal bonds, a setting where trade is infrequent: 70% of all municipal bonds held by mutual funds do not trade in a given month. We run our baseline regressions adding interactions of flow volatility with dummies indicating that a bond did not trade at all during the last three months. As we found in our cross-asset class results, the average municipal bond held by mutual funds is perceived to be significantly less liquid than the average corporate bond held by mutual funds. Municipal bonds that do not trade are perceived to be more illiquid than the average municipal bond, but the magnitudes are moderate. This suggests that transaction volume is not a strong proxy for perceived liquidity in the municipal bond market.

Finally, we examine how the perceived liquidity of corporate bonds has evolved over time. Market participants have expressed concern that liquidity has declined since the 2008-9 financial crisis, ascribing these declines in part to the Volcker Rule and banks' reluctance to use their balance sheets to intermediate the corporate bond market. However, standard measures of liquidity that are based on transactions suggest that liquidity is comparable to the pre-crisis period (e.g., Tobias et al. (2017)). Since our methodology fundamentally only relies on a single cross section, we can use it to measure how the perceived illiquidity of the bond market evolves over time. Specifically, we allow time variation in the cross-sectional relationship between fund cash holdings and flow volatility, running regressions of cash holdings on flow volatility interacted with dummies for the pre-crisis, crisis, and post-crisis periods. For investment grade corporate bonds and equities, we find that perceived liquidity deteriorated in the crisis, but returned to pre-crisis levels after the crisis. In contrast, the perceived liquidity of speculative grade corporate bonds deteriorated in the crisis, but did not recover.

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), Schestag, Schuster, and Uhrig-Homburg (2016), and many others. Most of these papers first estimate security-level liquidity and then aggregate up to market liquidity. Our approach differs from most of these papers in two ways. We focus on bonds held by mutual funds, and 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 mutual fund managers, an important group of market participants. Our approach offers two key advantages. First, it captures the forward-looking perceptions of fund managers. Second, it allows us to estimate liquidity for securities that do not trade very often.

These features are useful in light of debates about bond market liquidity since the 2008-9 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. (2018) 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. Tobias et al. (2017) finds little evidence of deterioration in a variety of price-based measures of liquidity, while Anderson and Stulz (2017) and Bao, O'Hara, and Alex Zhou (2018) find evidence of deterioration around stress events. One possible reconciliation of these differing perspectives is that standard measures do not fully capture perceived liquidity. This could be because fund managers worry about the risk of a sudden liquidity freeze that has not yet occurred or because liquidity has deteriorated for a subset of bonds that do not trade frequently. Our methodology allows us to assess these possibilities, and we find evidence for them.

Schultz (2017) shows that dealers increasingly rely on pre-arranged trades. Such trades offer better prices and lower price impact but at the cost of immediacy. This message is reinforced by Goldstein and Hotchkiss (2020), who argue that observed spreads may fail to capture cross-sectional and time-series variation in expected liquidity because dealers endogenously adjust their behavior. Our methodology captures mutual fund managers' perception of liquidity and the trade-off between price impact and immediacy.

Our approach shares some similarities with Mahanti et al. (2008). They define a bond's "latent liquidity" as the weighted average portfolio turnover of investors who hold the bond. Therefore, like our measure of perceived liquidity, latent liquidity does not rely on transactions data and can be used in markets with infrequent trading. There are some important differences, however. First, our perceived liquidity measure is forward looking, reflecting mutual fund managers' expectations of future liquidity and the risk that liquidity evaporates. Second, our measure allows for comparisons of liquidity over time and across asset classes. In contrast, turnover may be driven by factors other than liquidity in both the time series and across asset classes. For this reason, the Mahanti et al. (2008) measure of latent liquidity is defined as the bond's percentile ranking at a given point in time. Thus, it can only be used to measure liquidity in the cross section of a single asset class by construction.

2 Empirical Framework

2.1 Static Model

To help fix ideas and motivate our empirical procedure, we begin by presenting a simple static model linking the liquidity of a fund's assets to its cash holdings. Consider a single mutual fund with one dollar of assets that faces outflows x that are normally distributed with mean zero and variance σ^2. The fund can 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. We assume that cash is available in elastic supply and that each dollar of cash reserves is associated with carrying cost i. One can 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 uses cash to minimize the transaction costs it must incur to meet outflows. In a more realistic dynamic model like the one we explore below in simulations, a cash buffer also allows the fund to net inflows and outflows across time, reducing the total volume of the illiquid asset it needs to transact.

2.1.2 Optimal cash reserves

We now solve for the fund's optimal holdings of cash reserves R. Proposition 1 characterizes optimal cash 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 its 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. 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. These costs depend on the illiquidity of the noncash asset and expected total outflows, which in turn are determined by the volatility of outflows.

Proposition 2 *Assuming $i \leq \frac{c}{2}$, the optimal cash-to-assets ratio r^* satisfies 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.[4] 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.[5]

The model could be generalized in at least 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. 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 introduce uncertainty about the illiquidity of the noncash asset. Such uncertainty would capture liquidity risk and increase cash holdings for precautionary reasons.[6]

[4] In the model, cash holdings and the cash-to-assets ratio are the same because we assume without loss of generality that the fund has \$1 of assets.

[5] It is worth noting that the fund's cash holdings are not necessarily optimal from a social planner's perspective. If transaction costs are simply a transfer between funds and outside liquidity providers, a planner may prefer that funds not hold cash. Alternatively, if there are fire sale externalities, a planner would internalize these externalities and would have funds hold larger cash buffers (Chernenko and Sunderam, 2020). The fact that the funds' privately optimal cash buffers may be different from the socially optimal level does not affect the logic of our methodology. Our empirical approach relies on cross sectional variation in cash buffers, not on their absolute size.

[6] There are two ways to incorporate liquidity risk in the model. First, uncertainty about illiquidity could increase expected liquidation costs. Second, liquidation costs could covary with outflows. Formally, the first order condition in the baseline model takes the form $i - c\frac{d}{dR}E[x - R|x > R] = 0$. If we make c stochastic but uncorrelated with x, the first order condition would take the form $i - E[c]\frac{d}{dR}E[x - R|x > R] = 0$. If $E[c]$ is increasing in uncertainty about liquidation costs, then optimal cash reserves will be increasing in that

2.2 Methodology

We now discuss three aspects of our methodology for taking the basic intuition that arises from the model to our data on mutual fund holdings of corporate bond. First, we explain why we prefer to examine the cross-sectional relationship between cash and flow volatility, rather than simply examining the level of cash. Second, we explain why our methodology is best suited to estimating perceived liquidity at market level, rather than the bond level. Third, we explain why we prefer to run our regressions at the security-fund-time level, rather than the fund-time level.

In the simple model above, both the level of cash and its cross-sectional relationship with flow volatility are informative about the illiquidity of the noncash asset. In practice, cash holdings are determined by many factors other than liquidity management considerations. For instance, some funds may pursue strategies that involve holding dry powder until good investment opportunities arise. In addition, the use of derivatives and leverage, including short selling, involve margin accounts that require funds to have cash on hand. The cross-sectional relationship between cash and flow volatility is less likely to be contaminated by these factors and therefore is a better measure of perceived liquidity.

To see why our methodology is best suited to estimating perceived liquidity at market level, suppose that following the intuition of Proposition 2 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 portfolio securities.[7] 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 16,000 unique bonds, 300 funds, and 84 months worth of data, the system is not identified.

One way to make progress on identification is to assume that each bond has constant illiquidity over time

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

uncertainty. If c stochastic and correlated with x, the first order condition becomes

$$i - \frac{d}{dR}(E[c|x > R]E[x - R|x > R] + Cov[c, x - R|x > R]) = 0.$$

So optimal cash reserves increase with the covariance between liquidation costs and outflows.

[7] 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.

Equation 2 then reduces to $F \times T$ equations in B unknowns. Even though we have enough fund-date observations to identify bond-specific illiquidity, assuming time-invariant liquidity is rather unrealistic, and our power will be relatively low.

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

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

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.

A third question is whether to bring our model intuitions to the data at the fund-time level or security-fund-time level. At the fund-time level, we could calculate the share of each fund's portfolio invested in different categories and estimate a regression of the cash-to-assets ratio on the portfolio shares interacted with flow volatility

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

where $w_{k,f,t}$ is the share of the portfolio invested in category k bonds. The coefficients $\beta_{1,t}, \ldots, \beta_{K,t}$ would then capture the time-varying illiquidity of different categories.

Alternatively, we could estimate the regression at the security-fund-time level:

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

where $I(k)_{b,t}$ is an indicator variable for bond b belonging to category k at time t. An advantage of this approach is that it allows us to control for the endogeneity of security choice. If funds with volatile fund flows choose to hold more liquid securities and smaller cash buffers, this would bias downwards the estimated $\beta_{k,t}$ coefficients in Equation 3. With the inclusion of bond-date fixed effects in Equation 4, we can look at how cash holdings vary with flow volatility across funds holding the same bond, thus alleviating the selection problem at the cost of only being able to estimate perceived liquidity for bonds held by multiple mutual funds.[8] Because our explanatory variable is calculated at the fund level,

[8] If there is no selection problem and all bonds are held by multiple mutual funds, then running Equation 4 with appropriate weights should result in similar estimates to running Equation 3.

for proper statistical inference, we will need to adjust the standard errors for clustering by fund-time.

