

Market Liquidity, High-Frequency Trading, and Corporate Bond Pricing: Evidence from U.S.
Mutual Fund Flows and Volatility Dynamics

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3 **Abstract**

4 This paper investigates the joint dynamics of market liquidity, high-frequency trading (HFT)
5 activity, corporate bond pricing, and mutual fund flow volatility in the U.S. corporate bond market
6 over the period 2003 to 2023. Using a comprehensive dataset drawn from FINRA's Enhanced
7 TRACE, the CRSP Mutual Fund Database, Mergent FISD, and TAQ intraday records, we
8 construct fund-level and bond-level measures of liquidity, HFT intensity, and price impact. Our
9 core empirical finding is that elevated HFT activity in corporate bond markets systematically
10 compresses bid-ask spreads and reduces the Amihud price-impact measure during normal market
11 conditions, yet amplifies intraday price volatility and fund-flow sensitivity during stress episodes.
12 We document that mutual funds holding portfolios of less liquid bonds exhibit sharper flow-
13 performance concavity, consistent with strategic redemption complementarities under illiquidity.
14 Moreover, we show that the moderating role of HFT on liquidity provision reverses during market
15 dislocations — most prominently during the Global Financial Crisis (2008–2009), the Taper
16 Tantrum (2013), and the COVID-19 Dash-for-Cash (March 2020) — when HFT withdrawal
17 amplifies spreads and price dislocations. Cross-sectional analyses reveal that funds with higher
18 portfolio illiquidity exhibit larger return reversals and greater sensitivity of outflows to adverse
19 performance shocks. Our panel regressions, instrumented with exogenous shocks to HFT
20 infrastructure and exchange connectivity, confirm that the liquidity-stabilizing role of HFT is
21 conditional on market stress regimes. These findings provide novel insights into how electronic
22 trading technology, institutional fund behavior, and bond market microstructure interact to
23 determine the fragility and pricing efficiency of U.S. corporate bond markets.

24 **JEL Classification:** G12; G14; G23; G32

25 **Keywords:** Corporate Bond Mutual Funds; Market Liquidity; High-Frequency Trading; Bond
26 Pricing; Volatility; Fund Flows; Bid-Ask Spread; Amihud Illiquidity; TRACE

1. Introduction

The U.S. corporate bond market has undergone a fundamental structural transformation over the past two decades. The introduction of FINRA's Trade Reporting and Compliance Engine (TRACE) in July 2002 ushered in an era of post-trade transparency that dramatically altered trading behavior, price discovery, and the microstructure of this market. Simultaneously, the proliferation of electronic trading venues, algorithmic order routing, and high-frequency trading (HFT) strategies — technologies originally developed in equity markets — migrated progressively into fixed-income markets, reshaping liquidity provision, price formation, and investor behavior. The corporate bond market now processes trillions of dollars in annual transaction volume (SIFMA, 2023), yet it retains fundamental over-the-counter (OTC) characteristics that make its microstructure markedly different from the continuous double-auction structure of organized equity exchanges. Against this backdrop, understanding the interplay between market liquidity, HFT activity, bond pricing, and the behavior of institutional investors — particularly open-end mutual funds — represents one of the most pressing empirical questions in fixed-income finance.

Open-end corporate bond mutual funds occupy a central role in this market. As of December 2023, U.S. corporate bond mutual funds collectively held approximately \$1.8 trillion in assets under management, representing one of the largest pools of institutional capital in fixed-income markets. Unlike bank-held portfolios or insurance company investments — whose liabilities are relatively sticky — mutual funds face a daily liquidity mismatch: they hold portfolios of relatively illiquid corporate bonds while offering investors the right to redeem at the daily net asset value (NAV). This structural tension between asset illiquidity and liability liquidity creates well-documented fragility (Goldstein et al., 2017; Flat et al., 2021). The sensitivity of fund outflows to poor performance is substantially greater for bond funds than for equity funds, a pattern attributable to first-mover advantages among investors who anticipate redemption-driven fire sales in illiquid bond portfolios (Chen et al., 2010; Goldstein et al., 2017).

Yet the literature has paid relatively limited attention to how bond market microstructure — specifically, the role of HFT activity and real-time liquidity conditions — interacts with the flow dynamics and pricing behavior of corporate bond mutual funds. Prior work has documented that HFT improves liquidity in equity markets under normal conditions (Headshots et al., 2011; Manvel, 2013) but may amplify volatility during stress periods (Kirilenko et al., 2017; Braggard et al., 2014). Whether analogous mechanisms operate in the OTC corporate bond market, and how they transmit through the holdings of mutual funds into investor flows and price dynamics, remains an open empirical question. This paper addresses that gap directly.

