Can mutual funds harvest corporate bond liquidity premia?

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Abstract

This paper studies how the performance of corporate bond mutual funds varies with the liquidity of their bond holdings. I show that funds holding relatively illiquid corporate bonds on average underperform funds that hold more liquid portfolios on a risk-adjusted basis over the period 2010-2022. The relation between portfolio liquidity and fund performance is strongest within the set of high-yield funds, consistent with these funds' large exposure to redemption risk. Moreover, the underperformance of less liquid funds is driven by periods in which market liquidity drops, i.e., when flow-induced asset sales are most costly. My findings suggest a reduced ability of mutual funds to harvest illiquidity premia in corporate bonds, which might be caused by a structural liquidity mismatch arising from open-ended structures.

Keywords: Mutual funds, corporate bonds, liquidity, performance

JEL classification: G10, G11, G23

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1 Introduction

This paper examines the ability of mutual funds to harvest corporate bond liquidity premia. Liquidity may affect corporate bond returns in two different ways (Acharya and Pedersen, 2005). First, illiquid bonds may generate higher gross returns to compensate for their larger trading costs, which gives rise to a liquidity level premium. Second, corporate bond returns may be exposed to market-wide liquidity shocks, which may lead to a liquidity risk premium. While the presence of a liquidity risk premium in the corporate bond market has been subject to debate in recent studies (van Binsbergen and Schwert, 2022; Dickerson et al., 2023), the liquidity level premium has been widely documented (see, e.g., Bongaerts et al., 2017). This naturally leads to the prediction that funds holding illiquid corporate bonds on average achieve higher returns.

At the same time however, mutual funds can be subject to large and sudden investor withdrawals. These may force the fund manager to liquidate portfolio holdings at fire-sale prices (see, e.g., Coval and Stafford, 2007), which has a direct impact on fund performance. In particular, corporate bond funds with lower portfolio liquidity typically experience larger outflows during market downturns when market liquidity is low (Goldstein et al., 2017; Falato et al., 2021). The existing literature has offered two explanations for this result. First, strategic complementarities among fund investors resulting from a liquidity mismatch between a fund's assets and its redemption terms may trigger a run on the fund (Goldstein et al., 2017). When an investor redeems fund shares, the redemption value is typically equal to the investor's share of the fund's total net asset value at the end of the trading day, whereas transactions associated with this redemption take place in the days after. As such, part of the portfolio rebalancing costs associated with an investor's redemption are borne by the remaining investors, which gives rise to a first-mover advantage that might trigger a run and exacerbate outflows. This first-mover advantage is larger for funds investing in less liquid bonds because of the larger (fire-sale) costs associated with investor redemptions. Second, Stahel (2022) shows that competition for finite asset market liquidity, which affects all market participants including mutual fund investors, may also lead to larger observed outflows for funds holding illiquid assets. In summary, precisely those funds invested in illiquid bonds are most prone to sudden investor redemptions when market liquidity drops, which may lead to costly flow-induced asset sales that hurt fund performance. This leads to the prediction that funds investing in less liquid corporate bonds underperform during times when market-wide liquidity is low.

The main objective of this paper is to study whether funds holding less liquid assets (lower portfolio liquidity) have higher (risk-adjusted) returns than funds holding more liquid assets, and whether this relation varies with market-wide liquidity conditions. Based on the aforementioned predictions, I hypothesize that illiquid funds underperform more liquid funds when market liquidity is low, but outperform when market liquidity is high. The unconditional effect of portfolio liquidity on fund performance remains an empirical question, and also depends on the chosen sample period.

The focus on corporate bond funds is motivated by their liquidity mismatch, due to which the negative impact of flow-induced asset sales on fund performance is expected to be larger than for funds subject to a smaller liquidity mismatch (e.g. equity funds).

Based on holdings data from the CRSP Mutual Fund Database for 1022 distinct funds and corporate bond transaction data from TRACE, I construct a quarterly portfolio liquidity score for each fund in my sample during the period between 2010 and 2022. Using fixed-effect panel regressions, I first relate fund flows to lagged portfolio liquidity to revisit the question whether less liquid funds face larger redemption requests during times when market liquidity drops. To address the main research question, I also consider fixed-effect panel regressions in which I relate (risk-adjusted) fund performance to lagged portfolio liquidity while controlling for a variety of other fund characteristics. I amend this specification by interacting lagged portfolio liquidity with a market liquidity indicator, which allows me to assess how the relation between portfolio liquidity and fund performance varies with different market circumstances.

Portfolio liquidity turns out to be strongly driven by the funds' investment mandates. For instance, funds targeting high-yield bonds tend to have significantly lower portfolio liquidity compared with funds targeting short-term investment-grade bonds. In line with existing evidence, I confirm that funds holding less liquid corporate bonds face significantly larger outflows when market-wide transaction costs soar. Interestingly however, I find that controlling for the portfolio's credit rating profile absorbs the effect of portfolio liquidity on the cross-section of outflows. These findings suggest an alternative explanation beyond the first-mover advantage (Goldstein et al., 2017) and the competition for finite asset market liquidity (Stahel, 2022). Under this alternative explanation, the larger outflows from less liquid funds may be driven by increased credit risk concerns, as less liquid funds tend to hold lower-rated debt. While disentangling these potential drivers of outflows is beyond the scope of this paper, all channels predict that less liquid funds face larger outflows during times of stress, which in turn may hurt fund performance.

The main findings in this paper are as follows. First, I find that less liquid funds achieve larger raw excess returns than more liquid funds during periods in which market liquidity improves, whereas the opposite holds during periods in which market liquidity deteriorates. Over the full sample period between 2010 and 2022, portfolio liquidity does not significantly affect average excess returns. Second, based on risk-adjusted performance, I find that funds holding less liquid corporate bonds on average underperform their more liquid counterparts. Specifically, a one-standard deviation decrease in portfolio liquidity is associated with a 36-77 basis points decrease in annual risk-adjusted returns. Third, since high-yield funds face larger outflows during stressed periods, their managers may be forced to sell larger quantities of corporate bonds to accommodate these investor redemptions compared with managers of investment-grade funds. As such, I hypothesize that the effect of portfolio liquidity on fund performance is most pronounced within the subset of high-yield funds. Indeed, the results from a subsample analysis in which I separately consider investment-grade funds and high-yield funds confirm this hypothesis. Within the set of investment-grade funds, I find no significant effect of portfolio liquidity on risk-adjusted fund performance. In contrast, within the set of high-yield funds, a one standard deviation decrease in portfolio liquidity translates into a statistically significant decrease of 1.8% to 2.3% percentage points in annual risk-adjusted returns. This underperformance is strongly driven by periods in which market liquidity declines: during months in which market liquidity deteriorates, a one standard deviation decrease in portfolio liquidity leads to a reduction of 33 to 51 basis points in monthly risk-adjusted returns, while the relation between portfolio liquidity and fund performance is statistically insignificant during normal circumstances. The relatively short sample period in this paper forms a limitation when making statements about the unconditional effect of portfolio liquidity on fund performance. Nevertheless, even during a relatively short sample period, one would expect illiquid funds to outperform more liquid funds during normal circumstances. My results suggest that this is not the case. The result that portfolio illiquidity mainly hurts returns of high-yield funds can be explained by their greater vulnerability to outflows during times of stress. Finally, within the set of high-yield funds, I find that the adverse effect of portfolio illiquidity on fund performance is stronger in months after a fund faces low returns or low flows (large outflows). Since lagged flows and lagged returns predict next month's flows, these results are consistent with the notion that the effect of portfolio liquidity on fund performance is strongest when funds are facing outflows. Taken together, these findings provide novel insights into the effect of a liquidity mismatch on the performance of corporate bond funds.

This paper contributes to multiple strands in the literature. First of all, this paper relates to the literature on fragilities arising from the open-ended structure of mutual funds. Strategic complementarities among investors in an open-ended fund create a first-mover advantage which may trigger run dynamics and amplify outflows when market liquidity deteriorates (Chen et al., 2010; Goldstein et al., 2017; Agarwal et al., 2019; Falato et al., 2021). Jiang et al. (2022) shows that this first-mover advantage may lead to fire-sale externalities, thereby adversely impacting the stability of the underlying corporate bond market. I contribute to this literature by showing that a liquidity mismatch in investment funds may not only have financial stability implications, but also impacts fund performance. Moreover, this paper also provides a methodological contribution with respect to the measurement of the portfolio liquidity profile of corporate bond mutual funds. Following the standard in the literature, I match individual portfolio holdings with transaction data from TRACE Enhanced (Goldstein et al., 2017; Jiang et al., 2021; Falato et al., 2021; Jiang et al., 2022). However, TRACE Enhanced does not include corporate bonds issued under Rule 144A. I show that especially high-yield funds have large allocations towards Rule 144A bonds, with an average portfolio weight of over 40%. A large subset of the corporate bond holdings by high-yield funds would therefore be ignored in case one solely relies on TRACE Enhanced when measuring portfolio liquidity. This may be problematic because ignoring Rule 144A bonds could lead to an overestimation of the portfolio liquidity of high-yield funds, as Rule 144A bonds tend to be less liquid than ordinary, publicly issued corporate bonds (Chernenko and Sunderam, 2020;

Goldstein and Hotchkiss, 2020). To overcome this issue, I complement transaction data from TRACE Enhanced with data from the 144A BTDS feed within TRACE Standard which contains transaction data for Rule 144A bonds. However, institutional differences between the market for Rule 144A bonds and publicly issued corporate bonds give rise to another challenge. First of all, the average transaction size of Rule 144A bonds is substantially larger than for publicly issued corporate bonds, because the market for Rule 144A bonds is dominated by large institutional investors. Second, dealers endogenously adjust their market making activities to the illiquidity of Rule 144A bonds. Goldstein and Hotchkiss (2020) show that dealers are more likely to directly match buyers and sellers instead of using their inventory when trading Rule 144A bonds, in order to mitigate inventory risk. Since corporate bond transaction costs tend to decline in transaction size (Feldhütter, 2012), and since round-trip costs tend to be lower if no dealer inventory is involved (Goldstein and Hotchkiss, 2020), observed spreads in Rule 144A bonds may appear lower than those observed for publicly issued bonds. To overcome these issues, I discard retail-sized transactions and measure bond liquidity using imputed round-trip costs in which a dealer directly matches a buyer and a seller, so that no dealer inventory is involved.

Second, I contribute to the literature on mutual fund performance and the potential of open-ended fund structures to exploit mispricing. An open-ended fund structure may pose limits to arbitrage, as investors tend to withdraw their money in response to low fund returns. This may leave the fund manager with less capital to conduct arbitrage precisely when prices have moved further away from fundamentals (Shleifer and Vishny, 1997). As a result, an open-ended fund structure may discourage the fund manager from exploiting the type of long-term mispricing which may intensify in the short run before correcting itself in the long run. Given that recent literature on the financial stability implications of liquidity transformation by mutual funds has primarily focused on corporate bond funds, it is surprising that the impact of liquidity transformation on fund returns has only been studied empirically for equity funds (Giannetti and Kahraman, 2018) and hedge funds (Sadka, 2010; Teo, 2011; Agarwal et al., 2019). To the best of my knowledge, this paper is therefore the first to link the performance of corporate bond funds to their underlying liquidity mismatch. My findings offer a potential explanation why reaching for yield by corporate bond funds does not result in higher risk-adjusted performance (Choi and Kronlund, 2018) and why these funds on average fail to beat passive benchmarks (Cici and Gibson, 2012). My results are also in line with Qin and Wang (2021), who show that higher portfolio concentration leads to improved performance of corporate bond mutual funds, except for relatively illiquid funds that face large liquidity costs when faced with outflows. The potential limits to arbitrage as well as the financial stability concerns caused by a liquidity mismatch give rise to the question why the majority of mutual funds is open-ended. One possible explanation is the competition among funds for investors' money (Stein, 2005). A closed-end structure gives rise to agency problems as investors cannot withdraw their money in case of mismanagement. Stein (2005) shows that in combination with asymmetric information about fund manager quality, the equilibrium outcome might be a situation where all funds are open-ended. Moreover, the lower risk-adjusted performance of illiquid funds raises the question why investors are willing to invest in these funds. I show that illiquid funds generate higher raw returns, i.e., not corrected for risk exposures, during periods in which market liquidity improves. As such, reaching for yield behavior could explain why investors keep investing in these funds (Choi and Kronlund, 2018).

Third, this paper relates to studies on liquidity premia in the corporate bond market (Lin et al., 2011; Dick-Nielsen et al., 2012; Bongaerts et al., 2017; Bai et al., 2019; van Binsbergen and Schwert, 2022; Dickerson et al., 2023). These studies directly estimate liquidity premia from corporate bond returns. I contribute to this by studying the extent to which an important class of investors in the corporate bond market, i.e., mutual funds, is able to harvest these premia. Importantly, this is different from directly estimating liquidity premia from corporate bond returns. Even if liquidity premia would be present in the corporate bond market, mutual funds might not be able to harvest these premia if they face large outflows during unfavorable market conditions.

More generally, this study is also related to the literature on the relation between the investment horizon and portfolio choice. Amihud and Mendelson (1986) show that investors with longer horizons self-select into assets with larger bid-ask spreads, resulting in a positive and concave relation between bid-ask spreads and returns. Chen et al. (2020) empirically confirm these model predictions in the investment-grade corporate bond market using portfolio holdings data of insurance companies. Insurance companies have traditionally been the largest holders of corporate bonds, but in recent years mutual funds have become the second largest class of investors in the U.S. corporate bond market (Cai et al., 2019; Murray and Nikolova, 2022; Jiang et al., 2022). Moreover, even though the ownership share of mutual funds is lower than of insurance companies, mutual funds are the most active traders in the corporate bond market (Cai et al., 2019). Because mutual funds can be subject to sudden and large investor redemptions, they tend to have shorter investment horizons than insurance companies that have a more stable balance sheet (Timmer, 2018). Remarkably, Figure 1 shows that the ownership footprint of mutual funds in corporate bonds is actually declining in corporate bond liquidity. This result seems at odds with liquidity-based asset pricing models which predict a clientele effect where investors with a longer investment horizon select less liquid assets (Amihud and Mendelson, 1986; Beber et al., 2021). The larger presence of mutual funds in the less liquid segment of the corporate bond market may be explained by rating-based capital requirements that tilt the portfolios of insurance companies towards safely rated, more liquid corporate bonds (Ellul et al., 2011; Becker and Ivashina, 2015; Murray and Nikolova, 2022). The key question that arises from this observation is to what extent mutual funds are actually able to benefit from investing in illiquid corporate bonds, given they may be ill-suited to hold illiquid bonds. This paper aims to fill this gap.

2 Data and liquidity measures

2.1 Data sources

Fund information, portfolio holdings, and fund returns are obtained from the CRSP Mutual Fund Database. I classify a fund as a corporate bond fund when the Lipper Objective Code is in the set ('A','BBB', 'GHY', 'HY', 'SHY', 'SII', 'SID', 'IID'). This classification follows, among others, Choi et al. (2020), and is amended with the codes 'Global High Yield (GHY)' and 'Short High Yield (SHY)' as the Lipper Objective Codes of a substantial number of funds initially classified as 'HY' change to either 'GHY' or 'SHY' as of June 2019. I focus on open-ended corporate bond funds, excluding ETFs and index funds. Unless specified differently, I aggregate observations to the portfolio level by taking the average across shareclasses weighted by total net assets using portfolio identifiers based on *crsp_portno*.[1] Moreover, I discard funds with total net assets below 1 million USD. Because of limited reliability of holdings data in CRSP before June 2010, my sample starts in June 2010. I merge portfolio holdings with individual corporate bond characteristics from Mergent FISD and liquidity information based on transaction data from the Enhanced TRACE database, complemented with data from the BTDS 144A feed in TRACE Standard. After merging holdings data with Mergent FISD, I require funds to allocate at least 20% of their portfolios towards corporate bonds in the previous quarter.[2] This threshold balances the size of the cross section of funds and the presence of investment-grade funds against the portfolio share invested in corporate bonds (see also Anand et al., 2021). Investment-grade funds tend to invest in a broader range of fixed income, which apart from corporate bonds also includes larger allocations towards government bonds, asset-backet securities, and mortgage-backed securities. If I would require funds to allocate at least 50% of their portfolios towards corporate bonds, the resulting sample would predominantly consist of high-yield funds. Appendix A contains a detailed description of the cleaning procedure of TRACE data.

Figure 2 shows that not all corporate bonds held by the funds in my sample are covered by TRACE Enhanced. After merging individual portfolio holdings with bond information from Mergent FISD on 8-digit CUSIPs, it turns out that funds on average allocate over 50% to corporate bonds. However, the average portfolio fraction which can be matched with TRACE Enhanced ranges between 30% and 45% and shows a declining trend over time. It follows that this gap primarily results from Rule 144A corporate bonds, which are not covered by TRACE Enhanced. As of June 2014, transactions in Rule 144A bonds are disseminated through a separate feed in TRACE Standard (BTDS 144A). To close this gap, I complement TRACE Enhanced by transactions data from the BTDS 144A feed within TRACE Standard from June 1^{st}, 2015 onwards, after

[1]Zhu (2020) shows that virtually all share classes have a valid *crsp_portno* from 2009 onward.

[2]I classify bonds as corporate bonds when the bond type provided by Mergent FISD equals CCOV, CCPI, CDEB, CLOC, CMTN, CMTZ, CP, CPIK, CS, CUIT, CZ, RNT, UCID, or USBN.

counterparty indicators became available in TRACE BTDS 144A.[3] Figure 2 indicates that combining these databases results in nearly full coverage of corporate bond portfolios after June 2015. Since Rule 144A bonds tend to have lower liquidity (Chernenko and Sunderam, 2020; Goldstein and Hotchkiss, 2020), ignoring Rule 144A bonds leads to an underestimation of portfolio liquidity for funds with sizable exposures towards Rule 144A bonds.