2.3 Simulation

We next run two types of simulations to validate our methodology. In this section, we validate the idea of estimating position-level regressions by running a simulation showing that the coefficients $\beta_{k,t}$ in Equation 4 do indeed recover the average illiquidity of bonds in different categories. The simulation procedure is as follows:

1. Initialize a sample of 5,000 bonds.
   - Assign each bond to one of 10 categories. Bonds in different categories will vary in their average illiquidity.
   - For each bond in category $k \in \{1 \dots 10\}$, randomly draw its illiquidity from the log-normal distribution with $\mu = 0.15k$ 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 500 funds.
   - Assign each fund to one of 10 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 of 200 bonds from bonds that belong to the fund's objective.
3. Initialize a sample of 100 flexible funds that can invest in all bond categories.
   - Randomly sample each fund's portfolio of 200 bonds from all 5,000 bonds.
4. Calculate portfolio illiquidity as the mean of bond level illiquidity.
5. Draw each fund's flow volatility, σ_f, from a lognormal distribution with mean 0.051 and standard deviation 0.028. These values are set to approximately match the empirical distribution of flow volatility in our data.
6. Set each fund's cash-to-assets ratio according to

$$\left(\frac{Cash}{TNA}\right)_f = Illiquidity_f \times \sigma_f + 0.025 \times \varepsilon_f, \tag{5}$$

where ε is standard normal. The magnitude of the random shock is set to match the standard deviation of the residuals from the regression of the cash-to-assets ratio on fund characteristics in column 8 of Table 2.

7. In the simulated holdings data, estimate the regression

$$\left(\frac{Cash}{TNA}\right)_{b,f} = \alpha_b + \sum_k \beta_k \cdot (1)_k \times \sigma_f + \nu_{b,f} \tag{6}$$

adjusting the standard errors for clustering by fund.

8. Run the simulation 100 times.

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 category from a single run of the simulation. Figure 1b is a box plot of the estimated β_k coefficients across simulations measuring liquidity of each bond category. The figures show that our methodology does a good job of uncovering the average liquidity of bonds in each category. Furthermore, differences in the estimated coefficients map linearly into differences in liquidity. This means that our methodology allows us to use the estimated coefficients on flow volatility to compare liquidity in both the cross section and over time.

2.4 Dynamic model

The simulation in the previous section uses the simple static model in Section 2.1 and assumes that at each point in time the cash-to-assets ratio is set as a linear function of portfolio illiquidity. How well does our methodology measure illiquidity in a dynamic setting?

In this subsection, we investigate the performance of our methodology in the dynamic environment studied by Connor and Leland (1995) in their model of fund cash management. In their setting, a fund receives stochastic flows and can hold either cash or a non-cash illiquid asset (representing a basket of securities). The fund dynamically manages its response to flows and its cash position to trade off the carrying costs of cash against the transaction costs of trading the illiquid asset. The optimal solution is for funds to manage cash using an Ss-type rule. Funds accumulate inflows in cash until their cash-to-assets ratio reaches an upper bound L. If the cash-to-assets ratio exceeds L, the fund rebalances back to L. Funds accommodate outflows by drawing down their cash buffers until their cash-to-assets ratio reaches zero. If they have further outflows, they accommodate these outflows by liquidating some of their holdings of the non-cash illiquid asset.

We simulate funds' cash buffers under this policy and estimate regressions of the cash-to-assets ratio on flow volatility. To focus on the dynamics of cash holdings over time, we stick with the assumption in Connor and Leland (1995) that funds do not adjust their securities portfolio and that the only choice variable is the fraction of total assets invested in cash. Thus, in this simulation, each fund holds a single non-cash asset, with funds varying in the illiquidity of their noncash asset and in their flow volatility.

Specifically, we:

1. Create 10 liquidity categories. Funds in different categories will vary in the average illiquidity of their non-cash assets.

2. Simulate 500 funds in each category. Fund $j \in \{1 \ldots 500\}$ in category $k \in \{1 \ldots 10\}$, faces cost $0.01 + \frac{1}{10} \times k + \frac{1}{500} \times j$ per dollar of transacting in its illiquid asset.

3. Draw each fund's flow volatility, σ_f, from a lognormal distribution with mean 0.051 and standard deviation 0.028. These values are set to approximately match the empirical distribution of flow volatility in our data.

4. Given each fund's flow volatility, simulate a time series of 200 months of flows and the fund's optimal response to those flows.

5. Estimate each fund's flow volatility as the in-sample standard deviation of its realized flows.

6. Within each $k \in \{1 \ldots 10\}$, regress funds' realized cash-to-assets ratio on their estimated flow volatility using the pooled fund-month sample for funds in category k.

Figure 2 plots the regression coefficient for category k against the average illiquidity of the funds in category k. The figure shows that regression coefficients increase with illiquidity, demonstrating that the intuition for our procedure sketched in our static model does continue to hold in a more complex dynamic setting. Note furthermore that, in this setting, the relationship between regression coefficients and illiquidity appears to be slightly concave. This means that a doubling of regression coefficients is associated with a more than doubling in the illiquidity of the underlying asset. Thus, it is conservative to interpret our regression coefficients linearly – that is, to interpret a doubling in the coefficient as a doubling of illiquidity.

3 Data

Our main data set consists of long positions in corporate bonds held by actively managed open-end mutual funds that invest primarily in corporate bonds. Definitions of all variables can be found in the appendix. Fund holdings and characteristics are from Morningstar, while bond characteristics are from Mergent FISD. Corporate bonds are defined as the corporate debenture (CDEB) bond type in FISD. We define corporate bond mutual funds as funds that invest at least 50% of their total net assets (TNA) in corporate bonds and are in one of the following Morningstar categories: Corporate Bond, Emerging Markets Bond, High Yield Bond, Intermediate-Term Bond, Long-Term Bond, Multisector Bond, Nontraditional Bond, World Bond.

Since the relationship between flow volatility and cash holdings may not be informative of the portfolio holdings liquidity during the fund's incubation period, we exclude funds that are less than two years old (Evans, 2010) and funds with less than \$10 million in TNA. To guard against potential data errors, we require the ratio of the net market value of portfolio securities to fund TNA to be in the $[0.5, 1.5]$ interval. Such filters are common in the literature (e.g., Coval and Stafford (2007)).

In most of our analyses, the sample period is July 2009–June 2016. The sample period is limited by the availability of daily fund flows in Morningstar starting in July 2008. Rather than start the sample period in the middle of the financial crisis, we conduct our cross sectional analyses using post-crisis data. To study the effects of the financial crisis and the behavior of our measure of illiquidity in the time series, we construct an alternative measure of flow volatility that utilizes monthly fund flows estimated based on fund TNA and returns. Although this measure is coarser than daily fund flow volatility, it allows us to extend the sample period to July 2002–June 2016.

Overall, the main corporate bond sample consists of 286 funds holding 15,505 unique bonds.

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 "Mutual Fund - Open End" (security type code `FO`) or as "Equity - Unidentified" (`EQ`) rather than as "Mutual Fund - Money Market" (FM).[9] We use the 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" (texttQ).[10] 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.[11]

As previously mentioned, in calculating the level of cash holdings we include only long positions. Negative values of Morningstar security code C (Cash) correspond to short positions in CDS and other derivatives.[12] 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 3a shows the distribution of the cash-to-assets ratio over time. Except for the periods around the financial crisis and the European sovereign debt crisis, the distribution is relatively stable. The median fund holds about 3.2% of its portfolio in cash and equivalents.

3.2 Flow volatility

Our key explanatory variable is the volatility of fund flows. In our main analyses, we use the dollar value of actual daily fund flows reported by Morningstar. We scale these by the

[9] About 3% of all holdings of money market funds are misclassified this way.

[10] About 43% of CP holdings are classified as "Unidentified Holding" (Q), another 13% are classified as "Bond - Corporate Bond" (B).

[11] 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 (Bond - Corporate Bond) or Q (Unidentified Holding). 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.

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

TNA at the end of the previous month and calculate the standard deviation of scaled fund flows during the last three months, requiring at least twenty observations. Scaled fund flows are winsorized at the 1st and 99th percentiles within each month.

Since daily flows are available in Morningstar only starting in July 2008, to study time series changes in liquidity over the 2002–2016 period, we use the volatility of monthly fund flows. 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 at least nine observations.

Figure 3b shows the distribution of flow volatility over time. Over the full sample period, the interquartile range is between 3.2% and 6.3%. There are noticeable increases in flow volatility during the financial crisis, the European sovereign debt crisis, and in late 2015.

3.3 Municipal bonds

We use the sample of municipal bonds held by municipal bond funds to analyze the illiquidity of bonds that do not trade and that as a result lack standard transaction-based measures of liquidity. Municipal bonds are a good laboratory for comparing the liquidity of securities that do and do not trade. Our sample of municipal bonds consists of valid CUSIPs with Morningstar security types "Muni Bond - General Obligation", "Muni Bond - Revenue", and "Muni Bond - Unspecified". The sample of municipal bond funds consists of funds that invest at least 50% of their TNA in municipal bonds and whose Morningstar category includes the word "muni." Short-term funds (with the word "short" in their category name) are excluded as it is difficult to tell whether their cash holdings are driven by liquidity management or investment mandate.

As with corporate bond funds, we exclude a) funds that are less than two years old, b) funds with less than $10 million in TNA, and c) funds for which the ratio of the market value of portfolio securities to TNA is not in the $[0.5, 1.5]$ interval. Overall, the municipal bond sample consists of 482 unique funds holding 114,485 unique bonds.

3.4 Equity funds

As a benchmark, we also compute our measure of perceived liquidity for domestic and foreign equities. Our sample of domestic equities consists of CUSIPs with CRSP share codes 10 and 11 that are listed on stock exchanges with codes 1–3. The sample of domestic equity funds consists of funds that invest at least 50% of their TNA in domestic stocks. Overall, the domestic stock sample consists of 1,716 unique funds holding 4,891 unique stocks.

The sample of foreign stocks consists of securities that are identified by Morningstar as equities and that are either not in CRSP or have CRSP share codes 12 or 30–39.[13] Foreign equity funds are funds that invest at least 50% of their TNA in foreign stocks. Overall, the foreign equity sample consists of 759 unique funds holding 23,615 unique stocks.

3.5 Summary statistics

Table 1 reports summary statistics for our main sample of corporate bonds held by corporate bond mutual funds during the July 2009–June 2016 period. In panel A the unit of observation is fund-date. The median fund has TNA of $440 million, cash-to-assets ratio of 3.2%, and monthly flow volatility of 4.5%. Most funds take only long positions: the 75th percentile of the gross to net value of portfolio securities is 1.01. For most funds, the portfolio shares of TBA securities, equities, and ETFs, which could be potentially liquidated first to meet redemption requests, are very small. About 18% of all fund-date observations impose redemption fees.

Panel B reports summary statistics for bonds. The median bond has a par value of $500 million. Credit ratings are encoded so that $AAA = 0, AA+ = 1$, etc. Thus the 25th, 50th, and 75th percentiles of the distribution correspond to BBB+, BBB-, and BB- credit ratings. In a given quarter, the median bond is held by 8 funds in the final sample.

4 Results

We start by presenting results verifying there is a significant relationship between the cash-to-assets ratio and fund flow volatility. Subsection 4.2 establishes the robustness of these results by showing that the relation between fund flow volatility and the cash-to-assets ratio is not driven by the level of flows or by fund returns. In subsection 4.3 we examine the cross section of perceived liquidity, showing that speculative-grade and Rule 144A bonds are perceived to be less liquid. Subsection 4.4 shows that perceived illiquidity is priced. Finally, we conduct three exercises that demonstrate the advantages of our methodology. First, in subsection 4.5 we use our methodology to consistently compare perceived liquidity across asset classes. Second, in subsection 4.6 we measure the perceived illiquidity of municipal bonds, an asset class for which it is difficult to construct reliable transaction-based measures

[13] Share code 12 refers to Ordinary Common Shares of companies incorporated outside the US. Share codes 30–39 refer to American Depository Receipts (ADRs) of foreign firms.

of liquidity because trade is infrequent. Third, in subsection 4.7 we study time series changes in perceived liquidity. We show that perceived liquidity has declined substantially, especially for speculative-grade and Rule 144A bonds.

4.1 Baseline results

We begin by verifying a baseline implication of our motivating model in Section 2.1: that funds facing higher flow volatility do indeed hold more cash. Table 2 presents regressions of the cash-to-assets ratio on fund flow volatility:

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

We include the following controls in $X_{f,t}$: (i) the fund's log TNA and the fund family's log total TNA, which allow for economies of scale in cash management; (ii) the fund's leverage (ratio of gross assets to net assets) because the use of leverage, including short sales, involves holding cash in margin accounts; (iii) whether the fund has redemption fees, which can reduce the need for large cash buffers; (iv) the share of the fund's assets invested in agency MBS through the to-be-announced (TBA) market, which involves holding cash in margin accounts; (v) the share of the fund's assets invested in equities and ETFs, which are more liquid than corporate bonds. We standardize all continuous variables except for flow volatility so that their coefficients represent the effect of a one standard deviation change. Standard errors are adjusted for clustering by fund-date, the level at which we measure our key explanatory variable.

Columns 1–4 of Table 2 weight observations by their portfolio share, giving more weight to observations that make up a larger share of a fund's portfolio and that therefore contribute more to the overall illiquidity of a fund's portfolio.

In column 1, the coefficient on flow volatility is 0.166 and is highly statistically significant. The interpretation is that a one standard deviation increase in the annualized daily flow volatility of 2.78% is associated with a 46 basis point higher cash-to-assets ratio. Relative to the median cash-to-assets ratio of 320 basis points, this is a sizable effect.

The coefficient on fund size is positive. Although larger funds may enjoy certain economies of scale, they are also more likely to trade derivatives or to short securities, both of which require funds to hold cash collateral. Consistent with this idea, the coefficient on the ratio of gross to net assets is positive, indicating that funds that use leverage have higher cash-to-assets ratios. The coefficient on the portfolio share of TBA agency mortgage-backed securities is large and positive: funds that commit to purchasing such securities in the future set aside cash to cover these purchases. We do find evidence of significant economies of scale at the family level. Larger families help their funds economize on cash with liquidity management tools like external lines of credit, interfund lending programs, and systems for crossing trades across funds.[14] Finally, the coefficients on ETF share and equity share are negative, consistent with the idea these holdings are more liquid than the average corporate bond held by mutual funds.

One concern with the simple OLS regression in column 1 is that it may be picking up differences in fund objectives and strategies rather than differences in portfolio liquidity. For instance, high-yield funds may engage in more market timing and therefore hold larger cash buffers than other funds. If high-yield funds also face more volatile flows, this could bias the coefficient on flow volatility. In column 2, we add objective-date fixed effects, so we are only identifying the relationship between cash holdings and flow volatility within a given fund style. The coefficient on flow volatility is slightly larger at 0.186.

A second concern with the simple OLS regression in column 1 is selection—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 3 adds bond-date fixed effects. This regression 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 is 0.186, the same as in column 2. Including bond-date fixed effects makes a larger difference for the coefficient on the redemption fees dummy. This coefficient is positive and not statistically significant in columns 1 and 2, but is negative and statistically significant in column 3. These results suggest that funds holding more illiquid securities are more likely to impose redemption fees and to hold larger cash buffers. Column 4 controls for both bond-date and objective-date fixed effects. The results here are similar to column 3.

Columns 5–8 of Table 2 present the equal-weighted results. These are broadly similar in economic and statistical significance to the portfolio-share weighted results in columns 1–4. Comparing the results in columns 4 and 8, the economic magnitude of the coefficient on flow volatility in the equal-weighted regression in column 8 is about 80% of its value in the portfolio-share weighted regression in column 4. Going forward, we will focus on the portfolio-share weighted regressions with bond-date and objective-date fixed effects. The fixed effects help control for the portfolio selection effects, while portfolio share weights give more weight to observations that contribute more to the overall illiquidity of a fund's portfolio. We report the results of the equal-weighted regressions in the Internet Appendix.

[14] See Agarwal and Zhao (2018) on the use of interfund lending in liquidity management.

4.2 Robustness

In this subsection, we rule out alternative explanations for our baseline results in Table 2. In particular, we show our results are robust to controlling for a) past and future fund flows and b) past and future fund returns.

We control for past and future fund flows to show that funds' cash-to-assets ratios are responding to their ex-ante concerns about flow volatility, and not to the ex-post realized flows. For instance, suppose there were no relationship between ex-ante flow volatility and cash-to-assets ratios. A fund that has recently had large inflows may mechanically have high past flow volatility and could have a high cash-to-assets ratio because it is slow to invest those inflows. Conversely, a fund that knows it is likely to have future outflows may build up its cash-to-asset ratio in advance to meet those outflows.

To ensure that any changes in the coefficient on flow volatility are due to the additional controls and not due to changes in the sample, we hold the sample constant across all columns in Table 3 and always require funds to have past and future flows and returns. For brevity, we report only the coefficients on flow volatility and the new control variables. Full regression output is reported in the Internet Appendix.

Column 2 of Table 3 estimates Equation 7, adding the fund's last three months of flows as controls. The coefficients on past flows in column 2 suggest that funds are indeed slow to invest inflows: the cash-assets ratio rises temporarily when funds experience inflows. However, the coefficient on flow volatility is similar to the baseline result in column 1, suggesting that past realized flows do not explain our results. Column 3 adds three months of future flows as controls, and again the coefficient on flow volatility is little changed.

In columns 4 and 5 of Table 3, we control for the fund's past and future returns. Returns could explain our results for two reasons. First, if funds are slow to rebalance, then past returns will mechanically affect a fund's cash-assets ratio by changing the value of the non-cash assets. If returns are correlated with flow volatility, for instance because there is a performance-flow relationship, this could explain our baseline results. Column 4 controls for past returns and shows that the coefficient on flow volatility is unchanged relative to the baseline. The second reason returns could explain our results is that cash holdings may reflect managers' expectations of risk and return. Specifically, fund managers may choose to hold more cash whenever they expect future returns to be low or risk to be high. If these expectations correlate with flow volatility, they could explain our baseline results. Column 5 adds controls for future returns and shows that the coefficient on flow volatility is unchanged.[15] Finally, column 6 controls for past and future returns and past and future flows

[15] Future returns are negatively correlated with the time t cash-to-assets ratio, suggesting that corporate bond funds do have some market timing ability. While it could also be the case that higher cash buffers exert

simultaneously; the results are similar to the baseline. Overall, these results suggest that funds' cash-to-assets ratios are responding to their ex-ante concerns about flow volatility, consistent with our motivating model in Section 2.1.

4.3 Cross-sectional results

We next use our measure, the coefficient on fund flow volatility, to understand what types of bonds are perceived by mutual fund managers to be less liquid. To explore the cross section of perceived illiquidity, Table 4 estimates Equation 7, interacting flow volatility with bond characteristics. All specifications include bond-date and fund objective-date fixed effects, so we are comparing the cash holdings of two funds in the same objective with different flow volatility that hold the same bond at the same time. We weight observations by their portfolio share, giving more weight to observations that make up a larger share of a fund's portfolio and that therefore contribute more to the overall illiquidity of a fund's portfolio.

Column 1 examines the perceived illiquidity of bonds with different credit ratings. The omitted category is AAA, so the raw coefficient on flow volatility captures the liquidity of AAA-rated bonds. The negative coefficient on flow volatility suggests that AAA-rated bonds may be considered a substitute for cash holdings. Despite only small differences in credit risk, AA and A-rated bonds are perceived to be significantly less liquid than AAA-rated bonds. Furthermore, AA and A-rated bonds are perceived to have about the same liquidity. BBB-rated bonds, on the other hand, are perceived to be less liquid than AA and A-rated bonds. There is a large jump in perceived illiquidity from 0.199 to 0.314 at the boundary between investment grade and speculate grade bonds (i.e., between BBB and BB rated bonds). Within speculative grade, there is some evidence that BB-rated bonds are perceived to be somewhat more liquid than B or CCC-rated bonds. Interestingly, unrated bonds are perceived to have similar liquidity to speculative-grade bonds. Overall, these results are consistent with speculative-grade and unrated bonds being less liquid than investment-grade bonds because of greater scope for asymmetric information and because the set of investors who can hold these bonds is smaller, raising search costs (Duffie, Gârleanu, and Pedersen, 2005, 2007).