The final sample contains 1022 unique funds, whereas aggregate total net assets rose from 643 billion USD to 1.6 trillion USD between 2010 and 2022. Table 1 contains a summary of the fund sample. Cash buffers held by the funds in my sample show substantial dispersion, and some funds even report negative cash buffers. These negative cash buffers can be driven by the use of financial leverage or positions in derivatives. Some funds enter repurchase agreements, in which they lend securities and receive cash which they can invest in additional securities. This way, a fund obtains financial leverage and the repurchase agreement leads to a negative cash position. Moreover, portfolio allocations may include exposures resulting from derivatives, which is offset on the fund's balance sheet by a negative cash position. Panel B of Table 1 shows averages broken down by Lipper Objective Code. The unique Lipper Objective Codes considered include "A" (Corporate Debt Funds A Rated), "BBB" (Corporate Debt Funds BBB-Rated), "Global High Yield (GHY)", "HY" (High Current Yield Funds), "IID" (Intermediate Investment Grade Debt Funds), "Short High Yield (SHY)", "SID" (Short Investment Grade Debt Funds), and "SII" (Short-Intermediate Investment Grade Debt Funds). It follows that high-yield funds on average have the largest allocation towards corporate bonds as well as towards Rule 144A corporate bonds, and the smallest allocation towards government bonds. As expected, high-yield funds also have the lowest average numerical credit rating, corresponding to lower-rated corporate bond holdings.

2.2 Liquidity of the corporate bond market

Besides estimating liquidity at the bond level, I also construct a market-wide liquidity proxy using a methodology that builds on Glosten and Harris (1988). I start with the following regression equation for a given individual bond:

$$p_{t_i} - p_{t_{i-1}} = \alpha + \beta \left(Q_{t_i} - Q_{t_{i-1}} \right) + \varepsilon_{t_i} \tag{1}$$

Here, p_{t_i} denotes the log price of transaction i that took place at time t_i, and Q_{t_i} is the corresponding trade sign indicator. Specifically, Q_{t_i} equals -1 for a seller-initiated transaction, +1 for a buyer-initiated transaction, and 0 for an interdealer transaction. After running this regression, the estimated effective bid-ask spread is equal to $2 \times \hat{\beta}$. I use weighted least squares with weights given by $w_{t_i} = (t_i - t_{i-1})^{-1}$ to assign higher weight to trade pairs with a smaller time lapse, which can be motivated by the assumption that $Var(\varepsilon_{t_i}) = \sigma^2(t_i - t_{i-1})$.

[3] Counterparty indicators are required to identify interdealer transactions.

Instead of estimating the regression in Equation (1) bond by bond, I stack the vectors of trade pairs of each individual bond and estimate the following regression pooled across bonds:

$$p^j_{t_i} - p^j_{t_{i-1}} = \alpha + \beta \left(Q^j_{t_i} - Q^j_{t_{i-1}} \right) + \varepsilon^j_{t_i}, \tag{2}$$

where j indexes individual bonds, N^j denotes the number of transactions observed for bond j, and $i = 1, ..., N^j$. After estimating this regression in Equation (2) for each month separately, I obtain a monthly time series of market-wide effective bid-ask spreads.

Figure 3 shows the resulting estimated effective spreads. As expected, transaction costs soared during the dot-com crisis, the financial crisis in 2008, and during the COVID-19 market turmoil in March 2020. To validate this market-wide liquidity proxy, Figure 3 also plots the average bid-ask spread from the WRDS Bond Returns Database. Average bid-ask spreads from the WRDS Bond Returns Database show a higher level, but these may be partly based on smaller transaction sizes whereas I discard retail-sized transactions below 100.000 USD. Nevertheless, both proxies share a high correlation of 0.96. Moreover, my measure shares a correlation of 0.94 with the liquidity proxy of Dick-Nielsen et al. (2012) over the period between August 2002 and September 2020, during which the measure of Dick-Nielsen et al. (2012) is available. In the remainder of the paper, $MLIQ$ denotes the estimated effective spreads multiplied by minus one, such that a higher value for $MLIQ$ corresponds with higher market liquidity.

2.3 Measuring individual bond liquidity

I measure portfolio liquidity using imputed round-trip costs based on a similar approach as Kargar et al. (2021). The idea is that if a seller-initiated and a buyer-initiated transaction in the same bond take place within a short time span (i.e., 15 minutes), both transactions are likely part of a round-trip transaction prearranged by the dealer. In this case, the difference between both transaction prices can be used as a proxy for transaction costs. This approach extends Feldhütter (2012) by taking into account the buy and sell indicator and the counterparty of the transaction, which improves the accuracy of classifying multiple transactions within a 15-minute time span as a round-trip.[4] When estimating the liquidity of individual bonds, the difference between the Rule 144A corporate bond market and publicly issued corporate bonds warrants caution. First of all, the Rule 144A corporate bond market is dominated by so-called Qualified Institutional Buyers, and as a result average transaction volumes in Rule 144A bonds are substantially larger than those observed for publicly issued corporate bonds. Since larger transaction volumes in corporate bonds typically involve lower transaction costs (Feldhütter, 2012), not taking into account this difference may lead to a bias in estimated transaction costs. Secondly, dealers show a tendency to act like brokers in Rule 144A bonds by matching buyers with sellers instead of using their

[4]Using the academic version of TRACE, Kargar et al. (2021) also observe masked dealer identities, which further improves the accuracy of identifying round-trip transactions.

inventory to take the opposite side of the transaction, due to the higher inventory and search costs associated with these illiquid bonds (Goldstein and Hotchkiss, 2020). Observed round-trip costs are lower when no dealer inventory is involved, because inventory risks are mitigated. Hence, when one ignores whether dealers use their inventory in a round-trip, observed round-trip costs of Rule 144A bonds may appear lower than those observed for publicly issued corporate bonds, despite Rule 144A bonds being less liquid (Chernenko and Sunderam, 2020; Goldstein and Hotchkiss, 2020). To deal with these concerns, I discard retail-sized transactions with volumes below 100,000 USD and exclusively focus on round-trip transactions in which a customer-seller is matched with a customer-buyer. This approach may underestimate true transaction costs, but the primary goal is to obtain an accurate cross-sectional ranking of corporate bonds based on their liquidity. For robustness, I consider alternative bond liquidity proxies including: $Spread^{GH}$ denoting bid-ask spreads estimated using a regression-based approach building on Glosten and Harris (1988); $Spread^{HW}$ estimated as the average bid price minus the average ask price of all transactions on a given trading day as in (Hong and Warga, 2000; Jiang et al., 2022); and *Amihud* which is the price impact per dollar traded (Amihud and Mendelson, 1986). Appendix B contains a detailed description of all liquidity proxies.

To validate these liquidity proxies, I consider the following panel regression:

$$BLIQ_{i,t} = \beta_1 IssueSize_{i,t} + \beta_2 Age_{i,t} + \beta_3 TTM_{i,t} + \beta_4 Rating_{i,t} + \beta_5 Rule144A_{i,t} + \delta_t + \varepsilon_{i,t} \quad (3)$$

Here, $BLIQ_{i,t}$ denotes the liquidity of bond i during quarter t based on one of the four liquidity proxies. All liquidity proxies are multiplied by minus one to make sure that a higher value for $BLIQ_{i,t}$ implies higher liquidity, and standardized by subtracting the mean and dividing by the standard deviation. Moreover, $IssueSize_{i,t}$, $Age_{i,t}$, $TTM_{i,t}$, $Rating_{i,t}$ are the issue size, age, time to maturity, and credit rating of corporate bond i in quarter t, respectively.[5] Finally, $Rule144A_{i,t}$ is a dummy variable equal to 1 if bond i is a Rule 144A bond. Table 2 contains the results. It follows that liquidity tends to be higher when the issue size is higher, the bond is younger, the remaining time to maturity is smaller, and when the bond has a higher credit rating. These results are consistent with for instance Houweling et al. (2005), who consider similar bond characteristics to proxy for liquidity. Column 1 shows that Rule 144A bonds are significantly less liquid on average, consistent with Chernenko and Sunderam (2020) and Goldstein and Hotchkiss (2020). Remarkably, in Columns 2, 3, and 4, Rule 144A bonds appear to be more liquid as indicated by the significantly positive coefficient on the Rule 144A dummy. This shows the importance of taking into account differences between the market for Rule 144A versus publicly issued bonds and the endogenous behavior by dealers, and motivates why I consider imputed round-trip costs as the main measure of bond liquidity. Especially for high-yield funds, using the liquidity proxies

[5] Credit ratings are converted to a numerical scale, where 1 represents a rating of D and 22 a rating of AAA. After converting the credit ratings of S&P, Moody's, and Fitch to a numerical scale, I take the median across credit rating agencies.

from Columns 2-4 would overstate their true liquidity profiles given their large allocations towards Rule 144A bonds.

2.4 Measuring portfolio liquidity

Following Goldstein et al. (2017) and Jiang et al. (2022), portfolio liquidity is measured as the weighted average liquidity of the bonds held in a given quarter:

$$PFLIQ_{i,t} = \frac{\sum_j w_{i,j,t} \times BLIQ_{j,t}}{\sum_j w_{i,j,t}} \tag{4}$$

Here, $w_{i,j,t}$ denotes the portfolio weight fund i allocates to bond j at the end of quarter t. In case a fund does not report holdings at the end of quarter t, I use the fund's latest reported holdings in the corresponding quarter. If the fund did not report holdings at all in quarter t, I consider the fund's holdings as missing. The variable $BLIQ_{j,t}$ denotes the liquidity of bond j in quarter t proxied by one of the previously mentioned liquidity measures. A higher value for $PFLIQ_{i,t}$ corresponds to higher portfolio liquidity, and I standardize $PFLIQ_{i,t}$ by subtracting its mean and dividing by its standard deviation. I discard portfolio-quarter observations when I observe individual bond liquidity for less than 10% of the portfolio (in terms of dollars invested). Figure 4a shows the distribution of portfolio liquidity based on imputed round-trip costs over time. The upwards trend suggests that portfolio liquidity has improved over time, although Bao et al. (2018) provide evidence that corporate bond liquidity has actually declined as a result of the Volcker Rule. In my main specifications, I therefore include time fixed effects in order to focus on cross-sectional variation in portfolio liquidity, rather than time-series variation. Figure 4b shows the median portfolio liquidity for high-yield funds (Lipper Objective Codes GHY, HY, and SHY) and investment-grade funds (Lipper Objective Codes A, BBB, IID, SID, SII). As expected, high-yield funds tend to have lower portfolio liquidity, as lower-rated corporate bonds tend to be less liquid (Table 2).

In order to better understand the determinants of portfolio liquidity, I consider a panel regression in which I regress portfolio liquidity on fund style dummies based on Lipper Objective Codes. Panel A of Table 3 shows the results, where short-term investment grade funds serve as the baseline. As indicated by the high within adjusted R-squared ranging between 32 and 47 per cent, fund styles explain a substantial part of the cross-sectional variation in portfolio liquidity. Column 1 shows that in line with Figure 4b, high-yield funds (Lipper Objective Codes GHY, HY, and SHY) tend to have the lowest portfolio liquidity. Funds investing in short-term investment grade debt (SID) tend to have the most liquid portfolios, as all coefficients on the other fund styles are significantly negative. Funds investing in A- and BBB- rated corporate bonds (A and BBB) and intermediate investment grade debt (IID) show worse portfolio liquidity relative to funds investing in short and short-intermediate term investment grade debt (SID and SII). This may be explained by the larger remaining maturities of the corporate bond holdings by these funds (Table 1), which is associated with worse liquidity (Table 2). Somewhat surprisingly, in Columns 2-4, funds investing in A- and BBB- rated corporate bonds (A and BBB) and intermediate investment grade debt (IID) appear to hold less liquid portfolios relative to high-yield funds (especially HY and SHY). This is remarkable since high-yield bonds tend to be less liquid than investment-grade bonds (Table 2). This may be explained by the substantial allocation of high-yield funds towards Rule 144A bonds, which appear more liquid based on $Spread^{GH}$, $Spread^{HW}$, and $Amihud$ (Table 2). This again highlights the importance of properly taking into account the characteristics of the Rule 144A bond market when estimating bond and portfolio liquidity.

Next, I control for fund styles by including fund style fixed effects and relate portfolio liquidity to a set of additional fund characteristics using the following panel regression:

$$
\begin{aligned}
PFLIQ_{i,j,t} = \beta_1 log(TNA_{i,t}) + \beta_2 w_{i,t}^{Cash} + \beta_3 w_{i,t}^{Govt} + \beta_4 Retail_{i,t} + \beta_5 RearLoad_{i,t} \\
+ \beta_6 ExpRatio_{i,t} + \gamma_j + \delta_t + \varepsilon_{i,t}
\end{aligned}
\tag{5}
$$

Here, j refers to fund styles, $log(TNA_{i,t})$ is the logarithm of a fund's total net assets, $w_{i,t}^{Cash}$ ($w_{i,t}^{Govt}$) represents fund i's portfolio weight at time t allocated to cash (government bonds). The explanatory variable $Retail_{i,t}$ reflects the fraction of fund i's total net assets that is targeted towards retail investors, and $RearLoad_{i,t}$ reflects the fraction of fund i's total net assets for which a rear load applies. Moreover, $ExpRatio_{i,t}$ denotes the fund's expense ratio, which is averaged across shareclasses weighted by total net assets.[6] Finally, I consider year-quarter fixed effects (δ_t) and fund style fixed effects based on Lipper Objective Codes (γ_j). Panel B of Table 3 contains the results. The low within adjusted R-squared ranging between 1.6% and 6.0% suggests that fund characteristics beyond fund style only explain a limited proportion of the cross-sectional variation in portfolio liquidity. It follows from Column 1 that retail funds tend to have lower portfolio liquidity, but after controlling for expense ratios in Column 2 this effect disappears. The result that expense ratios tend to be higher for funds holding less liquid bonds is intuitive, as part of the larger costs of trading illiquid bonds are indirectly passed on to investors through these higher expense ratios. Moreover, funds holding more government bonds tend to hold more liquid corporate bonds as well. Finally, the overall corporate bond portfolios of funds with larger allocations towards Rule 144A bonds tend to be less liquid. This result also holds for the alternative liquidity proxies in Columns 3-8, even though Table 2 has shown that Rule 144A bonds appear more liquid based on $Spread^{GH}$, $Spread^{HW}$, and $Amihud$. Nevertheless, the magnitudes of the coefficients on the Rule 144A dummy and the corresponding t-statistics in Columns 1 and 2 are substantially larger than those in Columns 3-8.

[6] Different share classes of the same fund may target different investor types and may have different fee structures.

2.5 Measuring fund flows

In line with prior literature, I compute flows of fund i in month t in the following way:

$$f_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}\,(1 + r_{i,t}) - \Delta TNA_{i,t}^{Merger}}{TNA_{i,t-1}} \tag{6}$$

Here, $TNA_{i,t}$ denotes total net assets, $r_{i,t}$ denotes the monthly fund return, and $\Delta TNA_{i,t}^{Merger}$ denotes the change in total net assets due to a fund merger. I correct for changes in TNA that result from fund mergers using a similar approach as Lou (2012). Specifically, for each target fund, I obtain its latest total net asset value and the corresponding date. I link this to the acquiring fund by allowing the merger to take place within 1 year after the target fund reported it's latest total net asset value. Then, I select the month in which the acquiring fund experienced the largest flow as the event month. In that month, $\Delta TNA_{i,t}^{Merger}$ is set equal to the target fund's latest total net asset value. Figure 5 shows aggregate net flows for the corporate bond mutual funds in my sample. The COVID-19 crisis in March 2020 coincides with the largest aggregate net outflows, which amounted to 4% of aggregate total net assets.

3 Corporate bond liquidity and fund flows

3.1 Aggregate fund flows

Table 4 contains the results of regressing aggregate fund flows on market liquidity indicators. Apart from $MLIQ$ which is based on estimated market-wide effective spreads from Equation (2), I also consider the VIX index and the TED-spread to proxy for the liquidity of the corporate bond market. The VIX index reflects implied stock market volatility and is strongly correlated with the liquidity of the corporate bond market (Bao et al., 2011). The TED-spread has been widely used to proxy for the funding liquidity of financial institutions, which strongly affects asset market liquidity (Brunnermeier and Pedersen, 2009). In Columns 1 to 3, the independent variable is a dummy variable indicating whether the corporate bond market is illiquid. In Column 1, $IlliqPeriod$ equals 1 when $MLIQ$ falls below its 10^{th} percentile, and 0 otherwise. In Columns 2 and 3, $IlliqPeriod$ equals 1 when the VIX index or the TED spread exceeds its 90^{th} percentile, respectively, and 0 otherwise. The results show that none of the coefficients is statistically significant, and the adjusted R-squared is near zero.

In Columns 4 to 6, I replace the independent variable by AR(1)-innovations in $MLIQ$, the VIX index, and the TED spread, respectively. Regarding $MLIQ$, a negative innovation corresponds to a decrease in the liquidity of the corporate bond market. For the VIX index and the TED spread, a positive innovation implies a decrease in corporate bond market liquidity. During the sample period 2010-2022, the number of months characterised by a decrease in market liquidity equals 47, 54, or

36 based on AR(1)-innovations in $MLIQ$, VIX, or TED respectively. The results in Table 4 suggest that aggregate fund flows are strongly correlated with shocks in market liquidity, rather than its level. When corporate bond market liquidity falls, flows decline significantly. Specifically, the results in Column 4 imply that a one-standard deviation decrease in market liquidity is associated with a decrease in aggregate net flows (increase in outflows) of 0.58 percentage points, on average. Moreover, the adjusted R-squared has increased to 23 to 25 per cent.

It is important to stress that these results do not necessarily imply causality, as reverse causality or an omitted variables bias can not be ruled out. For instance, high aggregate outflows may in itself cause a contemporaneous drop in market liquidity, or there might be an unobserved factor that both leads to lower market liquidity as well as aggregate net outflows. An example of such a factor could be an increase in risk aversion during a crisis, which leads intermediaries to charge higher transaction costs and investors to reduce their allocation to risky assets. Nevertheless, the results in Table 4 show that aggregate net outflows and periods in which market liquidity drops tend to coincide.