Columns 3–7 examine other bond characteristics. Larger bond issues are perceived to

a negative drag of fund performance, such a mechanical effect is not large enough to explain the magnitude of the negative correlation. Assuming that the expected annual return on non-cash assets is five percentage points higher than the return on cash holdings, a one percentage point higher cash-to-assets ratio would be expected to lower monthly returns by about $0.01 \times \frac{500}{12} = 0.42$ basis points. In contrast, the results in column 5 indicate that a one standard deviation increase in month $t + 1$ returns of 172 basis points is associated with a $1.72 \times -0.623 = -1.07\%$ lower cash-to-assets ratio.

be slightly less liquid, though the magnitudes are small. A one standard deviation increase in (log) offering amount is associated with an increase in the coefficient on flow volatility of 0.018, which is about 10% of its value in column 4 of Table 2. Column 4 indicates that longer maturity bonds are perceived to be less liquid. This result is consistent with the evidence in Bao, Pan, and Wang (2011) and Feldhütter (2012), who find that the Roll (1984) and Imputed Roundtrip Trade measures of liquidity increase with bond maturity.

In column 5, we find a negative correlation between bond age and perceived liquidity. Bao, Pan, and Wang (2011) find that older bonds are less liquid according to the Roll (1984) measure, while Chen, Lesmond, and Wei (2007) find no effect of bond age on either the percentage of zero returns measure or the Lesmond, Ogden, and Trzcinka (1999) measure.

Rule 144A bonds are perceived to be significantly less liquid, presumably because they can be traded by a smaller set of investors: qualified institutional buyers. Secured bonds are also perceived to be less liquid, presumably due to selection—firms tend to issue secured bonds when they are distressed. Finally, column 8 includes the interactions of flow volatility with all bond characteristics. While the coefficients are somewhat attenuated once we try to distinguish between the effects of different bond characteristics, with the exception of bond maturity, all interaction terms remain statistically significant.

4.4 Is perceived illiquidity priced?

We next turn to the question of whether perceived illiquidity is priced. Since our procedure does not recover bond-level measures of illiquidity, we must take an indirect approach. We ask whether bonds that have high spreads also have high levels of perceived illiquidity according to our measure. Specifically, we estimate our baseline regressions interacting flow volatility with the bond's spread. Because the yield spread on low-rated distressed bonds is likely to be dominated by default risk, we focus our analysis on investment grade bonds, for which liquidity premia are likely to be an important component of yields.

We use two measures of yields. First, we use the bond's offering yield at issuance. Assuming that liquidity is a persistent characteristic, the offering yield will reflect expected future liquidity. Another advantage of the offering yield measure is that we obtain it directly from Mergent FISD. Second, we consider the bond's current yield-to-maturity, which we compute using data on the bond's price, maturity, and coupon payments.[16] While this measure has the potential to better reflect time t perceptions of a bond's liquidity, it may also be somewhat noisy because our calculations may not incorporate all of the bond's payment features.

[16] We use the median price reported by mutual funds holding the bond at the end of month t.

Columns 1–3 of Table 5 report results using the offering yield measure, while columns 4–6 report results using the current yield-to-maturity. In column 1, the interaction flow volatility with the bond's offering yield is positive and significant, indicating that bonds with higher yields are perceived to be less liquid. In other words, our measure of perceived illiquidity does appear to be priced. The economic magnitude is large: a one-standard deviation increase in offering yield is associated with a coefficient on flow volatility that is 0.022 larger, about 35% of the baseline value of 0.062 for the average bond.

Columns 2 and 3 show that similar results hold when we control for credit ratings and additional bond characteristics, as well as their interactions with flow volatility, allowing these characteristics to separately affect perceived illiquidity. Controlling for credit ratings in column 2 has little effect on the magnitude of the estimated coefficient, indicating that our results are not driven by the default component of the yield spread. We find a negative effect of bond size suggesting that larger investment-grade bonds are perceived to be more liquid. This contrasts with the results in Table 4, where we pool investment- and speculative-grade bonds and find that larger bonds are perceived to be less liquid.

In columns 4–6 of Table 5, we report the specifications where we interact flow volatility with the bond's current yield-to-maturity. We find similar results. In fact the magnitude of the effect is somewhat stronger. A one-standard deviation increase in the current yield-to-maturity is associated with a coefficient on flow volatility that is 0.046 larger, almost 60% of the baseline value of 0.080 for the average bond.

4.5 Comparisons across asset classes

One advantage of our methodology is that it can be used to compare perceived liquidity across different asset classes that may have different market microstructures and different degrees of data availability. Assuming that mutual fund managers in different asset classes face similar penalties for tracking error,[17] we can use Equation 7 to estimate their perceptions of illiquidity across different asset classes. This is helpful given that differences in market microstructure and data availability can make it difficult to compute and compare measures of liquidity across asset classes. For example, both the Bao, Pan, and Wang (2011) and Feldhütter (2012) measures can only be computed for asset classes with high-quality transaction data. Similarly, bid-ask spreads may vary across asset classes due to microstructure

[17] Specifically, they face similar penalties for the tracking error generated by allocating a given percentage of their portfolio to cash. This will be the case if investors scale tracking error by the expected return of the asset class. In other words, if equities return 5% and bonds return 2%, investors equally penalize the 5 basis point tracking error generated by an equity fund manager's 1% cash allocation and the 2 basis point tracking error generated by a bond fund manager's 1% cash allocation.

considerations.

Table 6 reports our estimates of perceived liquidity for four asset classes: domestic equities, foreign equities, corporate bonds, and municipal bonds. Comparing the liquidity of domestic versus foreign stocks can be challenging because stocks in different countries may be subject to different market microstructure issues.[18] Furthermore, measures of liquidity constructed using foreign transactions data may not accurately reflect the liquidity available to US-based investors in these markets. One advantage of our liquidity measure is that it captures the liquidity of foreign stocks as perceived by the US-based mutual funds, an important set of investors holding foreign stocks. Measuring liquidity in the municipal bond market is also challenging because, as we discuss in the next section, most municipal bonds trade infrequently, making it difficult to construct traditional transaction-based measures such as the Roll (1984) and Amihud (2002) measures.

Our Morningstar holdings data for mutual funds investing in these four assets classes are limited to January 2012–June 2016. For each asset class, we consider a mutual fund to specialize in that asset class if it invests at least 50% of its portfolio in that asset class. As with our main sample of corporate bond funds, we require funds to be actively managed and at least two years old, and to have TNA of at least $10 million. Summary statistics for the domestic and foreign equity funds and for municipal bond funds are reported in the Internet Appendix.

Table 6 shows that domestic and foreign equities are perceived to be more liquid than corporate and municipal bonds. Foreign equities are perceived to be about 50% less liquid than domestic equities.[19] Note that this estimate is based on the sample of foreign stocks that are held by US-based mutual funds and may thus be skewed toward the more liquid foreign stocks.[20] Corporate bonds are perceived to be significantly less liquid than domestic stocks. Assuming a linear relationship between illiquidity and our estimated coefficients, corporate bonds are almost seven times less liquid than domestic stocks. Municipal bonds (0.336) are even less liquid than corporate bonds (0.137).

[18] See Fong, Holden, and Trzcinka (2017) for discussion and tests of alternative liquidity proxies used in cross-country research.

[19] In unreported regressions we find that emerging markets stocks are perceived to be significantly less liquid than developed markets stocks.

[20] For example, stocks from the frontier markets account for less than 0.5% of all observations.

4.6 Perceived liquidity of securities that do not trade

Another advantage of our methodology is that it can be used to estimate the perceived liquidity of securities that do not trade, while most other liquidity measures rely on transactions data.

We illustrate this advantage in the context of municipal bonds, where a significant fraction of bonds do not trade regularly. Within our sample of municipal bonds held by the municipal bond mutual funds, 70% of all bonds do not trade during a given month. Even for bonds that do trade, many transactions are smaller than $100 thousand in face value, a typical cutoff for differentiating between retail and institutional trades. In our data, only 13% of bond-month observations have at least one customer-dealer transaction for at least $100 thousand in face value.

Table 7 reports our estimates of perceived illiquidity for the cross section of municipal bonds. Columns 1 and 2 of Table 7 show that municipal bonds with no trades during the last three months are perceived to be less liquid than other municipal bonds. The coefficient in column 1 is 0.024, which is about 6.5% of the 0.367 coefficient on flow volatility itself. It may seem surprising that bonds with no trades are perceived to be only slightly less liquid than other municipal bonds. Selection effects may bias us against finding a larger effect of no trade. First, because our regression specifications include bond-date fixed effects, our estimation results are limited to bonds that are held by at least two mutual funds. Out of all bond-month observations in our data, 71.5% are held by a single fund. The fact that a bond is held by multiple mutual funds may lower the search costs of finding a counterparty to trade with, meaning that bonds held by multiple funds are more liquid. Second, mutual funds may choose to invest in more liquid bonds, so bonds with zero transactions held by mutual funds may be significantly more liquid than bonds with zero transactions not held by mutual funds.

Table 7 studies the same bond characteristics as Table 4, where we examined the cross section of corporate bonds. In addition, we add a characteristic that is specific to the municipal bond market: whether the bond is a general obligation bond or not.[21] Mutual funds invest primarily in revenue bonds; general obligations bonds account for only 15% of the position-level observations in our data. The results in Table 7 suggest that general obligation bonds are perceived to be significantly less liquid than revenue bonds, helping to

[21] Another bond characteristic unique to the municipal bond market is bond insurance. Before the financial crisis, many municipalities obtained bond insurance from AAA-rated monoline insurance firms. By giving the bonds AAA ratings, bond insurance likely made them more liquid. During our sample period, however, less than 1% of insured bonds were rated AAA, and almost 60% were rated A+ or below. As a result, bond insurance does not have the same effect during our sample as it did in earlier periods, and we do not include it in our regression specifications.

explain why mutual funds invest only a small fraction of their portfolios in general obligation bonds.

Columns 3 and 4 of Table 7 repeat the analysis in columns 1 and 2 using a dummy variable for bonds with no trades with face value of at least \$100 thousand. We find somewhat stronger results with the coefficient on the no trades dummy in column 3 almost 40% larger than the coefficient in column 1. The difference in results is consistent with small retail trades having little effect on mutual funds' perceptions of liquidity.