3.2 The cross-section of fund flows

Goldstein et al. (2017) and Falato et al. (2021) have shown that funds with lower portfolio liquidity are confronted with larger outflows during times of stress. Apart from the different sample period considered in this paper, I also rely on an enhanced portfolio liquidity proxy that includes the liquidity of Rule 144A bonds as well. In this section, I therefore revisit the question whether portfolio liquidity affects the cross-section of flows. Multiple factors could lead to an amplification of outflows for precisely those funds holding less liquid corporate bonds. First of all, since the first-mover advantage is larger for less liquid funds and increases during periods of stress when corporate bond liquidity is low, less liquid funds should face stronger outflows during periods of stress (Goldstein et al., 2017; Falato et al., 2021). Second, mutual fund investors may redeem fund shares because of a competition for finite liquidity in the underlying asset market, which not only affects mutual fund investors but all market participants with overlapping portfolios (Stahel, 2022). This competition for finite asset market liquidity may also lead to larger observed outflows for less liquid funds. Third, lower-rated corporate bonds typically lose more value during crisis periods than bonds with a better credit rating.[7] As a result, investors may run more intensely on funds holding lower-rated debt during crisis periods, since flows are strongly related to lagged fund returns, also at higher frequencies (see, e.g., Dekker et al., 2023). Because lower-rated debt is typically less liquid, this credit risk channel may also lead to larger observed outflows for less liquid funds during illiquid periods. I examine the relationship between portfolio liquidity and net

[7] For instance, the ICE BofA US High Yield Index experienced a return of -16.3% during October 2008, versus -7.4% for the ICE BofA US Corporate Index which tracks investment-grade corporate debt. Moreover, during March 2020, the ICE BofA US High Yield Index experienced a return of -11.8% versus -7.5% for the ICE BofA US Corporate Index. Total returns for both indices are retrieved from FRED, Federal Reserve Bank of St. Louis.

flows using the following panel regression:

$$f_{i,t} = \beta_1 PFLIQ_{i,t-1} + \beta_2 \left(PFLIQ_{i,t-1} \times NegInno_t\right) + \gamma' Controls_{i,t-1} + \delta_t + \varepsilon_{i,t} \tag{7}$$

Here, $f_{i,t}$ denotes the net flow of share class i during month t, and $PFLIQ_{i,t-1}$ denotes the lagged liquidity of the portfolio corresponding to share class i, based on imputed round-trip costs. The variable $NegInno_t$ is a dummy variable that equals 1 if the AR(1)-innovation in market-wide corporate bond liquidity ($MLIQ$) is negative, i.e. when corporate bond market liquidity deteriorates, and 0 otherwise. Furthermore, the vector $Controls_{i,t-1}$ includes the fund's weight allocated to cash and government bonds, last month's flow, the logarithm of total net assets, the logarithm of fund age, a retail fund indicator, a rear load indicator, and the fund's expense ratio. Lower portfolio liquidity may be offset by a higher cash buffer (or larger holdings in other liquid assets), such that the overall liquidity profile of the portfolio remains similar (Chernenko and Sunderam, 2020). As such, controlling for liquidity buffers is important to prevent an omitted variables bias. The main coefficient of interest is β_2, which allows me to test whether illiquid funds face stronger outflows during months when market liquidity drops.

Table 5 reports the results. Column 1 shows that the coefficient on the interaction between the negative liquidity shock dummy and portfolio liquidity is significantly positive, indicating that less liquid funds face lower flows (larger outflows) during months when market liquidity deteriorates. During periods in which market liquidity drops, a one-standard deviation decrease in portfolio liquidity is associated with an average decline in net flows of 30 basis points per month. For comparison, the average flow during months in which market liquidity deriorates, equals -4 basis points. This result is consistent with Goldstein et al. (2017) and Falato et al. (2021). Moreover, flows appear to be persistent as lagged flows share a significantly positive relation with current flows. Also, funds with rear load fees and higher expense ratios have experienced lower flows on average. The results in Column 1 potentially suffer from an omitted variables bias, as portfolio liquidity is correlated with the portfolio's credit rating profile. In Column 2, I replace portfolio liquidity by the portfolio's average credit rating of the corporate bonds held. It follows that funds investing in lower rated corporate bonds on average face larger outflows during times when market liquidity deteriorates. What's more, after controlling for heterogeneity in credit ratings in Column 3, the effect of portfolio liquidity on flows during periods in which market liquidity drops has vanished. To delve deeper into the confounding effect of credit ratings, Columns 4 and 5 of Table 5 contain subsample analyses in which I separately consider investment-grade and high-yield funds, respectively. Both columns show that within the subsamples of investment-grade or high-yield funds, the coefficient on the interaction between portfolio liquidity and negative AR(1)-innovations in market liquidity is statistically insignificant.

In sum, the results in this section suggest that controlling for the effect of credit rating is crucial and challenge the robustness of previous findings on the causal effect of portfolio liquidity on the cross-section of fund flows. It could well be the case that outflows are still driven by a first-mover advantage specific to an open-ended fund structure, because portfolio liquidity is a latent variable while investors do observe the credit rating profile of the fund they invest in (which is correlated with portfolio liquidity). Nevertheless, based on the results in Table 5, it is impossible to disentangle these potential explanations. Importantly, even when the cross-sectional relationship between portfolio liquidity and fund flows is not causal, at the end of the day less liquid funds still face stronger outflows when market liquidity drops. As such, managers of less liquid funds may still be forced to sell larger quantities of bonds during periods of stress in order to accommodate the larger outflows they are confronted with. This may eat into the returns of these funds, thereby harming their ability to harvest any liquidity premium.

3.3 The cross-section of flow betas

Next, I study the sensitivity of individual funds' flows to aggregate flows by all corporate bond mutual funds in my sample. Mutual fund flows share a common, systematic component that is strongly related to macroeconomic variables (Ferson and Kim, 2012; Dou et al., 2022). Funds whose flows are more sensitive to this common component face stronger outflows during periods when the common component of fund flows is negative. In other words, these funds may be forced to sell large amounts of corporate bonds during periods when the mutual fund sector in aggregate is demanding liquidity. Given that mutual funds account for a substantial part of trading activity in the US corporate bond market, selling corporate bonds in periods when other funds are selling as well may be costly (Cai et al., 2019; Jiang et al., 2022).

To estimate the sensitivity of fund flows towards the common component of aggregate fund flows, I consider the following regression:

$$f_{i,t} = \alpha_i + \beta_i^{flow} \overline{f}_t + \varepsilon_{i,t}, \tag{8}$$

where $\overline{f}_t$ denotes the average value-weighted flow during month t across all funds in my sample. I estimate the regression in Equation (8) for each fund i using 36-month rolling windows and require at least 12 valid observations. Afterwards, I relate the estimated flow betas to portfolio liquidity and other fund characteristics using the following panel regression:

$$\widehat{\beta_{i,t}^{flow}} = \gamma PFLIQ_{i,t} + \delta' Controls_{i,t} + \lambda_t + \varepsilon_{i,t} \tag{9}$$

Table 6 contains the results. Column 1 shows that flow betas are declining in portfolio liquidity. Specifically, a one-standard deviation decline in portfolio liquidity is associated with an average increase in flow betas of 0.31. Column 2 shows a similar result for credit ratings, as funds holding lower rated bonds tend to have larger flow betas. In Column 3, I include both portfolio liquidity as well as credit rating as explanatory variables, and keep finding that flow betas are larger when the portfolio's liquidity or credit rating is lower. Columns 4 and 5 contain the results for subsamples of investment-grade and high-yield funds, respectively. Within both subsamples, flow betas still tend to be larger when portfolio liquidity is lower, although the effect is statistically insignificant for high-yield funds. Overall, these results are consistent with the idea that less liquid funds face larger redemption pressures when aggregate fund flows are negative as well.

4 Portfolio liquidity and fund performance

4.1 Fund performance based on raw returns

In this section, I study the relation between portfolio liquidity and fund performance. First, I consider a panel regression in which I regress monthly fund returns in excess of the risk-free rate on portfolio liquidity and a set of additional fund characteristics:

$$r_{i,t} - r_t^f = \beta_1 PFLIQ_{i,t-1} + \gamma' Controls_{i,t-1} + \delta_t + \varepsilon_{i,t}, \tag{10}$$

where $r_{i,t}$ denotes the monthly return of fund i during month t and r_t^f denotes the risk-free rate obtained from Kenneth French's website. Column 1 of Table 7 contains the results. It follows that on average, there is no significant relation between portfolio liquidity and fund excess returns. Columns 2 and 3 show that also within the subsets of investment-grade and high-yield funds, portfolio liquidity does not significantly affect fund excess returns. Next, I amend the specification from Equation (10) by including interactions between portfolio liquidity and a dummy variable $NegInno_t$ equal to 1 when the AR(1)-innovation in corporate bond market liquidity is negative, i.e., when market liquidity deteriorates:

$$r_{i,t} - r_t^f = \beta_1 PFLIQ_{i,t-1} + \beta_2 \left(PFLIQ_{i,t-1} \times NegInno_t\right) + \gamma' Controls_{i,t-1} + \delta_t + \varepsilon_{i,t} \tag{11}$$

Column 4 of Table 7 shows that less liquid funds significantly outperform when market liquidity improves as indicated by the significantly negative coefficient on portfolio liquidity as a standalone variable. A one-standard deviation decrease in portfolio liquidity is associated with an increase in monthly excess returns of 28 basis points. At the same time, the significantly positive coefficient on the interaction between portfolio liquidity and the market illiquidity dummy implies that less liquid funds significantly underperform when market liquidity drops. Here, a one-standard deviation decrease in portfolio liquidity is associated with a decrease in monthly excess returns of 54 basis points. Columns 5 and 6 show that the negative effect of portfolio liquidity on fund returns during times when market liquidity drops is strongest within the set of high-yield funds. However, a key concern is that the results in Table 7 may also be driven by funds' risk exposures, rather than by portfolio liquidity only. To alleviate the confounding effect of risk exposures, I measure fund performance using risk-adjusted returns in the remainder of this section.

4.2 Risk-adjusted fund performance

In order to measure risk-adjusted fund performance, I first regress mutual fund excess returns on a set of risk factors:

$$r_{i,t} - r_t^f = \alpha_i + \beta_i' F_t + \varepsilon_{i,t}, \tag{12}$$

where $r_{i,t}$ denotes the monthly return of fund i during month t, r_t^f denotes the risk-free rate obtained from Kenneth French's website, and F_t is a vector of risk factors. In order to make sure that the results do not depend on a specific factor model, I consider various specifications. In Model 1, I consider a 2-factor model which includes an aggregate bond market factor proxied by the excess return on the Vanguard Total Bond Market Index Fund, and a credit factor based on the ICE BofA US High Yield Index.[8] In Model 2, I follow Goldstein et al. (2017) and consider the same aggregate bond market factor as in Model 1, complemented with the excess return on the US equity market as proxied by the value-weighted CRSP market return. Finally, Model 3 follows Choi and Kronlund (2018) and consists of a 3-factor model which includes the TERM and DEF factors from Fama and French (1993), and the equity market factor from Model 2. The TERM factor denotes the difference between the return on long-term government bonds and the T-bill rate, and the DEF factor equals the difference between the return on long-term corporate bonds and the long-term government bond return.[9] The regression in Equation (12) is estimated for each fund i using 36-month rolling windows. Using estimated betas based on return data from months $t-36$ up to and including $t-1$, I compute expected returns in month t based on the realizations of the risk factors. The difference between these expected fund returns and actual fund returns in month t is then the fund's monthly alpha, denoted by $\widehat{\alpha}_{i,t}^k$, where $k = 1, 2, 3$ for Models 1, 2, and 3 respectively.

Using a similar specification as in Equation (10), I then consider a panel regression in which I regress the monthly alphas based on Equation (12) on portfolio liquidity and a set of additional fund characteristics:

$$\widehat{\alpha}_{i,t}^k = \beta_1 PFLIQ_{i,t-1} + \gamma' Controls_{i,t-1} + \delta_t + \varepsilon_{i,t}, \tag{13}$$

Columns 1-3 in Table 8 contain the results. Columns 1 and 2 show that on average, less liquid funds significantly underperform their more liquid counterparts over the period 2010-2022. Column 3 shows that alphas using Model 3 are still lower for funds with lower portfolio liquidity, but the coefficient is significant at the 10% level only. When portfolio liquidity decreases by one standard deviation, risk-adjusted returns on average decline by 3-6 additional basis points per month, or, equivalently, 36 to 77 basis points per year. Column 1 also shows that alphas based on Model 1

[8] Total returns for the ICE BofA US High Yield Index are retrieved from FRED, Federal Reserve Bank of St. Louis.

[9] The data to construct the TERM and DEF factors is available at Amit Goyal's website: `https://sites.google.com/view/agoyal145`.

are significantly lower for funds with higher expense ratios.

Next, I amend the specification from Equation (13) by including interactions between portfolio liquidity and the negative liquidity shock dummy ($NegInno_t$):

$$\widehat{\alpha}_{i,t}^{k} = \beta_1 PFLIQ_{i,t-1} + \beta_2 \left(PFLIQ_{i,t-1} \times NegInno_t\right) + \gamma' Controls_{i,t-1} + \delta_t + \varepsilon_{i,t} \qquad (14)$$

The main coefficients of interest are β_1 and β_2, which allow me to test the relation between fund liquidity and performance in periods during which market liquidity deteriorates/improves. Columns 4-6 in Table 8 show the results. In Model 1, the coefficient on the interaction term between the market illiquidity dummy and portfolio liquidity is statistically insignificant. For Models 2 and 3, underperformance by less liquid funds is strongly driven by periods in which market liquidity deteriorates (Columns 5 and 6), indicated by the significantly positive coefficients on the interaction between portfolio liquidity and the market illiquidity dummy. Specifically, the results in Columns 5 and 6 suggest that a one-standard deviation decline in portfolio liquidity is associated with an economically meaningful reduction in risk-adjusted performance of 18-19 basis points per month during illiquid periods. During periods in which market liquidity improves, the effect of portfolio liquidity on fund performance is statistically insignificant for all 3 models. The relatively short sample period considered in this paper presents a limitation when estimating the unconditional effect of portfolio liquidity on fund performance, as the results may hinge upon rare events with high impact such as the COVID-19 crisis. Hence, it would be desirable to estimate this effect over a longer sample period. Nevertheless, one would still expect illiquid funds to outperform more liquid funds during normal circumstances, which is not the case based on the results in Table 8.

The results in Section 3 have shown that funds holding lower-rated corporate bonds face larger outflows during times of stress. Consequently, managers of funds that hold lower-rated debt may be forced to sell a larger quantity of bonds to accommodate redemption requests. As such, I expect the effect of portfolio liquidity on risk-adjusted fund performance to be of larger importance for funds holding lower-rated debt. To test this conjecture, I again consider a subsample analysis in which I separately examine investment-grade funds and high-yield funds. Panel A of Table 9 contains the results based on the subset of investment-grade funds. It follows that on average, there is no significant effect of portfolio liquidity on risk-adjusted returns (Columns 1-3). The positive coefficients on the interactions between portfolio liquidity and the market illiquidity dummy in Columns 4-6 suggest that less liquid funds underperform during periods in which market liquidity declines, but this effect is only significant in Model 3 (Column 6). Hence, my results suggest that lower portfolio liquidity does not have a strong effect on fund performance within the set of investment-grade funds.

Panel B of Table 9 contains the results for the subsample of high-yield funds. Columns 1-3 show that over the full sample period between 2010 and 2022, lower portfolio liquidity leads to a significant reduction in risk-adjusted returns within the sample of high-yield funds. A one-standard deviation decrease in portfolio liquidity is associated with a decrease in risk-adjusted returns of 15 to 19 basis points per month, or, equivalently, 1.8% to 2.3% per year. To put these numbers into context, Houweling (2012) shows that high-yield ETFs underperform their benchmark indices by 384 basis points per year, due to the substantial transaction costs involved in trading high-yield bonds. Columns 4-6 show that this underperformance is driven by periods in which market liquidity drops, as the coefficients on the interaction between portfolio liquidity and the market illiquidity dummy are significantly positive. The coefficient magnitudes imply that a one-standard deviation decrease in portfolio liquidity leads to a 33-51 basis points decline in monthly alphas during illiquid periods. These losses are not compensated by outperformance during periods in which market liquidity improves, as the coefficients on portfolio liquidity as a standalone variable have all become statistically insignificant.

The market illiquidity dummy used in the analyses so far equals 1 during months in which the AR(1)-innovation in market liquidity is negative, and 0 otherwise. In order to test whether the underperformance of less liquid funds is strongest during months in which adverse market liquidity shocks are largest, I next consider a dummy variable that equals 1 when the AR(1)-innovation in market liquidity is below its 10^{th} percentile and 0 otherwise, denoted by $\mathbb{1}(L_t < Q_{10})$ where L_t denotes the innovation in market liquidity. Panel A of Table 11 contains the results. Regarding investment-grade funds, the effect of portfolio liquidity on fund performance is still statistically insignificant, also during times with large negative shocks in market liquidity. Regarding high-yield funds however, the coefficient on the interaction between portfolio liquidity and the market illiquidity indicator has increased in magnitude compared with Panel B in Table 9. Specifically, a one-standard deviation decline in portfolio liquidity of high-yield funds leads to a 71-112 basis points decline in monthly alphas during periods with larger deteriorations in market liquidity. These results are consistent with the idea that when market liquidity dries up, investor redemptions spike and accommodating these outflows is most costly.

It could be the case that the factor models used to compute risk-adjusted fund performance do not fully capture credit risk exposures. To alleviate the concern that my results are driven by credit risk exposures, Panel B of Table 11 contains the results of estimating Equation (14) with additional controls for portfolios' credit ratings. In line with my previous results, I keep finding that portfolio liquidity strongly affects performance of high-yield funds (Columns 4-6), whereas the effect on performance of investment-grade funds is much weaker (Columns 1-3). Moreover, regarding the subset of high-yield funds, the economic magnitude has reduced slightly but is broadly similar to the results in Table 9. In Columns 4-6, the coefficients on both the standalone rating variable as well as on the interaction between rating and the negative market liquidity shock dummy are statistically insignificant at the conventional levels. This suggests that credit risk exposures are adequately captured by the factor models used to compute risk-adjusted fund returns, at least within the set of high-yield funds.

So far, all specifications included time fixed effects as the focus is on the cross-sectional relation between portfolio liquidity and fund performance. Because these time fixed effects may absorb a substantial fraction of the variation in fund performance as well as the explanatory variables, Panel C of Table 11 shows the results of a specification without time fixed effects. Because portfolio liquidity shows a declining trend over time (see Figure 4a), I demean portfolio liquidity and scale it by its cross-sectional standard deviation for each period separately. This way, portfolio liquidity is free from any time trend. This is important because contrary to what the declining trend in portfolio liquidity suggests, Bao et al. (2018) argue that corporate bond liquidity has actually deteriorated during my sample period as a result of the Volcker Rule. Again, the primary objective of my bond liquidity measure is to achieve an accurate cross-sectional ranking of corporate bonds based on their liquidity. The results in Panel C of Table 11 yield similar conclusions compared with the baseline results in which time fixed effects are included.

As a final robustness check, I consider the alternative liquidity proxies to measure portfolio liquidity defined in Appendix B.2. In order to preserve space, I only present the results for risk-adjusted returns based on Model 1. Table 12 contains the results for investment-grade and high-yield funds in Panels A and B, respectively. In line with my previous results, I keep finding that portfolio liquidity on average does not affect fund performance for investment-grade funds, whereas less liquid high-yield funds significantly underperform more liquid high-yield funds. In unreported results, I find similar conclusions using alphas based on Models 2 and 3.

Overall, the results in this section are consistent with the notion that the larger outflows faced by illiquid funds translate into lower performance during times when market liquidity drops. These larger outflows may increase the need to sell corporate bonds while transaction costs have soared, which directly hurts fund returns. My results therefore question whether open-ended funds are well-suited to invest in the least liquid corporate bonds.

5 Moderating fund characteristics

In this section, I examine which fund characteristics moderate the effect of portfolio liquidity on fund performance to further flesh out the mechanism. I first focus on lagged flows and returns as these are indicative of redemption pressures the month after. Second, I test whether higher liquidity buffers and anti-dilution levies reduce the impact of portfolio illiquidity on fund performance. Finally, I examine whether the effect of portfolio liquidity on fund performance varies with fund size and differs across retail- versus institutional-oriented funds. To increase the size of the cross-section, I omit expense ratios as a control variable as these are missing for a nonnegligible fraction of the funds in my sample.

5.1 Lagged flows and returns

Because forced asset sales may lead to high liquidity costs, the negative effect of portfolio illiquidity on fund performance should be most pronounced for funds facing outflows. To test this conjecture, I consider the following regression which builds on Chen et al. (2010):

$$\widehat{\alpha}_{i,t}^{k} = \beta_1 PFLIQ_{i,t-1} + \beta_2 f_{i,t-1} + \beta_3 \left(PFLIQ_{i,t-1} \times f_{i,t-1}\right) + \gamma' Controls_{i,t-1} + \delta_t + \varepsilon_{i,t}, \tag{15}$$

The coefficient of interest is β_3, which indicates whether the effect of portfolio liquidity on fund performance varies with the fund's flow of last month. Because flows and returns are endogenously determined in equilibrium, I do not interact portfolio liquidity with contemporaneous flows but with lagged flows instead. Table 10 contains the results. It follows from Columns 1-3 in Panel A that lagged flows do not significantly moderate the effect of portfolio liquidity on fund performance within the subset of investment-grade funds. However, Columns 1-3 in Panel B show that within the set of high-yield funds, lower flows during the previous month strengthen the relationship between portfolio liquidity and fund performance. Two channels may be at play. First, part of the portfolio rebalancing associated with accommodating last month's flows may take place in the month after. Second, Table 5 shows that flows are persistent, suggesting that funds which faced net outflows last month are more likely to face net outflows the month after as well. Both situations would lead to higher liquidity costs which hurts fund performance, in line with the results in Table 10.

Table 5 suggests that at least within the subsamples of investment-grade and high-yield funds, lagged returns predict flows. As such, funds facing low returns are more likely to face net outflows the month after. I therefore hypothesize that the adverse effect of portfolio illiquidity on fund performance is stronger following low returns. To test this, I consider the following specification:

$$\widehat{\alpha}_{i,t}^{k} = \beta_1 PFLIQ_{i,t-1} + \beta_2 r_{i,t-1} + \beta_3 \left(PFLIQ_{i,t-1} \times r_{i,t-1}\right) + \gamma' Controls_{i,t-1} + \delta_t + \varepsilon_{i,t}, \tag{16}$$

The coefficient of interest is β_3, which indicates whether the effect of portfolio liquidity on fund performance varies with the fund's return of last month. Table 10 contains the results. It follows from Columns 4-6 in Panel A that lagged returns do not significantly moderate the effect of portfolio liquidity on fund performance within the subset of investment-grade funds. However, Columns 4-6 in Panel B again show that within the set of high-yield funds, lower returns during the previous month strengthen the relationship between portfolio liquidity and fund performance. These results are consistent with the explanation that low fund returns lead to increased redemption pressures the month after, which hurts fund performance through increased liquidity costs.

5.2 Liquidity management

Funds holding illiquid bonds might differ in their liquidity management practices. For instance, some fund managers may choose to hold relatively large cash buffers to compensate for the illiquidity of their corporate bond holdings. Such funds may be better able to withstand large outflows during times of stress, as they can meet a larger part of outflows by drawing down their liquidity buffers (see, e.g., Dekker et al., 2023). As a consequence, such funds need to sell a lower quantity of corporate bond funds, thereby limiting the impact of costly asset sales on fund performance. As such, I hypothesize that the effect of portfolio liquidity on fund performance is strongest for funds with low cash buffers. I consider the following regression:

$$\begin{aligned}\widehat{\alpha}^k_{i,t} = \beta_1 PFLIQ_{i,t-1} + \beta_2 LowCash_{i,t-1} + \beta_3 \left(PFLIQ_{i,t-1} \times LowCash_{i,t-1}\right) \\ + \gamma' Controls_{i,t-1} + \delta_t + \varepsilon_{i,t},\end{aligned} \tag{17}$$

where $LowCash_{i,t-1}$ is a dummy variable equal to 1 if fund i has a cash buffer below the median cash buffer of all funds with the same Lipper Objective Code, and 0 otherwise. Columns 1-3 in Panel A and Columns 1-3 in Panel B of Table 13 contain the results for investment-grade and high-yield funds, respectively. It follows from both panels that the impact of portfolio liquidity on fund returns is not stronger for funds with low cash buffers, as the coefficients on the interaction between portfolio liquidity and the low-cash dummy are statistically insignificant.

One of the potential drivers of outflows during times of stress is related to the first-mover advantage inherent to open-ended funds (Goldstein et al., 2017). As a consequence, funds that employ anti-dilution tools that limit the negative externalities created by redeeming investors may expect smaller outflows during times of stress. Since a reduction in outflows also lowers the need to sell portfolio assets, I hypothesize that the effect of portfolio liquidity on fund performance is weaker within funds employing anti-dilution tools. To test this, I distinguish between funds employing rear load fees versus funds that do not. I consider the following regression:

$$\begin{aligned}\widehat{\alpha}^k_{i,t} = \beta_1 PFLIQ_{i,t-1} + \beta_2 RearLoad_{i,t-1} + \beta_3 \left(PFLIQ_{i,t-1} \times RearLoad_{i,t-1}\right) \\ + \gamma' Controls_{i,t-1} + \delta_t + \varepsilon_{i,t},\end{aligned} \tag{18}$$

where $RearLoad_{i,t-1}$ is a dummy variable equal to 1 if fund i employs a rear load fee on at least one of its share classes, and 0 otherwise. Columns 4-6 in Panel A and Columns 4-6 in Panel B of Table 13 contain the results for investment-grade and high-yield funds, respectively. All coefficients on the interaction terms between the rear load dummy and portfolio liquidity are statistically insignificant, indicating that rear loads do not significantly reduce the cost of holding illiquid corporate bonds.

A potential reason why I do not find a moderating effect of liquidity buffers and rear load fees is that funds may instead employ other liquidity management tools that I do not observe. For instance, funds may use in-kind redemptions to meet investor withdrawals (Agarwal et al., 2023), swing pricing (Jin et al., 2022), have access to interfund lending (Agarwal and Zhao, 2019), or get liquidity from affiliated funds of funds (Bhattacharya et al., 2013). If funds substitute liquidity buffers and rear load fees by alternative liquidity management tools, this may explain why higher liquidity buffers and the presence of rear load fees do not alleviate the impact of portfolio illiquidity on fund performance.

5.3 Other fund characteristics

Since price impact is generally increasing in transaction size, larger funds may experience higher costs when accommodating investor flows. This mechanism would predict that the effect of portfolio liquidity on fund performance is strongest for larger funds. I consider the following regression:

$$\begin{aligned}\widehat{\alpha}_{i,t}^{k} = \beta_1 PFLIQ_{i,t-1} + \beta_2 LargeSize_{i,t-1} + \beta_3 \left(PFLIQ_{i,t-1} \times LargeSize_{i,t-1}\right) \\ + \gamma' Controls_{i,t-1} + \delta_t + \varepsilon_{i,t},\end{aligned} \tag{19}$$

where $LargeSize_{i,t-1}$ equals 1 if fund i has total net assets exceeding the median of all funds with the same Lipper Objective Code, and 0 otherwise. Columns 1-3 in Panels A and B of Table 14 show that fund size neither impacts the effect of portfolio liquidity on fund performance within the set of investment grade funds, nor within the set of high-yield funds.

Goldstein et al. (2017) argue that strategic complementarities are larger in retail-oriented funds, and as such illiquid retail-oriented funds are more fragile than illiquid institutional-oriented funds. Consequently, flow dynamics might be different for retail-oriented funds versus institutional-oriented funds. In line with this, Table 6 shows that at least within the set of high-yield funds, retail-oriented funds have higher flow betas. To test whether portfolio liquidity has a stronger effect on the performance of retail-oriented funds, I consider the following regression:

$$\begin{aligned}\widehat{\alpha}_{i,t}^{k} = \beta_1 PFLIQ_{i,t-1} + \beta_2 Retail_{i,t-1} + \beta_3 \left(PFLIQ_{i,t-1} \times Retail_{i,t-1}\right) \\ + \gamma' Controls_{i,t-1} + \delta_t + \varepsilon_{i,t},\end{aligned} \tag{20}$$

where $Retail_{i,t}$ is a dummy equal to 1 if more than 80% of the total net assets of fund i is distributed through retail share classes following Choi and Kronlund (2018). Columns 4-6 in Panels A and B of Table 14 contain the results for investment-grade and high-yield funds, respectively. The coefficients on the standalone retail fund dummy are all negative, and statistically significant in 3 out of 6 specifications, suggesting that retail funds tend to perform worse than institutional-oriented funds. This is likely driven by the higher expense ratios charged to retail investors. However, I do not find that the effect of portfolio liquidity on fund performance is stronger for retail-oriented funds as opposed to institutional-oriented funds.

6 Conclusion

Open-ended funds suffer from a liquidity mismatch when the liquidity of portfolio holdings is not aligned with the redemption terms offered to investors. When faced with sudden and large outflows, this could lead to costly forced asset sales that have a direct impact on fund performance. As such, an open-ended fund structure may pose limits to harvest corporate bond liquidity premia. Ironically, redemption risk is largest for precisely those funds with the highest liquidity mismatch. Funds investing in the least liquid securities may face stronger outflows during times of stress because of larger strategic complementarities (Goldstein et al., 2017), stronger competition for finite asset market liquidity (Stahel, 2022), or because the least liquid securities tend to be lower-rated and lose more value during times of stress.

In line with this story, this paper documents a negative effect of portfolio illiquidity on fund performance within a sample of US corporate bond mutual funds. I find that this effect is concentrated within the set of high-yield funds, consistent with the fact that these funds are subject to larger redemption risk. Moreover, the underperformance of less liquid funds is fully driven by periods in which the liquidity of the corporate bond market deteriorates. My results therefore suggest a reduced ability of mutual funds to harvest corporate bond liquidity premia that may be driven by their open-ended structure.

My results also have implications for policymakers. In recent years, a lot of attention has been spent on reducing the structural liquidity mismatch and the adoption of liquidity management tools to reduce the first-mover advantage in open-ended investment funds. While these policies have been designed to reduce vulnerabilities in the investment fund sector and to enhance the resilience of the wider financial system, my results imply that a reduction in the liquidity mismatch may ultimately benefit investors as well through enhanced performance.

References

Acharya, V. V. and Pedersen, L. H. (2005). Asset pricing with liquidity risk. *Journal of Financial Economics*, 77(2):375–410.

Agarwal, V., Aragon, G. O., and Shi, Z. (2019). Liquidity transformation and financial fragility: Evidence from funds of hedge funds. *Journal of Financial and Quantitative Analysis*, 54(6):2355–2381.

Agarwal, V., Ren, H., Shen, K., and Zhao, H. (2023). Redemption in kind and mutual fund liquidity management. *The Review of Financial Studies*, 36(6):2274–2318.

Agarwal, V. and Zhao, H. (2019). Interfund lending in mutual fund families: Role in liquidity management. *The Review of Financial Studies*, 32(10):4079–4115.

Amihud, Y. and Mendelson, H. (1986). Asset pricing and the bid-ask spread. *Journal of Financial Economics*, 17(2):223–249.

Anand, A., Jotikasthira, C., and Venkataraman, K. (2021). Mutual fund trading style and bond market fragility. *The Review of Financial Studies*, 34(6):2993–3044.

Bai, J., Bali, T. G., and Wen, Q. (2019). Common risk factors in the cross-section of corporate bond returns. *Journal of Financial Economics*, 131(3):619–642.

Bao, J., O'Hara, M., and Zhou, X. A. (2018). The Volcker Rule and corporate bond market making in times of stress. *Journal of Financial Economics*, 130(1):95–113.

Bao, J., Pan, J., and Wang, J. (2011). The illiquidity of corporate bonds. *The Journal of Finance*, 66(3):911–946.

Beber, A., Driessen, J., Neuberger, A., and Tuijp, P. (2021). Pricing liquidity risk with heterogeneous investment horizons. *Journal of Financial and Quantitative Analysis*, 56(2):373–408.

Becker, B. and Ivashina, V. (2015). Reaching for yield in the bond market. *The Journal of Finance*, 70(5):1863–1902.

Bhattacharya, U., Lee, J. H., and Pool, V. K. (2013). Conflicting family values in mutual fund families. *The Journal of Finance*, 68(1):173–200.

Bongaerts, D., De Jong, F., and Driessen, J. (2017). An asset pricing approach to liquidity effects in corporate bond markets. *The Review of Financial Studies*, 30(4):1229–1269.

Brunnermeier, M. K. and Pedersen, L. H. (2009). Market liquidity and funding liquidity. *The Review of Financial Studies*, 22(6):2201–2238.

Cai, F., Han, S., Li, D., and Li, Y. (2019). Institutional herding and its price impact: Evidence from the corporate bond market. *Journal of Financial Economics*, 131(1):139–167.

Chen, Q., Goldstein, I., and Jiang, W. (2010). Payoff complementarities and financial fragility: Evidence from mutual fund outflows. *Journal of Financial Economics*, 97(2):239–262.

Chen, X., Huang, J.-Z., Sun, Z., Yao, T., and Yu, T. (2020). Liquidity premium in the eye of the beholder: An analysis of the clientele effect in the corporate bond market. *Management Science*, 66(2):932–957.

Chernenko, S. and Sunderam, A. (2020). Measuring the perceived liquidity of the corporate bond market. Technical report, National Bureau of Economic Research.

Choi, J., Hoseinzade, S., Shin, S. S., and Tehranian, H. (2020). Corporate bond mutual funds and asset fire sales. *Journal of Financial Economics*, 138(2):432–457.

Choi, J., Huh, Y., and Seunghun Shin, S. (2023). Customer liquidity provision: Implications for corporate bond transaction costs. *Management Science*, forthcoming.

Choi, J. and Kronlund, M. (2018). Reaching for yield in corporate bond mutual funds. *The Review of Financial Studies*, 31(5):1930–1965.

Cici, G. and Gibson, S. (2012). The performance of corporate bond mutual funds: Evidence based on security-level holdings. *Journal of Financial and Quantitative Analysis*, 47(1):159–178.

Coval, J. and Stafford, E. (2007). Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics*, 86(2):479–512.

Dekker, L., Molestina Vivar, L., Wedow, M., and Weistroffer, C. (2023). Liquidity buffers and open-end investment funds: Containing outflows and reducing fire sales. *ECB Working Paper Series No 2825*.

Dick-Nielsen, J. (2009). Liquidity biases in trace. *The Journal of Fixed Income*, 19(2):43–55.

Dick-Nielsen, J. (2014). How to clean enhanced trace data. *Available at SSRN 2337908*.

Dick-Nielsen, J., Feldhütter, P., and Lando, D. (2012). Corporate bond liquidity before and after the onset of the subprime crisis. *Journal of Financial Economics*, 103(3):471–492.

Dickerson, A., Mueller, P., and Robotti, C. (2023). Priced risk in corporate bonds. *Available at SSRN*.

Dou, W. W., Kogan, L., and Wu, W. (2022). Common fund flows: Flow hedging and factor pricing. Technical report, National Bureau of Economic Research.