4.7 Time series results

Having shown that our measure behaves sensibly in the cross sections of corporate and municipal bonds, as well as across asset classes, we turn to examining the time series behavior of perceived liquidity. Market participants have expressed concern that liquidity has deteriorated since the 2008-9 financial crisis, ascribing declines in liquidity in part to the Volcker Rule and banks' reluctance to use their balance sheets to intermediate the corporate bond market. However, standard measures of liquidity that are based on transactions suggest that liquidity is comparable to the pre-crisis period.[22] Perceptions of illiquidity can deviate from these standard measures for several reasons. For example, fund managers may worry for the risk of a sudden liquidity freeze, which would not be captured by backwards-looking measures based on realized transactions. Similarly, they may worry about their ability to transact at larger-than-average volumes on short notice. In addition, they may place more weight on the liquidity of bonds they hold that do not trade often. Our measure can therefore be helpful in shedding light on how post-crisis liquidity is perceived by an important subset of investors in the corporate bond market.

Table 8 reports regression Equation 7, interacting flow volatility with indicator variables for various subperiods. The *Pre-crisis* period is July 2002–August 2008. We define the *Crisis* period as September 2008–June 2009. Finally, the *Post-crisis* period is July 2009–June 2016. Since daily flows data are not available before August 2008, we calculate flow volatility using monthly flows over the last twelve months, requiring at least nine observations.

In Panels A and B of Table 8, we include bond-date and fund objective-date fixed effects, so we are comparing the cash holdings of two funds in the same objective with different flow volatility that hold the same bond at the same time. We weight observations by their portfolio share, giving more weight to observations that make up a larger share of a fund's

[22] Bessembinder et al. (2018) 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. Tobias et al. (2017) find little evidence of deterioration in a variety of price-based measures of liquidity. Bao, O'Hara, and Alex Zhou (2018) find evidence of deterioration around stress events.

portfolio and that therefore contribute more to the overall illiquidity of a fund's portfolio.

Column 1 of Panel A shows that for corporate bond funds, our measure of perceived illiquidity, the coefficient on flow volatility, doubled from 0.066 during the pre-crisis period to 0.124 during the crisis. It then remained elevated in the post-crisis period at 0.160.

One potential issue in doing time series comparisons is that the carrying costs of cash may vary over time.[23] In the context of our model in Subsection 2.1, optimal cash holdings are set according to $R^* = \Phi^{-1}(1 - \frac{i}{c}) \times \sigma$. Carrying costs, i, and illiquidity, c, have opposite effects on the optimal cash holdings R^*. To control for changes in the carrying costs i, in columns 2 and 4 we add the interaction of flow volatility with the liquidity premium (the direct effect of the liquidity premium is absorbed by our time fixed effects). We define the liquidity premium following Nagel (2016) as the difference between the rate on the 3-month general collateral (GC) repo backed by Treasury collateral and 3-month Treasury Bills. As predicted by the model, the coefficient on the interaction of flow volatility and the liquidity premium is negative. When the liquidity premium and hence the cost of holding cash is high, mutual funds hold less cash, with funds subject to more volatile fund flows being particularly sensitive to liquidity premium because, all else equal, they hold more cash.

Controlling for the carrying costs of cash generates more intuitive results in column 2: illiquidity spikes during the crisis, then declines during the post-crisis period but remains above its pre-crisis level. The economic magnitudes are large: the post-crisis coefficient on flow volatility is more than 50% larger than the price-crisis coefficient. Columns 3 and 4 of Panel A of Table 8 show that, in contrast to the corporate bond market, the perceived liquidity of domestic stocks recovers after the financial crisis and may in fact be better than before the financial crisis.

In Panel B of Table 8, we examine the time series of perceived illiquidity for different subsamples of corporate bonds. Columns 1 and 2 split the sample into investment- versus speculative-grade bonds. The perceived liquidity of both groups deteriorates significantly during the crisis, with the coefficient on flow volatility increasing from 0.048 to 0.154 for investment-grade bonds and from 0.092 to 0.219 for speculative-grade bonds. After the crisis, the perceived liquidity of investment-grade bonds returns to its pre-crisis level. In contrast, the perceived illiquidity of speculative-grade bonds remains elevated and is about 80% greater than before the crisis (0.170 versus 0.092). In columns 3 and 4, we split the sample into

[23] Another concern 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 the behavior of flow volatility rather than changes in bond market liquidity. Internet Appendix Figure 1 shows that the autocorrelation of flow volatility has remained remarkably stable over time, ruling out this alternative explanation for our results.

registered bonds versus Rule 144A bonds. We once again see a spike in perceived illiquidity during the crisis. After the crisis, the perceived illiquidity of registered bonds declines to 0.136, which is about 60% greater than its pre-crisis value of 0.085. In comparison, the post-crisis perceived illiquidity of Rule 144A bonds, which can be traded only by qualified institutional buyers, is 140% greater than its pre-crisis value: 0.185 versus 0.076.[24]

Finally, Panel C of Table 8 shows the time series of liquidity using a standard, transaction-based measure. Specifically, we construct the Amihud (2002) measure for corporate bonds and equities. We then average the bond-level measures, weighting by portfolio share, to arrive at a portfolio-level measure of illiquidity. We then regress this measure on our period dummies. Columns 1 and 2 show that by the Amihud measure, corporate bonds are as liquid postcrisis as they were precrisis. Columns 3 and 4 show a similar pattern for equities. The contrast between the results in Panels A and C underscores the importance of having a measure of perceived illiquidity. In addition, Panel C shows that our results in Panel A are not driven by changes in the composition of mutual fund holdings over time. The key difference is that the Amihud measure is a transaction-based measure of realized liquidity, while our measure is a holdings-based measure of perceived liquidity.

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 their more liquid bonds and because many bonds do not trade much, transaction-based measures may not fully capture investors' perceptions of bond market liquidity and liquidity risk. 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. We can therefore measure perceived liquidity using the coefficient from a regression of cash-to-assets ratios on flow volatility. Our measure can be applied to asset-backed securities, syndicated loans, and municipal securities for which publicly available data on transactions are not available.

We find greater illiquidity for speculative-grade and Rule 144A 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

[24] Note that transactions in corporate bonds issued pursuant to Rule 144A were not disseminated through TRACE until June 30, 2014. This makes it difficult to construct traditional transaction-based measures of liquidity in the market for Rule 144A securities. One exception is Bessembinder et al. (2018) who use the regulatory version of TRACE that includes transactions in Rule 144A securities.

has recovered since the crisis, it has not returned to pre-crisis levels. In particular, the perceived liquidity of speculative-grade and Rule 144A bonds did not bounce back post-crisis and remains low.

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Appendix

Table A1
Variable definitions

Variable	Definition
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. For municipal bond funds, cash also includes holdings of Variable-Rate Demand Notes (VRDN). The list of VRDNs is obtained from N-MFP filings of municipal money market mutual funds. Cash-to-assets ratio is winsorized at the 99th percentile.
Credit Rating	Credit rating is set to the median of Moody's, S&P, and Fitch when all three ratings are available. Otherwise it is set to the lower rating. Credit ratings are from FISD.
Current YTM	Current yield-to-maturity is calculated based on the coupon and maturity information from FISD and price from the Morningstar holdings data. We calculate the implied price by dividing the market value of each fund's holdings of a given bond by its par value and average across all funds holding the bond at the end of month t. Current YTM is winsorized at the 99th percentile within each month.
Equity share	The net value of all equity (E) positions divided by TNA.
ETF share	The net value of fund's holdings of ETFs divided by TNA. ETFs are CUSIPs with CRSP share code 73.
Family TNA	The aggregate TNA of all funds within the fund family (identified based on Morningstar's branding name).
Fund age	Time in years since the inception of the fund's oldest share class (from Morningstar).
Gross/Net	Gross value of all positions divided by their net value.
Liquidity premium	The difference between the 3-month GC repo backed by Treasury collateral and 3-month T-Bills (Nagel, 2016). Repo rates are from Bloomberg. We take the average of daily values of the 3-month T-Bill yield (FRED series DTB3) during the month.
Offering amount	Offering amount in millions is from Mergent FISD for corporate bonds and from Capital IQ for municipal bonds.
Offering YTM	Offering yield-to-maturity is from Mergent FISD and is winsorized at the 99th percentile within each month.
No trades	Dummy variable equal to one for municipal bonds without any customer-dealer trades during the last three months. Municipal bond trades are from the MSRB Municipal Securities Transactions Data.

Table A1—*Continued*

Variable	Definition
Portfolio Amihud	Value-weighted average of Amihud (2002) of portfolio securities. For each securities, Amihud is calculated over the last three months. Amihud is winsorized at the 1st and 99th percentiles within each month.
Redemption fee	Binary variable equal to one if any one of the fund's share classes imposes redemption fees. Redemption fee information is from Morningstar.
σ (daily)	Standard deviation of daily fund flows over the last three months. Dollar value of daily fund flows is scaled by TNA at the end of previous month. Fund flows are winsorized at the 1st and 99th percentiles within each month. At least twenty observations are required.
σ (monthly)	Standard deviation of monthly fund flows over the last twelve months. Monthly fund flows are calculated as $\frac{TNA_{f,t}-(1+r_{f,t})\times TNA_{f,t-1}}{TNA_{f,t-1}}$. Fund flows are winsorized at the 1st and 99th percentiles within each month. At least nine monthly observations are required.
TBA share	The value of TBA agency MBS divided by TNA. We consider a long position to be a TBA agency MBS if a) its security type is Bond - Government Agency Pass-Thru (BG) and b) it does not have a valid CUSIP.
Fund TNA	Monthly total net assets (in millions) are from Morningstar.