Ellul, A., Jotikasthira, C., and Lundblad, C. T. (2011). Regulatory pressure and fire sales in the corporate bond market. *Journal of Financial Economics*, 101(3):596–620.

Falato, A., Goldstein, I., and Hortaçsu, A. (2021). Financial fragility in the covid-19 crisis: The case of investment funds in corporate bond markets. *Journal of Monetary Economics*, 123:35–52.

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56.

Feldhütter, P. (2012). The same bond at different prices: identifying search frictions and selling pressures. *The Review of Financial Studies*, 25(4):1155–1206.

Ferson, W. E. and Kim, M. S. (2012). The factor structure of mutual fund flows. *International Journal of Portfolio Analysis and Management*, 1(2):112–143.

Giannetti, M. and Kahraman, B. (2018). Open-end organizational structures and limits to arbitrage. *The Review of Financial Studies*, 31(2):773–810.

Glosten, L. R. and Harris, L. E. (1988). Estimating the components of the bid/ask spread. *Journal of Financial Economics*, 21(1):123–142.

Goldstein, I., Jiang, H., and Ng, D. T. (2017). Investor flows and fragility in corporate bond funds. *Journal of Financial Economics*, 126(3):592–613.

Goldstein, M. A. and Hotchkiss, E. S. (2020). Providing liquidity in an illiquid market: Dealer behavior in us corporate bonds. *Journal of Financial Economics*, 135(1):16–40.

Hong, G. and Warga, A. (2000). An empirical study of bond market transactions. *Financial Analysts Journal*, 56(2):32–46.

Houweling, P. (2012). On the performance of fixed-income exchange-traded funds. *The Journal of Beta Investment Strategies*, 3(1):39–44.

Houweling, P., Mentink, A., and Vorst, T. (2005). Comparing possible proxies of corporate bond liquidity. *Journal of Banking & Finance*, 29(6):1331–1358.

Jiang, H., Li, D., and Wang, A. (2021). Dynamic liquidity management by corporate bond mutual funds. *Journal of Financial and Quantitative Analysis*, 56(5):1622–1652.

Jiang, H., Li, Y., Sun, Z., and Wang, A. (2022). Does mutual fund illiquidity introduce fragility into asset prices? Evidence from the corporate bond market. *Journal of Financial Economics*, 143(1):277–302.

Jin, D., Kacperczyk, M., Kahraman, B., and Suntheim, F. (2022). Swing pricing and fragility in open-end mutual funds. *The Review of Financial Studies*, 35(1):1–50.

Kargar, M., Lester, B., Lindsay, D., Liu, S., Weill, P.-O., and Zúñiga, D. (2021). Corporate bond liquidity during the covid-19 crisis. *The Review of Financial Studies*, 34(11):5352–5401.

Lin, H., Wang, J., and Wu, C. (2011). Liquidity risk and expected corporate bond returns. *Journal of Financial Economics*, 99(3):628–650.

Lou, D. (2012). A flow-based explanation for return predictability. *The Review of Financial Studies*, 25(12):3457–3489.

Murray, S. and Nikolova, S. (2022). The bond-pricing implications of rating-based capital requirements. *Journal of Financial and Quantitative Analysis*, 57(6):2177–2207.

Qin, N. and Wang, Y. (2021). Does portfolio concentration affect performance? evidence from corporate bond mutual funds. *Journal of Banking & Finance*, 123:106033.

Sadka, R. (2010). Liquidity risk and the cross-section of hedge-fund returns. *Journal of Financial Economics*, 98(1):54–71.

Scheuch, C., Voigt, S., and Weiss, P. (2023). *Tidy Finance with R*. Chapman and Hall/CRC, 1st edition.

Shleifer, A. and Vishny, R. W. (1997). The limits of arbitrage. *The Journal of Finance*, 52(1):35–55.

Stahel, C. W. (2022). Strategic complementarity among investors with overlapping portfolios. *Available at SSRN 3952125*.

Stein, J. C. (2005). Why are most funds open-end? competition and the limits of arbitrage. *The Quarterly Journal of Economics*, 120(1):247–272.

Teo, M. (2011). The liquidity risk of liquid hedge funds. *Journal of Financial Economics*, 100(1):24–44.

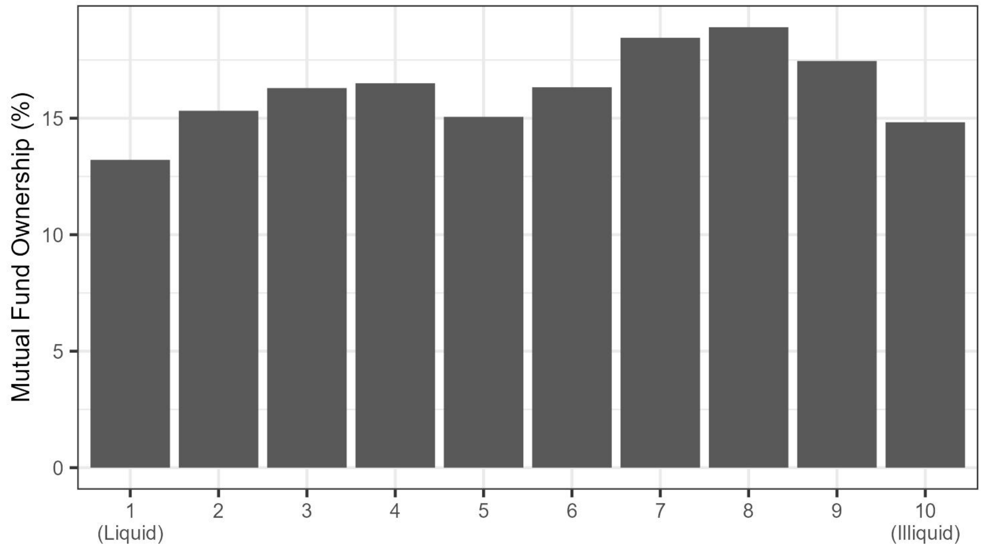
Timmer, Y. (2018). Cyclical investment behavior across financial institutions. *Journal of Financial Economics*, 129(2):268–286.

van Binsbergen, J. H. and Schwert, M. (2022). Duration-based valuation of corporate bonds. *Jacobs Levy Equity Management Center for Quantitative Financial Research Paper*.

Zhu, Q. (2020). The missing new funds. *Management Science*, 66(3):1193–1204.

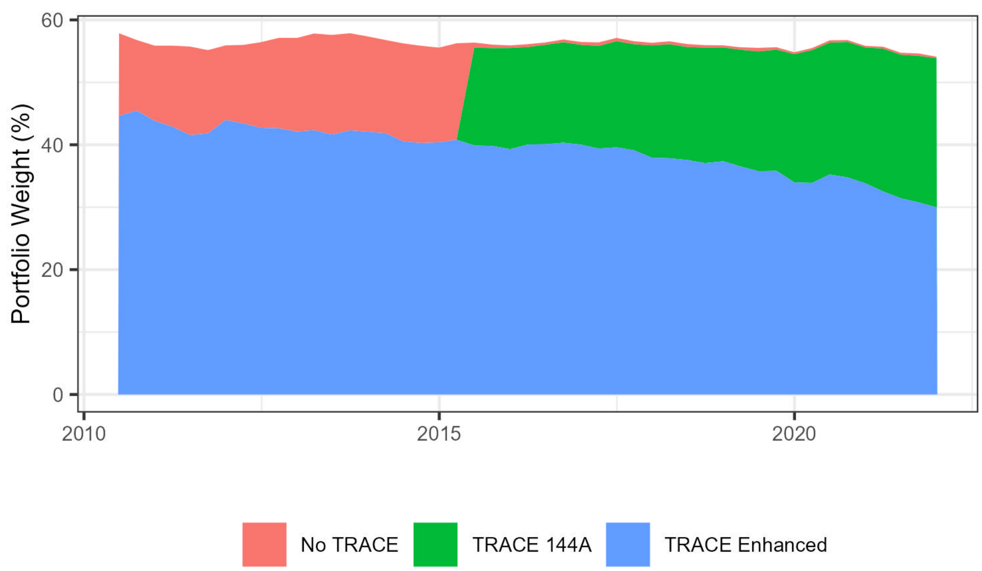
Figures

Figure 1: Mutual fund ownership of U.S. corporate bonds as of December 2022.



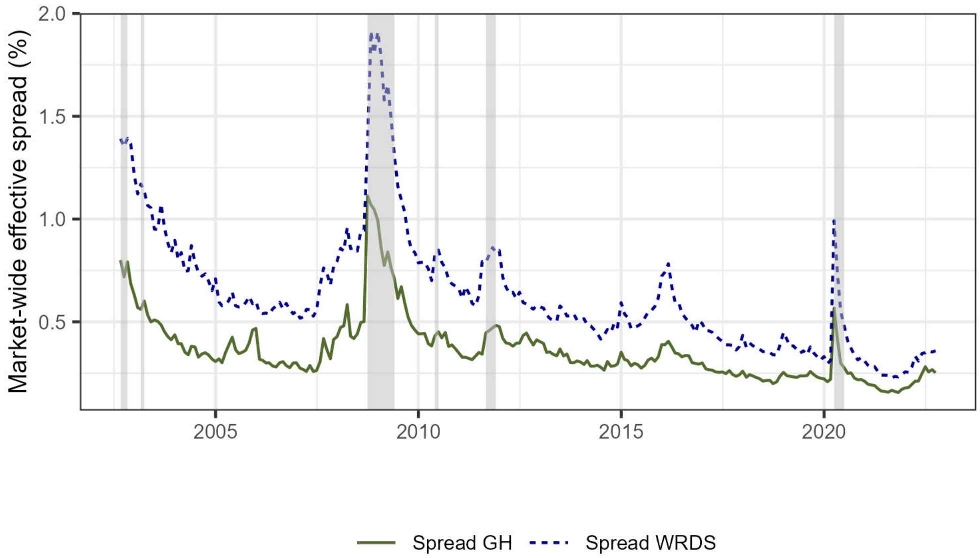
Notes: This figure shows the ownership share of U.S. mutual funds in the U.S. corporate bond market. First, I select all bonds from Mergent FISD with a bond type equal to CCOV, CCPI, CDEB, CLOC, CMTN, CMTZ, CP, CPIK, CS, CUIT, CZ, RNT, UCID, or USBN. Then, I restrict the set to all corporate bonds whose issuer is domiciled in the U.S., that are denominated in USD, that are not asset backed, and that are not preferred securities. For each unique bond, I aggregate the par value held by all corporate bond funds in the CRSP Mutual Fund Database as of December 2022, which I divide by the bond's total amount outstanding. I sort bonds into deciles based on their imputed round-trip costs, and compute the value-weighted mutual fund ownership share for each decile.

Figure 2: Corporate bond holdings matched with TRACE.



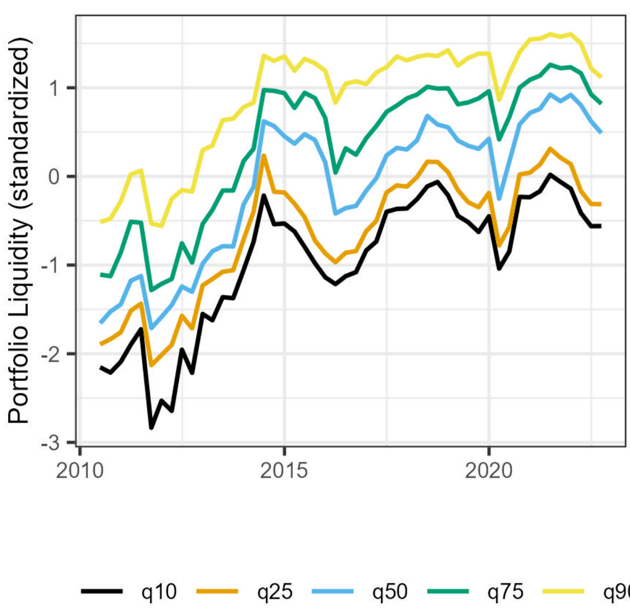
Notes: This figure shows the average portfolio weight that the corporate bond mutual funds in my sample allocate to corporate bonds over time. A distinction is made between corporate bonds that are available in TRACE Enhanced, corporate bonds that are available in TRACE 144A BTDS, and corporate bonds that cannot be matched with the TRACE database. A portfolio asset is classified as a corporate bond when the bond type from Mergent FISD equals CCOV, CCPI, CDEB, CLOC, CMTN, CMTZ, CP, CPIK, CS, CUIT, CZ, RNT, UCID, or USBN.

Figure 3: Illiquidity of the corporate bond market.

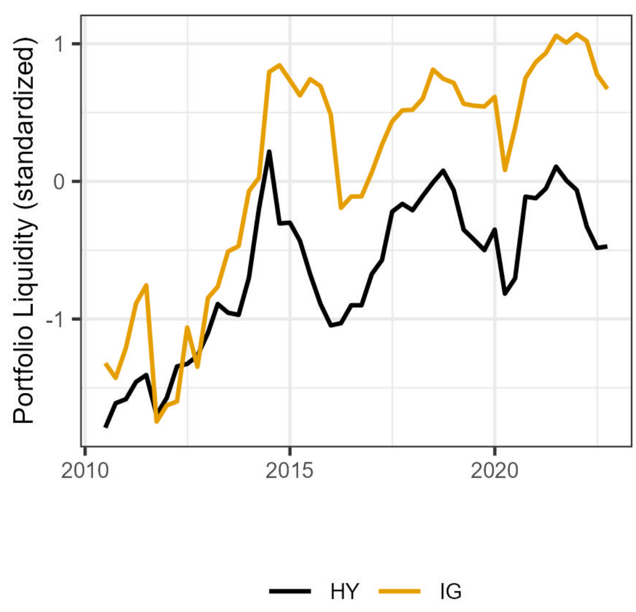


Notes: This figure shows the time-series of estimated market-wide transaction costs. *Spread GH* denotes the market's average effective spread estimated using a methodology based on Glosten and Harris (1988). For comparison, the figure also includes average bid-ask spreads from the WRDS Bond Returns Database (*Spread WRDS*). The grey areas indicate periods of stress during which the VIX exceeds its 90^{th} percentile.

Figure 4: Portfolio liquidity over time



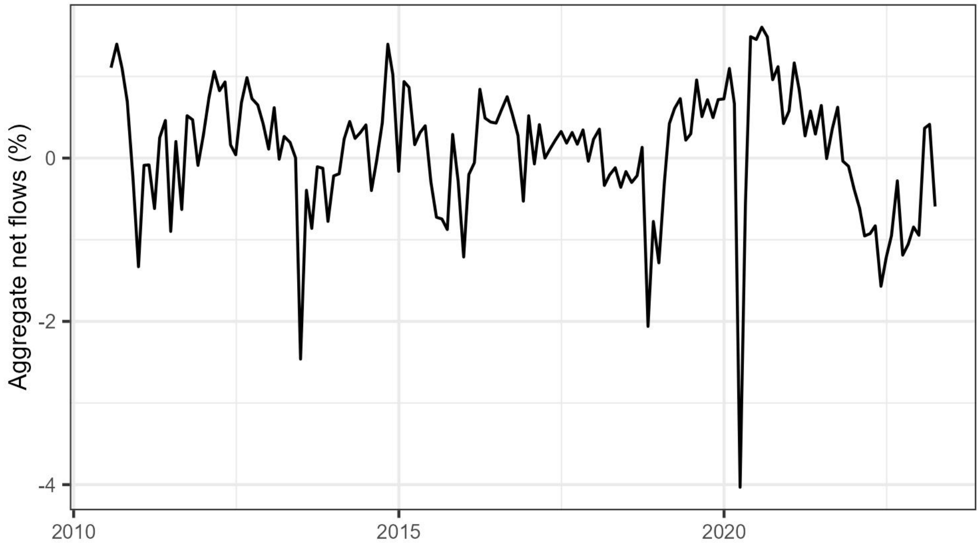
(a) Distribution portfolio liquidity.



(b) Median portfolio liquidity IG vs HY funds.

Notes: This figure shows the distribution of portfolio liquidity over time. I first compute imputed round-trip costs at the bond level. Then, I compute the value-weighted imputed round-trip costs for each fund based on their individual portfolio holdings. I multiply the resulting score by minus one such that a higher value of my portfolio liquidity measure corresponds to better portfolio liquidity. I then subtract the mean and divide by the standard deviation to get a standardized portfolio liquidity measure. Panel A shows the 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentiles of the resulting portfolio liquidity measure over time. Panel B shows the median of portfolio liquidity for investment-grade (Lipper Objective Codes A, BBB, IID, SID, SII) and high-yield funds (Lipper Objective Codes GHY, HY, and SHY) separately.

Figure 5: Monthly aggregate net fund flows.



Notes: This figure shows monthly aggregate net flows of the corporate bond mutual funds in my sample. Each month, I compute the average net flow across all funds in my sample, weighted by the funds' lagged Total Net Assets.

Tables

Table 1: Summary statistics fund sample.

Panel A: Summary statistics full sample.

	Mean	SD	5%	50%	95%
TNA (mln USD)	2,070	6,568	22	450	7,895
w_{Cash} (%)	0.28	8.48	-16.23	1.45	9.55
w_{Govt} (%)	13.77	14.51	0	9.27	41.32
w_{Corp} (%)	61	24.5	27.03	57.09	95.62
w_{144A} (%)	17.27	16.66	0.92	9.85	49.74
Composition corporate bond allocation:					
Issue Size (mln USD)	1,145	331	677	1,101	1,739
Age (years)	2.94	1.15	1.59	2.69	5.1
Maturity (years)	7.35	3.75	2.14	6.86	12.9
Rating	13.09	2.97	8.34	14.32	16.51

Panel B: Breakdown by Lipper Objective Code.

Lipper Obj. Code:	A	BBB	GHY	HY	IID	SHY	SID	SII
Avg # Funds	28	68	23	177	195	15	78	54
Total TNA (bln USD)	46	80	22	248	626	10	191	78
w_{Cash} (%)	-0.07	0.79	1.44	3.02	-2.31	2.72	0.01	0.18
w_{Govt} (%)	17.42	12.78	4.48	1.48	22.81	1.18	16.03	19.29
w_{Corp} (%)	50.27	70.76	82.93	86.52	41.23	81.21	51.21	53.11
w_{144A} (%)	5.83	10.95	47.23	40.55	6.52	40.22	8.74	7.52
Composition corporate bond allocation:								
Issue Size (mln USD)	1,200	1,276	969	872	1,353	864	1,128	1,171
Age (years)	3.71	3.39	2.52	2.43	2.98	3.95	3.07	3.39
Maturity (years)	11.02	11.08	6.49	6.58	9.14	3.53	2.61	3.86
Rating	15.23	14.52	9.07	8.94	14.71	9.72	15.55	15.34

Notes: This table shows summary statistics of the corporate bond mutual funds in my sample. TNA denotes a fund's total net assets, whereas w_{Cash}, w_{Govt}, w_{Corp}, and w_{144A} denote the portfolio weight allocated to cash, government bonds, corporate bonds, and Rule 144A bonds, respectively. Panel A shows the cross-sectional distribution of the full universe of corporate bond mutual funds. Panel B shows averages broken down by Lipper Objective Code. In both Panels A and B, I first compute cross-sectional statistics for each time period separately. The table then shows the resulting time-series averages of these cross-sectional statistics.

Table 2: Drivers of corporate bond liquidity.

BLIQ:	IRC	$Spread^{GH}$	$Spread^{HW}$	$Amihud$
Model:	(1)	(2)	(3)	(4)
log(Issue Size)	0.219**	0.279**	0.204**	0.140**
	(17.7)	(29.9)	(21.6)	(13.0)
Age	-0.028**	-0.011**	-0.031**	-0.020**
	(-23.0)	(-15.8)	(-25.9)	(-13.3)
TTM	-0.034**	-0.020**	-0.037**	-0.023**
	(-27.6)	(-25.3)	(-28.6)	(-26.0)
Rating	0.034**	0.012**	0.014**	0.028**
	(10.2)	(5.92)	(4.20)	(7.59)
Rule 144A	-0.185**	0.048**	0.112**	0.250**
	(-10.8)	(2.81)	(5.05)	(11.4)
Year-Quarter FE	Yes	Yes	Yes	Yes
Obs	277,141	519,621	425,873	450,393
Adj. R^2	0.254	0.232	0.245	0.130
Within Adj. R^2	0.193	0.203	0.204	0.100

Notes: This table contains the results of regressing corporate bond liquidity proxies ($BLIQ$) on a set of corporate bond characteristics. The unit of observation is on the bond-quarter level. The dependent variable equals imputed round-trip costs (IRC) in Column 1, estimated effective spreads based on Glosten and Harris (1988) ($Spread^{GH}$) in Column 2, estimated spreads based on Hong and Warga (2000) ($Spread^{HW}$) in Column 3, and Amihud and Mendelson (1986) illiquidity measure ($Amihud$) in Column 4. The set of bond characteristics includes the bond's age (Age), its remaining time to maturity (TTM), its numerical credit rating ($Rating$), and a dummy indicating whether the bond is a Rule 144A bond ($Rule144A$). All specifications include year-quarter fixed effects. Standard errors are clustered at the bond and year-quarter level, and the resulting t-statistics are presented in brackets. * p<0.05; ** p<0.01.

Table 3: Drivers of portfolio liquidity.

Panel A. The relation between portfolio liquidity and fund style.

PFLIQ:	IRC	$Spread^{GH}$	$Spread^{HW}$	$Amihud$
Model:	(1)	(2)	(3)	(4)
A	-1.06**	-1.43**	-1.57**	-1.41**
	(-12.1)	(-13.3)	(-13.4)	(-15.4)
BBB	-1.09**	-1.42**	-1.57**	-1.47**
	(-22.6)	(-22.9)	(-24.7)	(-24.3)
IID	-0.894**	-1.08**	-1.20**	-1.15**
	(-28.7)	(-28.1)	(-32.5)	(-30.8)
SII	-0.242**	-0.387**	-0.407**	-0.453**
	(-4.84)	(-5.67)	(-6.49)	(-7.29)
HY	-1.47**	-1.03**	-1.14**	-0.912**
	(-50.8)	(-27.9)	(-34.0)	(-23.4)
GHY	-1.77**	-1.42**	-1.36**	-1.34**
	(-42.4)	(-26.3)	(-33.7)	(-25.8)
SHY	-1.28**	-0.963**	-1.06**	-0.945**
	(-15.4)	(-11.4)	(-13.5)	(-10.3)
Year-Quarter FE	Yes	Yes	Yes	Yes
Obs	29,471	29,471	29,471	29,471
Adj. R^2	0.729	0.640	0.667	0.600
Within Adj. R^2	0.470	0.341	0.409	0.326

Panel B. The relation between portfolio liquidity and fund characteristics.

PFLIQ:	IRC		$Spread^{GH}$		$Spread^{HW}$		$Amihud$	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(tna_latest)	-0.0001	-0.008	0.018*	0.012	0.019*	0.018*	0.031**	0.030**
	(-0.019)	(-1.24)	(2.43)	(1.45)	(2.53)	(2.09)	(4.03)	(3.55)
Retail	-0.090**	-0.020	-0.163**	-0.073	-0.166**	-0.118*	-0.166**	-0.086
	(-2.83)	(-0.469)	(-3.78)	(-1.40)	(-4.08)	(-2.30)	(-3.78)	(-1.60)
w^{Cash}	0.0003	0.0006	-0.002*	-0.002	-0.001	-0.0002	-0.002*	-0.002
	(0.426)	(0.564)	(-2.36)	(-1.58)	(-1.03)	(-0.180)	(-2.47)	(-1.64)
w^{Govt}	0.003*	0.003*	0.004**	0.004**	0.004*	0.004*	0.002	0.002
	(2.39)	(2.11)	(2.91)	(2.63)	(2.55)	(2.23)	(1.08)	(1.13)
RearLoad	0.014	0.039	0.024	0.058	0.040	0.065	0.041	0.084
	(0.418)	(1.07)	(0.534)	(1.24)	(1.00)	(1.55)	(0.891)	(1.66)
$w^{Rule144A}$	-0.013**	-0.012**	-0.006**	-0.005*	-0.006**	-0.005**	-0.005	-0.003
	(-9.90)	(-8.45)	(-2.93)	(-2.12)	(-3.72)	(-2.85)	(-1.79)	(-1.01)
Exp. Ratio		-17.9*		-15.7		0.984		-4.93
		(-2.13)		(-1.60)		(0.106)		(-0.402)
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	30,515	23,236	30,515	23,236	30,515	23,236	30,515	23,236
Adj. R^2	0.746	0.732	0.653	0.642	0.678	0.670	0.613	0.600
Within Adj. R^2	0.059	0.060	0.029	0.027	0.030	0.022	0.022	0.016

Notes: This table contains the results of regressing portfolio liquidity proxies on a set of fund characteristics. The unit of observation is on the fund-quarter level. The dependent variable is portfolio liquidity based on either imputed round-trip costs (IRC), estimated effective spreads based on Glosten and Harris (1988) ($Spread^{GH}$), estimated spreads based on Hong and Warga (2000) ($Spread^{HW}$), or Amihud and Mendelson (1986) illiquidity measure ($Amihud$). In Panel A, portfolio liquidity is regressed on a set of fund style dummies based on Lipper Objective Codes, which include A (Corporate Debt Funds A Rated), "BBB" (Corporate Debt Funds BBB-Rated), "GHY" (Global High Yield Funds), "HY" (High Current Yield Funds), "IID" (Intermediate Investment Grade Debt Funds), "SHY" (Short High Yield Funds), "SID" (Short Investment Grade Debt Funds), and "SII" (Short-Intermediate Investment Grade Debt Funds). Short Investment Grade Debt funds serve as the baseline. In Panel B, portfolio liquidity is regressed on the logarithm of a fund's Total Net Assets ($log(TNA)$), the fraction of the fund's total net assets targeted at retail investors (*Retail*), the portfolio weight allocated to cash (w^{Cash}), the portfolio weight allocated to government bonds (w^{Govt}), the portfolio weight allocated to Rule 144A bonds (w^{144A}), the fraction of a fund's total net assets to which a rear load applies (*RearLoad*), and the fund's expense ratio (*Exp.Ratio*). The specifications in Panel A include year-quarter fixed effects, while the specifications in Panel B contain both year-quarter as well as fund style fixed effects. In both panels, standard errors are clustered at the fund and year-quarter level, and the resulting t-statistics are presented in brackets. * p<0.05; ** p<0.01.

Table 4: Aggregate fund flows and market liquidity.

Dep. Var.	Aggregate monthly fund flows					
Liq. Proxy:	MLIQ	VIX	TED	MLIQ	VIX	TED
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.118	0.149	0.218*	0.071	0.102	0.113
	(1.031)	(1.603)	(1.996)	(0.704)	(0.984)	(1.357)
IlliqPeriod	0.003	-0.298	-0.388			
	(0.008)	(-0.642)	(-1.063)			
Liquidity shock				0.580**	-0.347**	-0.744**
				(10.381)	(-8.757)	(-5.406)
Obs	147	147	139	147	147	139
Adj. R^2	-0.007	0.007	0.019	0.253	0.264	0.231

Notes: This table contains the results of time series regressions in which aggregate monthly net flows are regressed on variables related to the liquidity of the corporate bond market. Each month, I compute the average net flow across all funds in my sample, weighted by the funds' lagged Total Net Assets. In Columns 1-3, the explanatory variable ($IlliqPeriod$) denotes a dummy variable indicating whether corporate bond market liquidity ($MLIQ$) is below its 10^{th} percentile, the VIX index exceeds its 90^{th} percentile, or the TED-spread exceeds its 90^{th} percentile, respectively. In Columns 4-6, the explanatory variable (*Liquidity shock*) denotes AR(1)-innovations in corporate bond market liquidity ($MLIQ$), the VIX index, and the TED-spread, respectively. Corporate bond market liquidity is defined as the estimated market-wide effective spread based on the methodology of Glosten and Harris (1988), multiplied by minus one such that a higher value indicates higher liquidity. T-statistics based on Newey-West standard errors are presented in brackets. * p<0.05; ** p<0.01.

Table 5: The determinants of monthly fund flows.

Dependent Variable:	Monthly flows				
Funds:	All	All	All	IG	HY
Model:	(1)	(2)	(3)	(4)	(5)
PFLIQ	-0.001		0.000	-0.001*	0.002
	(-1.519)		(0.321)	(-1.993)	(1.012)
w^{liq}	-0.003	-0.002	-0.002	-0.003	-0.009
	(-1.406)	(-1.215)	(-1.207)	(-1.562)	(-1.416)
Lagged Return	0.032	0.026	0.025	0.292**	0.235**
	(0.656)	(0.544)	(0.537)	(5.936)	(3.123)
Lagged Flow	0.184**	0.184**	0.184**	0.212**	0.128**
	(21.109)	(21.132)	(21.138)	(24.373)	(7.949)
log(TNA)	0.000	0.000	0.000	0.000	0.000
	(-0.528)	(-0.692)	(-0.658)	(0.052)	(-1.602)
log(Fund Age)	-0.009**	-0.009**	-0.009**	-0.008**	-0.010**
	(-22.398)	(-22.366)	(-22.342)	(-19.644)	(-13.150)
Retail Fund	0.001	0.001	0.001	0.001	0.001
	(1.180)	(1.291)	(1.261)	(0.904)	(0.579)
RearLoad	-0.001*	-0.001*	-0.001*	-0.001*	0.000
	(-2.106)	(-2.192)	(-2.244)	(-2.068)	(0.268)
Exp. Ratio	-1.303**	-1.330**	-1.322**	-1.211**	-1.433**
	(-13.807)	(-13.092)	(-13.037)	(-11.711)	(-7.439)
NegInno × PFLIQ	0.003**		0.001	0.001	0.003
	(2.741)		(0.875)	(0.893)	(1.410)
Rating		0.000	0.000		
		(-1.955)	(-1.685)		
NegInno × rating		0.001*	0.001		
		(2.143)	(1.519)		
Year-Month FE	Yes	Yes	Yes	Yes	Yes
Obs	219,740	219,740	219,740	149,334	70,406
Adj. R^2	0.098	0.098	0.098	0.114	0.105
Within Adj. R^2	0.084	0.084	0.084	0.097	0.065

Notes: This table contains the results of panel regressions in which monthly net fund flows serve as the dependent variable. The unit of observation is on the shareclass-month level. Fund and portfolio characteristics include the portfolio liquidity of the corresponding shareclass estimated using imputed round-trip costs ($PFLIQ$), the portfolio allocation towards cash and government bonds (w^{liq}), the weighted average credit rating of the portfolio's corporate bond holdings (*Rating*), the shareclass' lagged monthly return (*LaggedReturn*), the shareclass' lagged monthly flow (*Lagged Flow*), the logarithm of the shareclass' total net assets ($log(TNA)$), the logarithm of the shareclass' age ($log(FundAge)$), a dummy indicating whether the shareclass targets retail investors (*Retail Fund*), a dummy indicating whether a rear load fee applies to the shareclass (*Rear Load*), and the shareclass' expense ratio (*Exp. Ratio*). Finally, the set of independent variables includes a dummy variable $NegInno$ which equals 1 when the AR(1)-innovation in market liquidity is negative, and 0 otherwise. All specifications include year-month fixed effects. Standard errors are clustered at the shareclass and year-month level, and the corresponding t-statistics are presented in brackets. * p<0.05; ** p<0.01.

Table 6: Determinants of flow betas.

Dep. Var.:	Flow beta				
Funds:	All	All	All	IG	HY
Model:	(1)	(2)	(3)	(4)	(5)
PFLIQ	-0.310**		-0.209**	-0.218**	-0.043
	(-5.644)		(-3.963)	(-3.579)	(-0.277)
w^{liq}	-0.155	0.106	0.098	0.140	-0.456
	(-0.900)	(0.588)	(0.549)	(0.773)	(-0.572)
log(TNA)	0.111**	0.107**	0.105**	0.108**	0.093**
	(7.164)	(6.823)	(6.683)	(6.111)	(2.789)
log(Fund Age)	-0.226**	-0.204**	-0.206**	-0.274**	-0.045
	(-3.947)	(-3.507)	(-3.561)	(-4.081)	(-0.439)
Retail Fund	0.124	0.135	0.143*	0.036	0.386**
	(1.730)	(1.879)	(2.001)	(0.445)	(2.655)
RearLoad	0.033	-0.009	0.007	-0.032	-0.006
	(0.484)	(-0.134)	(0.098)	(-0.383)	(-0.043)
Exp. Ratio	-5.309	-8.699	-11.563	-3.376	-28.970
	(-0.570)	(-0.918)	(-1.213)	(-0.297)	(-1.719)
Rating		-0.080**	-0.049**		
		(-5.385)	(-3.358)		
Year-Month FE	Yes	Yes	Yes	Yes	Yes
Obs	217,888	217,888	217,888	148,132	69,756
Adj. R^2	0.033	0.033	0.035	0.042	0.023
Within Adj. R^2	0.018	0.017	0.019	0.016	0.010

Notes: This table contains the results of panel regressions in which flow betas serve as the dependent variable. The unit of observation is on the shareclass-month level. Flow betas are based on time-series regressions of individual fund flows on the aggregate net flow of all funds in my sample, estimated using 36-month rolling windows. Fund and portfolio characteristics include the portfolio liquidity of the corresponding shareclass estimated using imputed round-trip costs ($PFLIQ$), the portfolio allocation towards cash and government bonds (w^{liq}), the weighted average credit rating of the portfolio's corporate bond holdings (*Rating*), the shareclass' lagged monthly return (*LaggedReturn*), the shareclass' lagged monthly flow (*Lagged Flow*), the logarithm of the shareclass' total net assets ($log(TNA)$), the logarithm of the shareclass' age ($log(FundAge)$), a dummy indicating whether the shareclass targets retail investors (*Retail Fund*), a dummy indicating whether a rear load fee applies to the shareclass (*Rear Load*), and the shareclass' expense ratio (*Exp. Ratio*). All specifications include year-month fixed effects. Standard errors are clustered at the shareclass and year-month level, and the corresponding t-statistics are presented in brackets. * p<0.05; ** p<0.01.