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

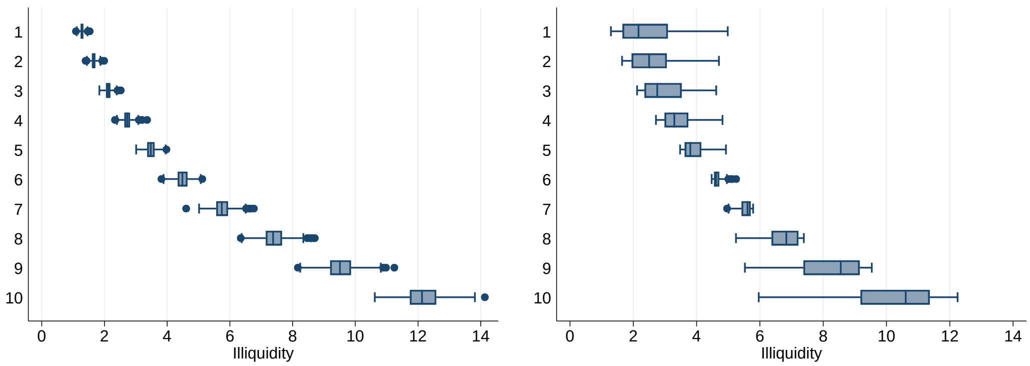


Figure 2
Simulation of Dynamic Model

This figure reports the results of the simulation of our empirical methodology in the dynamic environment studied by Connor and Leland (1995). Simulation setup is described in text. The figure plots the coefficient from the regression of the cash-to-assets ratio on the in-sample flow volatility, estimated separately for funds in each illiquidity category.

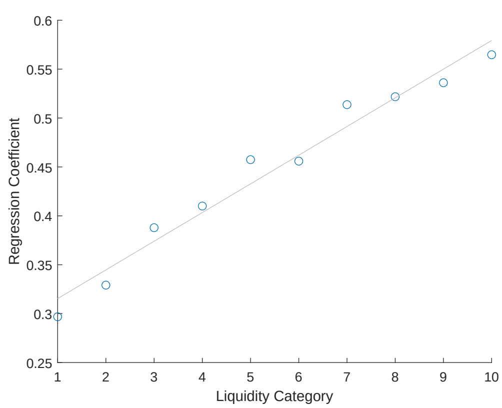
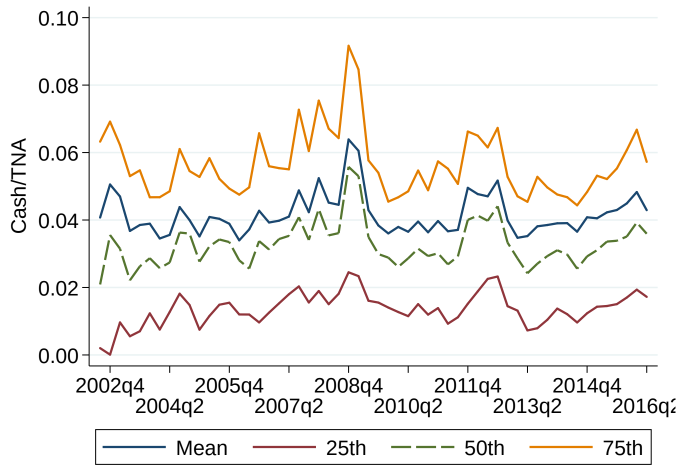


Figure 3
Distribution of Cash/Assets and σ over Time

This figure shows the distribution of the cash-to-assets ratio and flow volatility (σ) over time. The sample of corporate bond mutual funds consists of funds that a) invest at least 50% of their TNA in corporate bonds, b) are in one of the following Morningstar categories: Corporate Bond, Emerging Markets Bond, High Yield Bond, Intermediate-Term Bond, Long-Term Bond, Multisector Bond, Nontraditional Bond, and World Bond, c) have TNA of at least \$10 million, d) have the ratio of the market value of portfolio securities to fund TNA in the $[0.5, 1.5]$ interval, and e) have non-missing value of monthly flow volatility.

(a) Cash/TNA



(b) σ

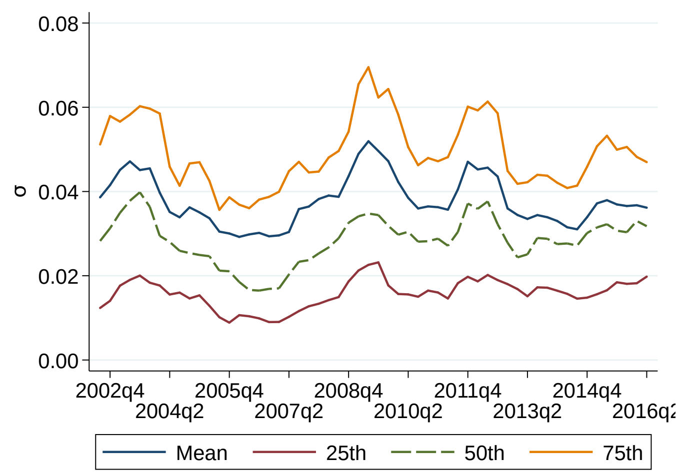


Table 1
Summary Statistics

This table reports summary statistics for the main sample of corporate bonds held by corporate bond mutual funds during the July 2009–June 2016 period. Corporate bonds are identified based on the corporate debenture (CDEB) bond type in Mergent FISD. The sample of corporate bond mutual funds consists of funds that a) invest at least 50% of their TNA in corporate bonds, b) are in one of the following Morningstar categories: Corporate Bond, Emerging Markets Bond, High Yield Bond, Intermediate-Term Bond, Long-Term Bond, Multisector Bond, Nontraditional Bond, and World Bond, c) have TNA of at least \$10 million, d) have the ratio of the market value of portfolio securities to fund TNA in the $[0.5, 1.5]$ interval, and e) have non-missing value of daily flow volatility. σ is the standard deviation of daily fund flows, scaled by last month's TNA, over the last three months. Flows are winsorized at the 1st and 99th percentiles within each month. At least twenty observations are required.

				Percentile		
	N	Mean	SD	25	50	75
Panel A: Fund-dates						
TNA (\$ million)	9,819	1,006.11	1,833.27	117.16	439.91	1,086.85
Family TNA (\$ million)	9,819	75,198.73	259,194.20	8,122.62	31,514.21	70,202.36
Cash/TNA (%)	9,819	4.16	4.61	1.35	3.20	5.54
σ (%)	9,819	5.07	2.78	3.20	4.53	6.30
Fund age	9,819	15.16	10.32	7.67	13.42	19.25
Gross/Net	9,819	1.02	0.07	1.00	1.00	1.01
TBA share (%)	9,819	0.13	1.03	0.00	0.00	0.00
ETF share (%)	9,819	0.08	0.66	0.00	0.00	0.00
Equity share (%)	9,819	0.64	1.71	0.00	0.00	0.46
Has redemption fees	9,819	0.18	0.38	0.00	0.00	0.00
Panel B: Bond-dates						
Issue size (million \$)	386,741	673.53	591.19	300.00	500.00	800.00
Rating	382,632	9.35	3.69	7.00	9.00	12.00
Maturity	386,752	10.29	10.48	4.67	6.92	9.83
Bond age	386,752	3.48	3.81	0.92	2.33	4.50
Rule 144A	386,752	0.22	0.41	0.00	0.00	0.00
Secured	386,752	0.10	0.30	0.00	0.00	0.00
Num. funds	386,752	15.32	17.67	4.00	8.00	20.00
Panel C: Fund-bond-dates (Positions)						
Portfolio weight (bps)	1,960,279	32.28	37.58	9.74	21.32	41.62

Table 2
Perceived Illiquidity of Corporate Bonds

This table reports our baseline estimates of perceived illiquidity. The table reports the results of the regressions of the cash-to-assets ratio on fund flow volatility:

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

where b indexes bonds, f indexes funds, and t indexes time in months. σ is the standard deviation of daily fund flows, scaled by last month's TNA, over the last three months. Flows are winsorized at the 1st and 99th percentiles within each month. At least twenty observations are required. In columns 1–4, observations are weighted by the bond's portfolio share. Columns 5–8 report equal-weighted regressions. The sample period is July 2009–June 2016. All continuous variables except for σ are standardized. The number of observations is 1,960,279. Standard errors are adjusted for clustering by fund-date. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

	Portfolio share-weighted				Equal-weighted			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\sigma_{f,t}$	0.166***	0.186***	0.186***	0.192***	0.150***	0.153***	0.159***	0.158***
	(0.015)	(0.016)	(0.014)	(0.015)	(0.016)	(0.017)	(0.016)	(0.017)
$Ln(Fund\ TNA)_{f,t}$	0.179***	0.150***	0.150***	0.133***	0.258***	0.240***	0.229***	0.230***
	(0.044)	(0.042)	(0.038)	(0.039)	(0.049)	(0.047)	(0.047)	(0.046)
$Ln(Family\ TNA)_{f,t}$	−0.267***	−0.258***	−0.165***	−0.138***	−0.450***	−0.331***	−0.290***	−0.267***
	(0.046)	(0.044)	(0.038)	(0.038)	(0.051)	(0.044)	(0.044)	(0.044)
$Gross/Net_{f,t}$	0.428***	0.415***	0.463***	0.446***	0.527***	0.544***	0.510***	0.520***
	(0.046)	(0.048)	(0.042)	(0.045)	(0.049)	(0.052)	(0.045)	(0.050)
$Has\ redemption\ fees_{f,t}$	0.062	0.027	−0.178**	−0.147*	−0.408***	−0.519***	−0.539***	−0.545***
	(0.093)	(0.092)	(0.082)	(0.083)	(0.092)	(0.092)	(0.092)	(0.093)
$TBA\ share_{f,t}$	0.195***	0.340***	0.266***	0.316***	0.221***	0.379***	0.264***	0.346***
	(0.046)	(0.038)	(0.039)	(0.035)	(0.064)	(0.041)	(0.054)	(0.039)
$ETF\ share_{f,t}$	−0.050	−0.143***	−0.105***	−0.130***	−0.014	−0.158***	−0.081***	−0.155***
	(0.034)	(0.035)	(0.031)	(0.032)	(0.029)	(0.033)	(0.029)	(0.033)
$Equity\ share_{f,t}$	−0.256***	−0.279***	−0.282***	−0.285***	−0.279***	−0.308***	−0.301***	−0.306***
	(0.025)	(0.025)	(0.022)	(0.022)	(0.025)	(0.025)	(0.025)	(0.026)
N	1,960,279							
Adjusted R^2	0.050	0.172	0.256	0.295	0.072	0.201	0.148	0.201
Bond-date FEs			✓	✓			✓	✓
Objective-date FEs		✓		✓		✓		✓