Table 7: Raw fund returns

Dep. Var.:	Monthly excess return					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Funds:	All	IG	HY	All	IG	HY
PFLIQ	-0.048	-0.071	-0.019	-0.283**	-0.118*	-0.343**
	(-0.831)	(-1.743)	(-0.205)	(-4.436)	(-2.152)	(-4.343)
w^{liq}	-0.003	-0.001	-0.002	-0.002	-0.001	-0.002
	(-1.719)	(-1.211)	(-1.379)	(-1.564)	(-1.197)	(-1.353)
Lagged Return	0.072	0.079	0.110	0.059	0.078	0.091
	(0.831)	(0.920)	(1.660)	(0.729)	(0.911)	(1.488)
Lagged Flow	0.001	-0.003	0.000	0.002	-0.003	0.000
	(0.531)	(-1.952)	(0.140)	(0.720)	(-1.936)	(0.079)
log(TNA)	0.005	0.000	0.007	0.005	0.000	0.008
	(1.226)	(0.169)	(1.287)	(1.193)	(0.029)	(1.358)
Retail	-0.014	0.016*	-0.017	-0.009	0.017*	-0.019
	(-0.870)	(2.029)	(-0.677)	(-0.524)	(2.066)	(-0.783)
RearLoad	0.046	-0.005	0.013	0.041	-0.006	0.015
	(1.725)	(-0.414)	(0.835)	(1.555)	(-0.495)	(0.999)
Exp. Ratio	0.023	-0.077*	-0.043	-0.003	-0.080*	-0.046
	(0.367)	(-2.431)	(-0.994)	(-0.051)	(-2.530)	(-1.047)
PFLIQ × NegInno				0.541**	0.106	0.782**
				(4.251)	(1.411)	(4.635)
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	66,616	46,088	20,528	66,616	46,088	20,528
Adj. R^2	0.617	0.705	0.907	0.633	0.706	0.911
Within Adj. R^2	0.010	0.014	0.013	0.052	0.017	0.052

Notes: This table contains the results of panel regressions in which monthly fund excess return serve as the dependent variable. The unit of observation is on the fund-month level. Fund and portfolio characteristics include the portfolio liquidity of the corresponding fund estimated using imputed round-trip costs ($PFLIQ$), the portfolio allocation towards cash and government bonds (w^{liq}), the fund's lagged monthly return (*LaggedReturn*), the fund's lagged monthly flow (*Lagged Flow*), the logarithm of the fund's total net assets ($log(TNA)$), the fund's fraction targeting retail investors (*Retail*), the fund's fraction to which a rear load fee applies (*Rear Load*), and the fund's weighted average expense ratio (*Exp. Ratio*). Moreover, the set of independent variables includes a dummy variable $NegInno$ which equals 1 when the AR(1)-innovation in market liquidity is negative, and 0 otherwise. In Columns 1, 3, and 5, attention is restricted to the set of investment-grade funds (Lipper Objective Code not equal to "GHY", "HY", or "SHY"). In Columns 2, 4, and 6, attention is restricted to the set of high-yield funds (Lipper Objective Code equal to "GHY", "HY", or "SHY"). All specifications include month fixed effects. Standard errors are clustered at the fund and year-month level, and the corresponding t-statistics are presented in brackets. * p<0.05; ** p<0.01.

Table 8: Risk-adjusted fund performance.

Dep. Var.:	α^1	α^2	α^3	α^1	α^2	α^3
Model:	(1)	(2)	(3)	(4)	(5)	(6)
PFLIQ	0.030**	0.064*	0.058	0.020	-0.019	-0.022
	(2.672)	(2.047)	(1.896)	(1.449)	(-0.545)	(-0.615)
w^{liq}	0.000	0.000	0.000	0.000	0.000	0.000
	(-1.032)	(0.063)	(-0.165)	(-1.005)	(0.143)	(-0.077)
Lagged Return	0.006	0.087	0.073	0.005	0.082	0.069
	(0.435)	(1.572)	(1.815)	(0.391)	(1.467)	(1.695)
Lagged Flow	0.001	0.000	0.001	0.001	0.000	0.001
	(0.920)	(0.178)	(0.899)	(0.933)	(0.254)	(0.991)
log(TNA)	0.004	0.002	0.003	0.004	0.002	0.003
	(1.950)	(0.673)	(1.160)	(1.943)	(0.648)	(1.134)
Retail	-0.009	-0.008	-0.009	-0.009	-0.006	-0.007
	(-0.954)	(-0.702)	(-0.812)	(-0.933)	(-0.524)	(-0.636)
RearLoad	0.012	-0.005	0.005	0.011	-0.007	0.003
	(1.083)	(-0.317)	(0.310)	(1.062)	(-0.430)	(0.199)
Exp. Ratio	-0.068**	-0.066	-0.049	-0.070**	-0.076*	-0.058
	(-3.310)	(-1.856)	(-1.534)	(-3.375)	(-2.071)	(-1.798)
PFLIQ × NegInno				0.022	0.193*	0.184*
				(1.061)	(2.516)	(2.505)
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	64,902	64,902	64,902	64,902	64,902	64,902
Adj. R^2	0.184	0.454	0.547	0.185	0.460	0.552
Within Adj. R^2	0.005	0.023	0.018	0.005	0.034	0.030

Notes: This table contains the results of panel regressions in which monthly risk-adjusted fund returns serve as the dependent variable. A distinction is made between risk-adjusted returns based on 3 different models, as indicated by α^1, α^2, α^3. α^1 is based on a 2-factor model including the excess return on the aggregate US bond market and the excess return on the ICE BofA US High Yield Index. α^2 is based on the 2-factor model in Goldstein et al. (2017), which includes the excess return on the aggregate US bond market and the value weighted CRSP market excess return. α^3 is based on the 3-factor model in Choi and Kronlund (2018), which includes the TERM and DEF factors (Fama and French, 1993), and the value weighted CRSP market excess return. The unit of observation is on the fund-month level. Fund and portfolio characteristics include the portfolio liquidity of the corresponding fund estimated using imputed round-trip costs ($PFLIQ$), the portfolio allocation towards cash and government bonds (w^{liq}), the fund's lagged monthly return ($LaggedReturn$), the fund's lagged monthly flow (*Lagged Flow*), the logarithm of the fund's total net assets ($log(TNA)$), the fund's fraction targeting retail investors (*Retail*), the fund's fraction to which a rear load fee applies (*Rear Load*), and the fund's weighted average expense ratio (*Exp. Ratio*). Moreover, the set of independent variables includes a dummy variable $NegInno$ which equals 1 when the AR(1)-innovation in market liquidity is negative, and 0 otherwise. All specifications include year-month fixed effects. Standard errors are clustered at the fund and year-month level, and the corresponding t-statistics are presented in brackets. * $p<0.05$; ** $p<0.01$.

Table 9: Investment-grade versus high-yield funds

Panel A: Investment-Grade Funds						
Dep. Var.:	α^1	α^2	α^3	α^1	α^2	α^3
Model:	(1)	(2)	(3)	(4)	(5)	(6)
PFLIQ	0.009	0.014	0.013	-0.002	-0.005	-0.018
	(0.718)	(1.040)	(0.963)	(-0.134)	(-0.341)	(-1.005)
PFLIQ × NegInno				0.024	0.043	0.069*
				(0.994)	(1.451)	(2.451)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	44,974	44,974	44,974	44,974	44,974	44,974
Adj. R^2	0.287	0.412	0.618	0.288	0.412	0.619
Within Adj. R^2	0.002	0.007	0.009	0.003	0.008	0.013

Panel B: High-Yield Funds						
Dep. Var.:	α^1	α^2	α^3	α^1	α^2	α^3
Model:	(1)	(2)	(3)	(4)	(5)	(6)
PFLIQ	0.154*	0.193**	0.166*	0.020	-0.011	-0.043
	(2.486)	(2.674)	(2.326)	(0.402)	(-0.201)	(-0.740)
PFLIQ × NegInno				0.326**	0.497**	0.507**
				(2.707)	(3.583)	(3.871)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	19,928	19,928	19,928	19,928	19,928	19,928
Adj. R^2	0.145	0.790	0.777	0.152	0.794	0.781
Within Adj. R^2	0.018	0.038	0.025	0.026	0.055	0.042

Notes: This table contains the results of panel regressions in which monthly risk-adjusted fund returns serve as the dependent variable. A distinction is made between risk-adjusted returns based on 3 different models, as indicated by α^1, α^2, α^3. α^1 is based on a 2-factor model including the excess return on the aggregate US bond market and the excess return on the ICE BofA US High Yield Index. α^2 is based on the 2-factor model in Goldstein et al. (2017), which includes the excess return on the aggregate US bond market and the value weighted CRSP market excess return. α^3 is based on the 3-factor model in Choi and Kronlund (2018), which includes the TERM and DEF factors (Fama and French, 1993), and the value weighted CRSP market excess return. The unit of observation is on the fund-month level. Fund and portfolio characteristics include the portfolio liquidity of the corresponding fund estimated using imputed round-trip costs ($PFLIQ$), the portfolio allocation towards cash and government bonds, the fund's lagged monthly return, the fund's lagged monthly flow, the logarithm of the fund's total net assets, the fund's fraction targeting retail investors, the fund's fraction to which a rear load fee applies, and the fund's weighted average expense ratio. Moreover, the set of independent variables includes a dummy variable $NegInno$ which equals 1 when the AR(1)-innovation in market liquidity is negative, and 0 otherwise. Panel A focuses on investment-grade funds, while Panel B contains the results for high-yield funds. All specifications include year-month fixed effects. Standard errors are clustered at the fund and year-month level, and the corresponding t-statistics are presented in brackets. * p<0.05; ** p<0.01.

Table 10: Moderating effect of lagged flows and returns.

Panel A: Investment-Grade Funds

Dep. Var.:	α^1	α^2	α^3	α^1	α^2	α^3
Model:	(1)	(2)	(3)	(4)	(5)	(6)
PFLIQ	0.009	0.015	0.015	0.007	0.013	0.017
	(0.784)	(1.143)	(1.045)	(0.593)	(1.056)	(1.154)
Lagged Flow	0.001	0.001	0.001	0.001	0.001	0.000
	(1.496)	(1.175)	(1.246)	(1.217)	(1.095)	(0.696)
Lagged Return	0.005	0.046	0.054*	0.010	0.050	0.049*
	(0.200)	(1.836)	(2.328)	(0.438)	(1.955)	(2.149)
PFLIQ × Lagged Flow	-0.001	0.000	-0.001			
	(-1.520)	(-0.856)	(-1.933)			
PFLIQ × Lagged Return				0.010	0.008	-0.010
				(1.290)	(0.724)	(-0.781)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	58,062	58,062	58,062	58,062	58,062	58,062
Adj. R^2	0.295	0.420	0.628	0.295	0.420	0.628
Within Adj. R^2	0.001	0.006	0.008	0.002	0.006	0.008

Panel B: High-Yield Funds

Dep. Var.:	α^1	α^2	α^3	α^1	α^2	α^3
Model:	(1)	(2)	(3)	(4)	(5)	(6)
PFLIQ	0.142*	0.183**	0.161*	0.174**	0.219**	0.196**
	(2.507)	(2.682)	(2.404)	(2.945)	(3.230)	(2.964)
Lagged Flow	-0.001	-0.002	-0.003	0.002	0.002	0.002
	(-0.985)	(-1.073)	(-1.860)	(1.704)	(1.511)	(1.472)
Lagged Return	0.063	0.134**	0.107**	-0.052	0.005	-0.024
	(1.807)	(2.682)	(2.659)	(-0.997)	(0.075)	(-0.417)
PFLIQ × Lagged Flow	-0.005*	-0.006*	-0.008**			
	(-2.165)	(-2.051)	(-2.689)			
PFLIQ × Lagged Return				-0.103*	-0.116*	-0.118*
				(-2.434)	(-2.558)	(-2.598)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	26,237	26,237	26,237	26,237	26,237	26,237
Adj. R^2	0.141	0.799	0.788	0.155	0.803	0.792
Within Adj. R^2	0.014	0.030	0.021	0.030	0.048	0.038

Notes: This table contains the results of panel regressions in which monthly risk-adjusted fund returns serve as the dependent variable. A distinction is made between risk-adjusted returns based on 3 different models, as indicated by α^1, α^2, α^3. α^1 is based on a 2-factor model including the excess return on the aggregate US bond market and the excess return on the ICE BofA US High Yield Index. α^2 is based on the 2-factor model in Goldstein et al. (2017), which includes the excess return on the aggregate US bond market and the value weighted CRSP market excess return. α^3 is based on the 3-factor model in Choi and Kronlund (2018), which includes the TERM and DEF factors (Fama and French, 1993), and the value weighted CRSP market excess return. The unit of observation is on the fund-month level. Fund and portfolio characteristics include the portfolio liquidity of the corresponding fund estimated using imputed round-trip costs ($PFLIQ$), the fund's lagged monthly return (*LaggedReturn*), the fund's lagged monthly flow (*Lagged Flow*), the portfolio allocation towards cash and government bonds, the logarithm of the fund's total net assets, the fund's fraction targeting retail investors, and the fund's fraction to which a rear load fee applies. Panel A focuses on investment-grade funds, while Panel B contains the results for high-yield funds. All specifications include year-month fixed effects. Standard errors are clustered at the fund and year-month level, and the corresponding t-statistics are presented in brackets. * p<0.05; ** p<0.01.

Table 11: Robustness tests.

Panel A: Alternative market illiquidity dummy						
Dep. Var.:	α^1	α^2	α^3	α^1	α^2	α^3
Funds:	IG	IG	IG	HY	HY	HY
Model:	(1)	(2)	(3)	(4)	(5)	(6)
PFLIQ	0.005	0.001	-0.001	0.075	0.070	0.051
	(0.406)	(0.088)	(-0.084)	(1.719)	(1.364)	(0.966)
PFLIQ $\times$ $\mathbb{1}(L_t < Q_{10})$	0.030	0.107	0.118	0.713*	1.117**	1.041**
	(0.713)	(1.640)	(1.900)	(2.594)	(3.580)	(3.561)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	44,974	44,974	44,974	19,928	19,928	19,928
Adj. R^2	0.288	0.413	0.619	0.159	0.798	0.783
Panel B: Controls for credit rating						
Dep. Var.:	α^1	α^2	α^3	α^1	α^2	α^3
Funds:	IG	IG	IG	HY	HY	HY
Model:	(1)	(2)	(3)	(4)	(5)	(6)
PFLIQ	0.005	0.008	-0.007	-0.002	-0.029	-0.055
	(0.284)	(0.499)	(-0.391)	(-0.034)	(-0.606)	(-1.077)
Rating	-0.009	-0.017*	-0.014**	0.020	0.016	0.011
	(-1.455)	(-2.389)	(-2.758)	(0.914)	(0.711)	(0.492)
PFLIQ $\times$ NegInno	0.008	0.009	0.045*	0.283*	0.451**	0.458**
	(0.338)	(0.376)	(2.087)	(2.503)	(3.716)	(3.948)
NegInno $\times$ Rating	0.021	0.045*	0.032	0.052	0.055	0.056
	(1.335)	(2.413)	(1.843)	(1.639)	(1.534)	(1.561)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	44,974	44,974	44,974	19,928	19,928	19,928
Adj. R^2	0.288	0.414	0.619	0.154	0.795	0.781
Panel C: No Time Fixed Effects						
Dep. Var.:	α^1	α^2	α^3	α^1	α^2	α^3
Funds:	IG	IG	IG	HY	HY	HY
Model:	(1)	(2)	(3)	(4)	(5)	(6)
PFLIQ	-0.005	-0.004	-0.011	0.086**	-0.036	0.003
	(-0.416)	(-0.341)	(-0.745)	(2.721)	(-0.413)	(0.030)
NegInno	-0.069	-0.151*	-0.238*	0.022	0.038	0.186
	(-1.292)	(-2.024)	(-2.495)	(0.382)	(0.207)	(1.099)
PFLIQ $\times$ NegInno	0.020	0.021	0.031	0.085	0.635**	0.762**
	(1.210)	(1.031)	(1.487)	(1.174)	(3.033)	(3.610)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs	44,974	44,974	44,974	19,928	19,928	19,928
Adj. R^2	0.005	0.021	0.047	0.023	0.096	0.112

Notes: This table contains the results of panel regressions in which monthly risk-adjusted fund returns serve as the dependent variable. Risk-adjusted returns are based on 3 different models, as indicated by α^1, α^2, α^3. α^1 is based on a 2-factor model including the excess return on the aggregate US bond market and the excess return on the ICE BofA US High Yield Index. α^2 is based on the 2-factor model in Goldstein et al. (2017), which includes the excess return on the aggregate US bond market and the value weighted CRSP market excess return. α^3 is based on the 3-factor model in Choi and Kronlund (2018), which includes the TERM and DEF factors (Fama and French, 1993), and the value weighted CRSP market excess return. The unit of observation is on the fund-month level. Fund and portfolio characteristics include the portfolio liquidity of the corresponding fund estimated using imputed round-trip costs (*PFLIQ*), the portfolio allocation towards cash and government bonds, the fund's lagged monthly return, the fund's lagged monthly flow, the logarithm of the fund's total net assets, the fund's fraction targeting retail investors, the fund's fraction to which a rear load fee applies, and the fund's weighted average expense ratio. Moreover, the set of independent variables includes a dummy variable $\mathbb{1}(L_t < Q_{10})$ which equals 1 when the AR(1)-innovation in market liquidity is below its 10^{th} percentile, and 0 otherwise in Panel A. In Panels B and C, the set of regressors includes a dummy variable *NegInno* which equals 1 when the AR(1)-innovation in market liquidity is negative, and 0 otherwise. In Panel B, I include the weighted average credit rating of the corporate bonds held (*Rating*) as an additional control variable, as well as its interaction with *NegInno*. Panels A and B contain year-month fixed effects. Standard errors are clustered at the fund and year-month level, and the corresponding t-statistics are presented in brackets. * p<0.05; ** p<0.01.

Table 12: Alternative portfolio liquidity proxies.

Panel A: Investment-Grade Funds						
PFLIQ:	*GH*	*HW*	*Ami*	*GH*	*HW*	*Ami*
Model:	(1)	(2)	(3)	(4)	(5)	(6)
PFLIQ	0.020	0.018	0.021	0.008	0.011	0.013
	(1.578)	(1.574)	(1.702)	(0.572)	(0.777)	(0.913)
PFLIQ × NegInno				0.027	0.017	0.019
				(1.299)	(0.803)	(0.855)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	46,083	46,083	46,083	46,083	46,083	46,083
Adj. R^2	0.279	0.279	0.279	0.279	0.279	0.279
Within Adj. R^2	0.004	0.004	0.004	0.005	0.004	0.005
Panel B: High-Yield Funds						
PFLIQ:	*GH*	*HW*	*Ami*	*GH*	*HW*	*Ami*
Model:	(1)	(2)	(3)	(4)	(5)	(6)
PFLIQ	0.134**	0.144**	0.099**	0.062	0.056	0.038
	(3.516)	(3.938)	(3.454)	(1.623)	(1.622)	(1.258)
PFLIQ × NegInno				0.152*	0.197**	0.141**
				(2.481)	(2.702)	(2.640)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	19,928	19,928	19,928	19,928	19,928	19,928
Adj. R^2	0.147	0.144	0.145	0.150	0.147	0.149
Within Adj. R^2	0.020	0.017	0.018	0.024	0.020	0.023

Notes: This table contains the results of panel regressions in which monthly risk-adjusted fund returns serve as the dependent variable. Risk-adjusted returns are based on a 2-factor model including the excess return on the aggregate US bond market and the excess return on the ICE BofA US High Yield Index. The unit of observation is on the fund-month level. The main explanatory variable is the portfolio liquidity of the corresponding fund ($PFLIQ$), which is measured using estimated effective spreads based on Glosten and Harris (1988) (GH), estimated spreads based on Hong and Warga (2000) (HW), and Amihud and Mendelson (1986) illiquidity measure (*Ami*). The remaining fund and portfolio characteristics include the portfolio allocation towards cash and government bonds (w^{liq}), the fund's lagged monthly return ($LaggedReturn$), the fund's lagged monthly flow (*Lagged Flow*), the logarithm of the fund's total net assets ($log(TNA)$), the fund's fraction targeting retail investors (*Retail*), the fund's fraction to which a rear load fee applies (*Rear Load*), and the fund's weighted average expense ratio (*Exp. Ratio*). Moreover, the set of independent variables includes a dummy variable $NegInno$ which equals 1 when the AR(1)-innovation in market liquidity is negative, and 0 otherwise. All specifications include year-month fixed effects. Standard errors are clustered at the fund and year-month level, and the corresponding t-statistics are presented in brackets. * p<0.05; ** p<0.01.

Table 13: Moderating effect of liquidity management tools.

Panel A: Investment-Grade Funds

Dep. Var.:	α^1	α^2	α^3	α^1	α^2	α^3
Model:	(1)	(2)	(3)	(4)	(5)	(6)
PFLIQ	0.009	0.013	0.014	0.009	0.016	0.017
	(0.726)	(0.896)	(0.913)	(0.771)	(1.187)	(1.154)
Low Cash	0.000	-0.001	-0.002			
	(-0.027)	(-0.126)	(-0.301)			
PFLIQ × Low Cash	-0.001	0.004	0.002			
	(-0.083)	(0.654)	(0.382)			
RearLoad				-0.001	0.002	0.000
				(-0.113)	(0.353)	(0.027)
PFLIQ × RearLoad				0.000	-0.004	-0.006
				(0.037)	(-0.608)	(-0.968)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	58,062	58,062	58,062	58,062	58,062	58,062
Adj. R^2	0.295	0.420	0.628	0.295	0.420	0.628
Within Adj. R^2	0.0009	0.005	0.008	0.001	0.006	0.008

Panel B: High-Yield Funds

Dep. Var.:	α^1	α^2	α^3	α^1	α^2	α^3
Model:	(1)	(2)	(3)	(4)	(5)	(6)
PFLIQ	0.128*	0.164*	0.144*	0.136**	0.180**	0.164**
	(2.423)	(2.545)	(2.271)	(2.844)	(2.859)	(2.685)
Low Cash	0.011	0.012	0.010			
	(0.881)	(0.950)	(0.776)			
PFLIQ × Low Cash	0.027	0.038	0.030			
	(0.921)	(1.259)	(1.062)			
RearLoad				0.007	0.006	-0.001
				(0.414)	(0.332)	(-0.066)
PFLIQ × RearLoad				0.008	0.002	-0.014
				(0.319)	(0.066)	(-0.537)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	26,237	26,237	26,237	26,237	26,237	26,237
Adj. R^2	0.140	0.799	0.788	0.140	0.799	0.788
Within Adj. R^2	0.013	0.029	0.019	0.013	0.029	0.019

Notes: This table contains the results of panel regressions in which monthly risk-adjusted fund returns serve as the dependent variable. A distinction is made between risk-adjusted returns based on 3 different models, as indicated by α^1, α^2, α^3. α^1 is based on a 2-factor model including the excess return on the aggregate US bond market and the excess return on the ICE BofA US High Yield Index. α^2 is based on the 2-factor model in Goldstein et al. (2017), which includes the excess return on the aggregate US bond market and the value weighted CRSP market excess return. α^3 is based on the 3-factor model in Choi and Kronlund (2018), which includes the TERM and DEF factors (Fama and French, 1993), and the value weighted CRSP market excess return. The unit of observation is on the fund-month level. Fund and portfolio characteristics include the portfolio liquidity of the corresponding fund estimated using imputed round-trip costs ($PFLIQ$), a dummy whether a fund's cash buffer falls below the median cash buffer of all funds having the same Lipper Objective Code (*Low Cash*), and a dummy equal to 1 when a fund applies a rear load fee to at least one of its shareclasses (*RearLoad*). I furthermore control for the portfolio allocation towards cash and government bonds, the fund's lagged monthly return, the fund's lagged monthly flow, the logarithm of the fund's total net assets, the fund's fraction targeting retail investors, and the fund's fraction to which a rear load fee applies. Panel A focuses on investment-grade funds, while Panel B contains the results for high-yield funds. All specifications include year-month fixed effects. Standard errors are clustered at the fund and year-month level, and the corresponding t-statistics are presented in brackets. * p<0.05; ** p<0.01.

Table 14: Moderating effect of fund size and investor base.

Panel A: Investment-Grade Funds						
Dep. Var.:	α^1	α^2	α^3	α^1	α^2	α^3
Model:	(1)	(2)	(3)	(4)	(5)	(6)
PFLIQ	0.010	0.016	0.018	0.008	0.015	0.015
	(0.881)	(1.223)	(1.288)	(0.674)	(1.123)	(1.064)
Large Size	0.013**	0.011*	0.015*			
	(2.611)	(2.189)	(2.466)			
PFLIQ × Large Size	-0.003	-0.003	-0.008			
	(-0.665)	(-0.535)	(-1.170)			
Retail Fund				-0.013*	-0.013*	-0.006
				(-2.232)	(-2.159)	(-1.074)
PFLIQ × Retail Fund				0.007	0.002	-0.002
				(1.193)	(0.305)	(-0.310)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	58,062	58,062	58,062	58,062	58,062	58,062
Adj. R^2	0.295	0.420	0.628	0.295	0.420	0.628
Within Adj. R^2	0.0009	0.005	0.008	0.0010	0.005	0.008
Panel B: High-Yield Funds						
Dep. Var.:	α^1	α^2	α^3	α^1	α^2	α^3
Model:	(1)	(2)	(3)	(4)	(5)	(6)
PFLIQ	0.140*	0.184*	0.156*	0.138*	0.181**	0.160*
	(2.163)	(2.462)	(2.123)	(2.531)	(2.707)	(2.444)
Large Size	-0.002	-0.009	-0.007			
	(-0.173)	(-0.768)	(-0.584)			
PFLIQ × Large Size	0.002	-0.005	0.004			
	(0.057)	(-0.189)	(0.154)			
Retail Fund				-0.015	-0.024*	-0.024
				(-1.107)	(-2.086)	(-1.813)
PFLIQ × Retail Fund				0.016	0.003	-0.006
				(0.835)	(0.186)	(-0.277)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	26,237	26,237	26,237	26,237	26,237	26,237
Adj. R^2	0.140	0.799	0.788	0.140	0.799	0.788
Within Adj. R^2	0.013	0.029	0.020	0.013	0.029	0.019

Notes: This table contains the results of panel regressions in which monthly risk-adjusted fund returns serve as the dependent variable. The universe of funds is restricted to the set of investment-grade funds. A distinction is made between risk-adjusted returns based on 3 different models, as indicated by α^1, α^2, α^3. α^1 is based on a 2-factor model including the excess return on the aggregate US bond market and the excess return on the ICE BofA US High Yield Index. α^2 is based on the 2-factor model in Goldstein et al. (2017), which includes the excess return on the aggregate US bond market and the value weighted CRSP market excess return. α^3 is based on the 3-factor model in Choi and Kronlund (2018), which includes the TERM and DEF factors (Fama and French, 1993), and the value weighted CRSP market excess return. The unit of observation is on the fund-month level. Fund and portfolio characteristics include the portfolio liquidity of the corresponding fund estimated using imputed round-trip costs ($PFLIQ$), a dummy whether fund size exceeds the median size of all funds having the same Lipper Objective Code (*Large Size*), and a dummy equal to 1 when over 80% of a fund's total net assets is distributed through retail shareclasses (*Retail Fund*). I furthermore control for the portfolio allocation towards cash and government bonds, the fund's lagged monthly return, the fund's lagged monthly flow, the logarithm of the fund's total net assets, the fund's fraction targeting retail investors, and the fund's fraction to which a rear load fee applies. Panel A focuses on investment-grade funds, while Panel B contains the results for high-yield funds. All specifications include year-month fixed effects. Standard errors are clustered at the fund and year-month level, and the corresponding t-statistics are presented in brackets. * $p<0.05$; ** $p<0.01$.

A Cleaning TRACE data

This appendix contains details about the filters applied to TRACE database. The construction of the transaction database used in this paper relies heavily on the code made available by Scheuch et al. (2023).

Following Dick-Nielsen (2009) and Dick-Nielsen (2014), I first clean the TRACE Enhanced database for trade corrections, cancellations, and reversals. Second, I remove dealer-customer transactions corresponding to an agency transaction without commission.[10] Third, I remove transactions with non-FINRA affiliates that often stem from bookkeeping purposes (Choi et al., 2023). Affiliate transactions often follow closely after a real customer-dealer transaction with the same price and quantity and in the opposite direction. Keeping affiliate transactions in the data would therefore suggest a round-trip transaction cost of zero and lead to a downward bias in transaction cost estimates. Transactions with affiliates are flagged only as of November 2015 ($cntra\_mp\_id = A$). Before that, transactions with affiliates are disseminated as ordinary dealer-to-customer transactions. I use an algorithm similar to the one employed by Choi et al. (2023) for detecting and removing affiliate transactions before November 2015. When two offsetting transactions in the same bond with the same price and quantity take place within one minute of each other, I assume that one side is a transaction with a non-FINRA affiliate for bookkeeping purposes.[11] The pairs of matched transactions can be of two types: 1) both transactions are dealer-customer transactions, or 2) one transaction is a dealer-customer transaction and one transaction is an inter-dealer trade. Combinations of two inter-dealer trades are ignored as affiliate transactions are disseminated as dealer-customer transactions before November 2015, and hence none of these inter-dealer trades can be an affiliate transaction. In the first case, when both transactions are dealer-customer trades, I remove both of them as it is impossible to identify which of the two is an affiliate transaction. In the second case, I keep the inter-dealer transaction but remove the dealer-customer transaction as this is assumed to be an affiliate transaction. Fourth, I remove double-reported interdealer transactions by keeping interdealer trades reported by the selling party as well as unmatched interdealer trades reported by the buying party.[12] Finally, I impose the following additional filters:

1. Remove trades on a when-issued basis.
   - $wis\_fl ==$ "N"
2. Remove trades which are not secondary market.

[10] During my sample period, the variable *cmsn_trd* which flags commissioned trades has been replaced by the actual commissions paid (*buy_cmsn_rt* and *sell_cmsn_rt*). Hence, I amend the filter in Dick-Nielsen (2014) by also deleting dealer-customer agency transactions for which the actual reported commission is zero.

[11] Choi et al. (2023) also observe dealer identities, which increases the accuracy of the algorithm.

[12] I consider transactions for which the counterparty is an Automated Trading System ($cntra\_mp\_id = T$) as inter-dealer transactions as well.

- $trdg\_mkt\_cd$ %in% c("$S2$", "$P1$", "$P2$") $== FALSE$

3. Remove trades with a special price indicator.

   - $is.na(spcl\_trd\_fl)$ or $spcl\_trd\_fl ==$ ""

4. Remove trades that do not correspond to a corporate bond.[13]

   - $scrty\_type\_cd ==$ "C" or $sub\_prdct ==$ "$CORP$"

5. Remove trades with more than 7 days to settlement.[14]

   - $is.na(days\_to\_sttl\_ct)$ or $as.numeric(days\_to\_sttl\_ct) <= 7$
   - $is.na(stlmnt\_dt)$ or $as.numeric(stlmnt\_dt - trd\_exctn\_dt) <= 7$

6. Remove locked-in trades.

   - $is.na(lckd\_in\_ind)$ or $lckd\_in\_ind! =$ "Y"

7. Remove trades with special conditions.[15]

   - $sale\_cndtn\_cd$ %in% c("A", "Z", "W") $== FALSE$
   - $sale\_cndtn2\_cd$ %in% c("A", "Z") $== FALSE$
   - trd_mod_3 %in% c("Z", "T", "U") $== FALSE$
   - $trd\_mod\_4! =$ "W" or $is.na(trd\_mod\_4)$

8. Remove retail-sized trades with a volume below 100.000 USD.

B Liquidity measures

B.1 Imputed Roundtrip Costs

I proxy bond liquidity using imputed round-trip costs based on a similar approach as Kargar et al. (2021). This approach extends Feldhütter (2012) by taking into account the buy and sell indicator and the counterparty of the transaction, which improves the accuracy of classifying multiple transactions as a roundtrip. When estimating the liquidity of individual bonds, the difference between the Rule 144A corporate bond market and publicly issued corporate bonds warrants caution. First of all, the Rule 144A corporate bond market is dominated by so-called Qualified Institutional Buyers, and as a result average transaction volumes in Rule 144A bonds

[13] The variable $scrty\_type\_cd$ has been replaced by the variable sub_prdct.

[14] Initially, TRACE disseminated the number of days until settlement. This has been replaced by the settlement date itself, which requires computing the days to settlement manually.

[15] The variables $sale\_cndtn\_cd$ and $sale\_cndtn2\_cd$ have been replaced by trd_mod_3 and trd_mod_4.

are substantially larger than those observed for publicly issued corporate bonds. Since larger transaction volumes in corporate bonds typically involve lower transaction costs (Feldhütter, 2012), not taking into account this difference may lead to a bias in estimated transaction costs. Secondly, dealers show a tendency to act like brokers in Rule 144A bonds by matching buyers with sellers instead of using their inventory to take the opposite side of the transaction, due to the higher inventory and search costs associated with Rule 144A bonds (Goldstein and Hotchkiss, 2020). Observed round-trip costs are lower when no dealer inventory is involved, because inventory risks are mitigated. Hence, when one ignores whether dealers use their inventory in a round-trip, observed round-trip costs of Rule 144A bonds may appear lower than those observed for publicly issued corporate bonds, despite Rule 144a bonds being less liquid (Chernenko and Sunderam, 2020; Goldstein and Hotchkiss, 2020).

To deal with these concerns, I exclusively focus on round-trip transactions in which a customer-seller is matched with a customer-buyer and I discard retail-sized transactions with volumes below 100,000 USD. Specifically, I employ the following procedure:

1. Discard interdealer trades and separate customer buys from customer sells.
2. Match customer buys with customer sells on CUSIP, transaction date, and transaction volume and only keep pairs of transactions that took place within 15 minutes of each other.
3. Each customer buy may be matched with multiple customer sells and vice versa. I deduplicate the pairs of matched transactions using the following algorithm:
    (a) Extract pairs of transactions in which neither the customer buy nor the customer sell is matched with a different transaction. These pairs do not need to be deduplicated as both trades are uniquely matched.
    (b) Extract pairs of transactions in which a customer buy is matched with multiple customer sells, where none of the matched customer sells is matched with another customer buy. For each unique customer buy, select the match for which the time difference is smallest.
    (c) Extract pairs of transactions in which a customer sell is matched with multiple customer buys, where none of the matched customer buys is matched with another customer sell. For each unique customer sell, select the match for which the time difference is smallest.
    (d) For the remaining customer buys, I select the customer sell that is closest in time. I then delete both transactions from the remaining set of matched pairs to prevent these transactions from ending up in a next match. I repeat this step until all pairs of transactions have been deduplicated.

    In the resulting set of paired transactions, none of the customer buys is matched with more than one customer sell, and no customer sell is matched with more than one customer buy.

B.2 Alternative liquidity measures

This section provides a detailed description of the liquidity proxies considered in this paper.

- *Spread*^{GH}: Using a simplified version of the approach in Glosten and Harris (1988), I estimate effective bid-ask spreads using the following regression:

$$p_{t_i} - p_{t_{i-1}} = \alpha + \beta \left(Q_{t_i} - Q_{t_{i-1}}\right) + \varepsilon_{t_i} \tag{21}$$

  Here, p_{t_i} denotes the log price of transaction i that took place at time t_i, and Q_{t_i} is the corresponding trade sign indicator. Specifically, Q_{t_i} equals -1 for a seller-initiated transaction, +1 for a buyer-initiated transaction, and 0 for an interdealer transaction. I run this regression for each bond-quarter pair to estimate the quarterly effective bid-ask spread, equal to $2 \times \hat{\beta}$, for each bond in my sample. I use a weighted least squares with weights given by $w_{t_i} = (t_i - t_{i-1})^{-1}$ to attach higher weight to trade pairs with a smaller time lapse, which can be motivated by the assumption that $Var(\varepsilon_{t_i}) = \sigma^2(t_i - t_{i-1})$.

- *Spread*^{HW}:

$$Spread_i^{HW} = \frac{\sum_{i=1}^{N} P_i^A V_i^A}{\sum_{i=1}^{N} V_i^A} - \frac{\sum_{j=1}^{M} P_j^B V_j^B}{\sum_{j=1}^{M} V_j^B} \tag{22}$$

  Here, P_i^A (P_j^B) denotes the price of transaction i (j) at the ask (bid). V_i^A (V_j^B) denotes the volume of transaction i (j) at the ask (bid), and N (M) denotes the number of transactions at the ask (bid). The quarterly spread is obtained by taking the average of daily spreads within a given quarter.

- *Amihud*:

$$Amihud_i = \frac{1}{N} \sum_{i=1}^{N} \frac{\left|\frac{P_i - P_{i-1}}{P_{i-1}}\right|}{V_i} \tag{23}$$

  Here, N denotes the number of transactions, P_i denotes the price of transaction i, and V_i is the trade size corresponding to transaction i. The quarterly Amihud measure is obtained by taking the average of daily measures within the quarter.