Table 3
Robustness to Controlling for Fund Flows and Returns

This table shows that the results in Table 2 are robust to controlling for past and future fund flows and returns:

$$\left(\frac{Cash}{TNA}\right)_{b,f,t} = \alpha_{b,t} + \delta_{obj(f),t} + \beta \cdot \sigma_{f,t} + \sum_{h=-2}^{3} (\gamma_h \cdot Flows_{f,t+h} + \theta_h \cdot R_{f,t+h}) + \varepsilon_{b,f,t},$$

where b indexes bonds, f indexes funds, and t indexes time. σ is the standard deviation of daily fund flows, scaled by last month's TNA, over the last three months. Flows are winsorized at the 1st and 99th percentiles within each month. At least twenty observations are required. All regression specifications use a fixed sample with valid values of both lagged and future fund flows and returns. For brevity the coefficients on the controls—log of fund TNA, log of family TNA, Gross/Net, redemption fees, TBA share, ETF share, and equity share—are omitted. Full regression output is reported in the Online Appendix. Observations are weighted by the bond's portfolio share. All continuous variables except for σ are standardized. Standard errors are adjusted for clustering by fund-date. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

	(1)	(2)	(3)	(4)	(5)	(6)
$\sigma_{f,t}$	0.193***	0.155***	0.153***	0.193***	0.193***	0.152***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
$Flows_{f,t}$		0.571***	0.551***			0.548***
		(0.112)	(0.112)			(0.111)
$Flows_{f,t-1}$		0.118***	0.114**			0.114**
		(0.044)	(0.044)			(0.045)
$Flows_{f,t-2}$		0.152***	0.138***			0.138***
		(0.035)	(0.035)			(0.035)
$Flows_{f,t+1}$			0.056*			0.064**
			(0.030)			(0.030)
$Flows_{f,t+2}$			0.015			0.021
			(0.031)			(0.031)
$Flows_{f,t+3}$			0.098**			0.107**
			(0.046)			(0.046)
$R_{f,t}$				0.121	0.266**	0.141
				(0.127)	(0.128)	(0.124)
$R_{f,t-1}$				0.169	0.198	0.116
				(0.124)	(0.124)	(0.119)
$R_{f,t-2}$				−0.332***	−0.282**	−0.308***
				(0.120)	(0.120)	(0.116)
$R_{f,t+1}$					−0.623***	−0.584***
					(0.113)	(0.109)
$R_{f,t+2}$					−0.317***	−0.368***
					(0.119)	(0.114)
$R_{f,t+3}$					−0.264**	−0.309***
					(0.114)	(0.110)
N			1,787,870			
Adjusted R^2	0.299	0.333	0.335	0.300	0.304	0.339
Bond-date FEs	✓	✓	✓	✓	✓	✓
Objective-date FEs	✓	✓	✓	✓	✓	✓

Table 4
Cross-Section of Perceived Illiquidity

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

$$\left(\frac{Cash}{TNA}\right)_{b,f,t} = \alpha_{b,t} + \delta_{obj(f),t} + \sum_j \beta_j \cdot \sigma_{f,t} \times X^j_{b,t} + \varepsilon_{b,f,t},$$

where b indexes bonds, f indexes funds, t indexes time, and j indexes bond characteristics. σ is the standard deviation of daily fund flows, scaled by last month's TNA, over the last three months. Flows are winsorized at the 1st and 99th percentiles within each month. At least twenty observations are required. For brevity the coefficients on the controls—log of fund TNA, log of family TNA, Gross/Net, redemption fees, TBA share, ETF share, and equity share—are omitted. Full regression output is reported in the Online Appendix. All continuous variables except for σ are standardized. Observations are weighted by the bond's portfolio share. Standard errors are adjusted for clustering by fund-date. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\sigma_{f,t}$	-0.117^{**}	0.067^{***}	0.057^{***}	0.063^{***}	0.068^{***}	0.062^{***}	0.065^{***}	0.051^{***}
	(0.048)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
$\sigma_{f,t} \times AA_{b,t}$	0.145^{***}							
	(0.047)							
$\sigma_{f,t} \times A_{b,t}$	0.130^{***}							
	(0.045)							
$\sigma_{f,t} \times BBB_{b,t}$	0.199^{***}							
	(0.048)							
$\sigma_{f,t} \times BB_{b,t}$	0.314^{***}							
	(0.051)							
$\sigma_{f,t} \times B_{b,t}$	0.334^{***}							
	(0.051)							
$\sigma_{f,t} \times CCC_{b,t}$	0.341^{***}							
	(0.051)							
$\sigma_{f,t} \times Unrated_{b,t}$	0.308^{***}	0.124^{***}	0.135^{***}	0.132^{***}	0.111^{***}	0.109^{***}	0.107^{***}	0.105^{***}
	(0.054)	(0.029)	(0.029)	(0.030)	(0.029)	(0.029)	(0.029)	(0.028)
$\sigma_{f,t} \times \mathit{Speculative\ grade}_{b,t}$		0.142^{***}	0.150^{***}	0.148^{***}	0.138^{***}	0.136^{***}	0.134^{***}	0.139^{***}
		(0.020)	(0.021)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
$\sigma_{f,t} \times Ln(\mathit{Offering\ amount})_b$			0.018^{***}					0.016^{***}
			(0.004)					(0.004)
$\sigma_{f,t} \times Ln(Maturity)_{b,t}$				0.009^{**}				0.006
				(0.005)				(0.004)
$\sigma_{f,t} \times Ln(\mathit{Bond\ age})_{b,t}$					-0.019^{***}			-0.013^{***}
					(0.004)			(0.004)
$\sigma_{f,t} \times \mathit{Rule\ 144A}_b$						0.029^{***}		0.019^{***}
						(0.006)		(0.006)
$\sigma_{f,t} \times Secured_b$							0.055^{***}	0.047^{***}
							(0.008)	(0.009)
N				1,960,113				
Adjusted R^2	0.296	0.296	0.296	0.296	0.296	0.296	0.296	0.297
Bond-date FEs	✓	✓	✓	✓	✓	✓	✓	✓
Objective-date FEs	✓	✓	✓	✓	✓	✓	✓	✓

Table 5
Is Perceived Illiquidity Priced?

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

$$\left(\frac{Cash}{TNA}\right)_{b,f,t} = \alpha_{b,t} + \delta_{obj(f),t} + \beta_0 \cdot \sigma_{f,t} + \beta_1 \cdot \sigma_{f,t} \times Yield_b + \sum_j \gamma_j \cdot \sigma_{f,t} \times X^j_{b,t} + \varepsilon_{b,f,t},$$

where b indexes bonds, f indexes funds, and t indexes time. The sample consists of investment-grade bonds. σ is the standard deviation of daily fund flows, scaled by last month's TNA, over the last three months. Flows are winsorized at the 1st and 99th percentiles within each month. At least twenty observations are required. All continuous variables except for σ are standardized. Observations are weighted by the bond's portfolio share. For brevity the coefficients on the controls—log of fund TNA, log of family TNA, Gross/Net, redemption fees, TBA share, ETF share, and equity share—are omitted. Full regression output is reported in the Online Appendix. Standard errors are adjusted for clustering by fund-date. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

	Offering YTM			Current YTM		
	(1)	(2)	(3)	(4)	(5)	(6)
$\sigma_{f,t}$	0.062***	−0.061	−0.045	0.080***	−0.053	−0.032
	(0.020)	(0.054)	(0.055)	(0.021)	(0.055)	(0.057)
$\sigma_{f,t} \times \mathit{Offering\ YTM}_b$	0.022**	0.021*	0.025*			
	(0.011)	(0.012)	(0.014)			
$\sigma_{f,t} \times \mathit{Current\ YTM}_{b,t}$				0.046**	0.038**	0.048**
				(0.019)	(0.019)	(0.024)
$\sigma_{f,t} \times AA_{b,t}$		0.137***	0.132***		0.131***	0.126**
		(0.049)	(0.049)		(0.049)	(0.049)
$\sigma_{f,t} \times A_{b,t}$		0.098**	0.090*		0.100**	0.094*
		(0.049)	(0.049)		(0.048)	(0.050)
$\sigma_{f,t} \times BBB_{b,t}$		0.129**	0.108**		0.136***	0.118**
		(0.052)	(0.053)		(0.052)	(0.054)
$\sigma_{f,t} \times Ln(\mathit{Offering\ amount})_b$			−0.010**			−0.008*
			(0.005)			(0.005)
$\sigma_{f,t} \times Ln(\mathit{Maturity})_{b,t}$			−0.005			−0.009
			(0.008)			(0.009)
$\sigma_{f,t} \times Ln(\mathit{Bond\ age})_{b,t}$			−0.009			−0.008
			(0.008)			(0.006)
$\sigma_{f,t} \times \mathit{Rule\ 144A}_b$			0.058***			0.051***
			(0.012)			(0.011)
$\sigma_{f,t} \times \mathit{Secured}_b$			0.012			0.005
			(0.031)			(0.023)
N	364,042	364,042	364,042	432,043	432,043	432,043
Adjusted R^2	0.437	0.437	0.438	0.420	0.421	0.421
Bond-date FEs	✓	✓	✓	✓	✓	✓
Objective-date FEs	✓	✓	✓	✓	✓	✓

Table 6
Perceived Illiquidity Across Asset Classes

This table reports the results of regressions of the cash-to-assets ratio on fund flow volatility estimated separately for different asset classes:

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

where s indexes securities, f indexes funds, and t indexes time in months. In column (1) the sample consists of domestic stocks held by funds that invest at least 50% of their portfolio in domestic stocks. Domestic stocks are CUSIPs with CRSP share codes 10 and 11, listed on stock exchange codes 1–3. In column (2) the sample consists of foreign stocks held by funds that invest at least 50% of their portfolio in foreign stocks. Foreign stocks are CUSIPs that a) are identified by Morningstar as equities and b) are either not in CRSP or have CRSP share codes 12 or 30–39. In column (3) the sample consists of corporate bonds held by funds that invest at least 50% of their portfolio in corporate bonds. Corporate bonds are CUSIPs with FISD bond type equal to CDEB. In column (4) the sample consists of municipal bonds held by funds that invest at least 50% of their portfolio in municipal bonds. Municipal bonds are CUSIPs with Morningstar security types Muni Bond - General Obligation, Muni Bond - Revenue, and Muni Bond - Unspecified. σ is the standard deviation of daily fund flows, scaled by last month's TNA, over the last three months. Flows are winsorized at the 1st and 99th percentiles within each month. At least twenty observations are required. Observations are weighted by the bond's portfolio share. Standard errors are adjusted for clustering by fund-date. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

	Stocks		Bonds	
	Domestic	Foreign	Corporate	Municipal
	(1)	(2)	(3)	(4)
$\sigma_{f,t}$	0.021***	0.030***	0.137***	0.336***
	(0.004)	(0.007)	(0.018)	(0.016)
$Ln(Fund\ TNA)_{f,t}$	0.128***	0.161***	0.010	0.051
	(0.014)	(0.020)	(0.046)	(0.034)
$Ln(Family\ TNA)_{f,t}$	−0.411***	−0.237***	−0.114**	−0.437***
	(0.016)	(0.018)	(0.045)	(0.025)
$Gross/Net_{f,t}$	0.318***	0.328***	0.299***	0.222***
	(0.023)	(0.028)	(0.043)	(0.024)
$Has\ redemption\ fees_{f,t}$	0.445***	−0.008	−0.326***	1.101**
	(0.068)	(0.064)	(0.102)	(0.454)
N	7,527,311	5,017,169	1,452,097	1,612,816
Adjusted R^2	0.111	0.176	0.279	0.485
Security-date FEs	✓	✓	✓	✓
Objective-date FEs	✓	✓	✓	✓

Table 7
Perceived Illiquidity of Municipal Bonds

This table shows that municipal bonds that do not trade are perceived by fund managers to be less liquid than bonds that do trade. The table reports the results of regressions of the cash-to-assets ratio on fund flow volatility interacted with bond and fund characteristics

$$\left(\frac{Cash}{TNA}\right)_{b,f,t} = \alpha_{b,t} + \delta_{obj(f),t} + \sum_j \beta_j \cdot \sigma_{f,t} \times X^j_{b,f,t} + \varepsilon_{b,f,t},$$

where b indexes bonds, f indexes funds, and t indexes time. *No trades* dummy is equal to one if the municipal bond does not have any customer-dealer secondary market transactions over the last three months. Refunded bonds are excluded. σ is the standard deviation of daily fund flows, scaled by last month's TNA, over the last three months. Flows are winsorized at the 1st and 99th percentiles within each month. At least twenty observations are required. Observations are weighted by the bond's portfolio share. Standard errors are adjusted for clustering by fund-date. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

	No trades		No trades ≥ \$100K	
	(1)	(2)	(3)	(4)
$\sigma_{f,t}$	0.367***	0.271***	0.355***	0.258***
	(0.026)	(0.019)	(0.025)	(0.016)
$\sigma_{f,t} \times$ *No trades*$_{b,t}$	0.024***	0.020**		
	(0.008)	(0.008)		
$\sigma_{f,t} \times$ *No trades* $\geq \$100K_{b,t}$			0.033***	0.032***
			(0.010)	(0.009)
$\sigma_{f,t} \times$ *General obligation*$_b$	0.049***	0.061***	0.051***	0.063***
	(0.015)	(0.015)	(0.015)	(0.015)
$\sigma_{f,t} \times$ *Ln(Offering amount)*$_b$	0.039***	0.039***	0.043***	0.044***
	(0.008)	(0.008)	(0.008)	(0.008)
$\sigma_{f,t} \times$ *Ln(Maturity)*$_{b,t}$	0.004	0.000	0.003	−0.001
	(0.008)	(0.008)	(0.008)	(0.008)
$\sigma_{f,t} \times$ *Ln(Bond age)*$_{b,t}$	−0.046***	−0.045***	−0.048***	−0.047***
	(0.008)	(0.008)	(0.007)	(0.008)
$\sigma_{f,t} \times AA_{b,t}$	−0.072***		−0.073***	
	(0.022)		(0.022)	
$\sigma_{f,t} \times A_{b,t}$	−0.102***		−0.103***	
	(0.026)		(0.026)	
$\sigma_{f,t} \times BBB_{b,t}$	−0.131***		−0.131***	
	(0.026)		(0.026)	
$\sigma_{f,t} \times BB_{b,t}$	−0.122***		−0.121***	
	(0.031)		(0.031)	
$\sigma_{f,t} \times B_{b,t}$	−0.072**		−0.070**	
	(0.034)		(0.034)	
$\sigma_{f,t} \times$ *Unrated*$_{b,t}$	−0.084***	0.015	−0.084***	0.016
	(0.027)	(0.016)	(0.027)	(0.016)
$\sigma_{f,t} \times$ *Speculative grade*$_{b,t}$		0.004		0.006
		(0.020)		(0.020)
N	1,425,275			
Adjusted R^2	0.466	0.466	0.466	0.466
Security-date FEs	✓	✓	✓	✓
Objective-date FEs	✓	✓	✓	✓

Table 8
Time Series of Perceived Illiquidity

Panel A reports the results of regressions of the cash-to-assets ratio on fund flow volatility interacted with dummies for different periods. *Pre* is July 2002–August 2008. *Crisis* is September 2008–June 2009. *Post* is July 2009–June 2016. Bond fund characteristics include log of fund TNA, log of fund family TNA, fund leverage, TBA share, ETF share, and equity share. Equity fund characteristics include log of fund TNA, log of fund family TNA, and fund leverage. Panel B reports the results of subsample splits for corporate bond funds. In Panel C, we calculate portfolio illiquidity as the weighted-average of Amihud (2002) of the individual portfolio securities and regress portfolio illiquidity on the period dummies. In Panels A and B, observations are weighted by the security's portfolio share; standard errors are adjusted for clustering by fund-date. In Panel C, we estimate equal-weighted regressions with fund-date as the unit observations; standard errors are adjusted for clustering by date and fund. All continuous variables except for σ are standardized. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

Panel A: Perceived Illiquidity				
	Corporate bonds		Domestic stocks	
	(1)	(2)	(3)	(4)
$\sigma_{f,t} \times$ *Pre-crisis*$_t$	0.066***	0.117***	0.019***	0.019***
	(0.015)	(0.020)	(0.005)	(0.007)
$\sigma_{f,t} \times$ *Crisis*$_t$	0.124***	0.245***	0.047***	0.048**
	(0.035)	(0.046)	(0.015)	(0.021)
$\sigma_{f,t} \times$ *Post-crisis*$_t$	0.160***	0.185***	0.016***	0.016***
	(0.012)	(0.014)	(0.004)	(0.005)
$\sigma_{f,t} \times$ *Liquidity premium*$_t$		−0.079***		−0.001
		(0.020)		(0.008)
N	3,114,558	3,114,558	14,243,594	14,243,594
Adjusted R^2	0.271	0.272	0.113	0.113
p-value Pre = Crisis	0.128	0.002	0.071	0.120
p-value Pre = Post	0.000	0.001	0.678	0.671
p-value Post = Crisis	0.323	0.178	0.042	0.096
Security-date FEs	✓	✓	✓	✓
Objective-date FEs	✓	✓	✓	✓
Panel B: Subsample Splits				
	By Grade		Registered versus Rule 144A	
	Investment	Speculative	Registered	Rule 144A
	(1)	(2)	(3)	(4)
$\sigma_{f,t} \times$ *Pre-crisis*$_t$	0.048***	0.092***	0.085***	0.076***
	(0.015)	(0.017)	(0.016)	(0.017)
$\sigma_{f,t} \times$ *Crisis*$_t$	0.154*	0.219***	0.222***	0.168***
	(0.079)	(0.043)	(0.042)	(0.040)
$\sigma_{f,t} \times$ *Post-crisis*$_t$	0.044**	0.170***	0.136***	0.185***
	(0.017)	(0.014)	(0.012)	(0.014)
$\sigma_{f,t} \times$ *Liquidity premium*$_t$	−0.042***	−0.035***	−0.039***	−0.034***
	(0.009)	(0.010)	(0.010)	(0.010)
N	620,095	2,470,885	2,235,057	879,496
Adjusted ^{2}	0.400	0.251	0.283	0.244
p-value Pre = Crisis	0.171	0.004	0.001	0.028
p-value Pre = Post	0.864	0.000	0.013	0.000
p-value Post = Crisis	0.172	0.291	0.057	0.694
Security-date FEs	✓	✓	✓	✓
Objective-date FEs	✓	✓	✓	✓
Panel C: Portfolio Amihud				
	Corporate bonds		Domestic stocks	
	(1)	(2)	(3)	(4)
Pre-crisis	0.017***	0.017***	0.007***	0.008**
	(0.001)	(0.001)	(0.002)	(0.002)
Crisis	0.042***	0.025***	0.028***	0.028***
	(0.005)	(0.005)	(0.009)	(0.009)
Post-crisis	0.015***	0.015***	0.004***	0.004***
	(0.000)	(0.000)	(0.001)	(0.001)
N	29,977	29,977	107,812	107,812
Adjusted R^2	0.322	0.334	0.004	0.019
p-value Pre = Crisis	0.000	0.000	0.015	0.016
p-value Pre = Post	0.126	0.101	0.036	0.016
p-value Post = Crisis	0.000	0.000	0.005	0.005
Objective FEs		✓		✓