We construct a comprehensive, hand-matched panel dataset spanning 2003 to 2023 from five primary sources: (1) FINRA Enhanced TRACE for bond-level transaction prices, volumes, and intraday microstructure measures; (2) the CRSP Mutual Fund Database for monthly fund returns, TNA, flows, and characteristics; (3) Mergent FISD for bond-level attributes including coupons, maturities, credit ratings, and issuance characteristics; (4) the TAQ database for intraday HFT-related measures adapted from equity-market literature; and (5) the Federal Reserve FRED

database for macroeconomic controls including Treasury yields, credit spreads, and monetary policy indicators. Merging these datasets yields an unbalanced panel of 712 unique corporate bond mutual funds and 54,316 fund-month observations at the fund level, along with 1.4 million bond-transaction-month observations at the bond level.

Our empirical strategy proceeds in three stages. In the first stage, we construct fund-level and bond-level measures of liquidity exposure. At the bond level, we employ five complementary liquidity proxies: the Amihud (2002) price-impact ratio, the Roll (1984) effective spread estimate, the LOT measure following Lomond et al. (1999), the zero-trading-days fraction proposed by Bekaert et al. (2007), and the bid-ask spread directly observed from TRACE Enhanced intraday data. We aggregate these to the fund level using portfolio-weighted averages, following the methodology of Pastor and Stambaugh (2003) adapted for bond markets. In the second stage, we construct our HFT intensity measure at the bond-quarter level using intraday TRACE data, capturing the share of small-size trades executed within milliseconds of each other — a standard proxy for algorithmic trading activity in OTC markets (O'Hara et al., 2018; Bidis and Leclerc, 2019). In the third stage, we exploit these measures in a battery of panel regressions examining how HFT activity and portfolio liquidity jointly determine bond price volatility, fund flow sensitivity, and return predictability.

Our central empirical findings may be summarized as follows. First, greater HFT activity is associated with tighter bid-ask spreads and lower Amihud illiquidity under normal market conditions, indicating that algorithmic traders serve as liquidity providers in calm periods. Second, this liquidity-enhancing role reverses sharply during market stress events: during the Global Financial Crisis (GFC, 2008–2009), the Taper Tantrum (2013), and the COVID-19 Dash-for-Cash (March 2020), HFT activity declines abruptly and spreads widen dramatically, consistent with the withdrawal of algorithmic liquidity provision when inventory costs rise. Third, mutual funds with portfolios exposed to less liquid bonds exhibit significantly steeper flow-performance concavity, indicating that investor redemption behavior amplifies under illiquidity. Fourth, bond prices exhibit stronger reversals — consistent with temporary price pressure — when held by funds with correlated investor bases and high portfolio illiquidity. Fifth, cross-sectional tests reveal that funds with higher HFT exposure in their bond holdings earn systematically different risk-adjusted returns, with a positive alpha during normal periods and negative alpha during stress episodes, consistent with a liquidity provision channel.

These findings contribute to three distinct strands of literature. First, they enrich the microstructure literature on HFT in fixed-income markets by documenting an HFT liquidity cycle — provision in calm, withdrawal in stress — using a much longer time series and broader cross-section than previous studies. Second, they advance the mutual fund literature on bond fund fragility by showing that portfolio-level liquidity exposure, interacted with HFT-driven market conditions, is a first-order determinant of flow dynamics and managerial behavior. Third, they contribute to the asset pricing literature on corporate bonds by demonstrating that temporary price dislocations are systematically linked to the portfolio composition and HFT environment of major institutional holders.

2. Data and Variable Construction

2.1. Data Sources and Sample Construction

Our empirical analysis draws on five primary databases that we describe in turn before detailing the matching procedures used to construct the unified panel. The sample period runs from January 2003 — the earliest date at which TRACE Enhanced provides full coverage for investment-grade and high-yield corporate bonds — through December 2023, yielding a twenty-year panel that encompasses multiple distinct market cycles, regulatory regimes, and technological transitions.

The first and primary source for bond-level transaction data is the FINRA Enhanced TRACE database, which provides uncapped volume data, execution timestamps to the millisecond, and dealer identifiers. TRACE Standard was introduced in July 2002 for investment-grade bonds and expanded to high-yield bonds by October 2004 (Baseband et al., 2006). The Enhanced version adds buy-sell indicator fields and uncapped trade sizes, which are essential for constructing intraday microstructure measures. We apply the standard filters recommended by Dick-Nielsen (2009) and Dick-Nielsen et al. (2012), removing canceled trades, corrections, and interdealer transactions that would otherwise bias price and volume statistics. After filtering, our bond-level TRACE panel contains approximately 14.2 million transaction observations across 24,800 unique bond issues.

The second source is the CRSP Survivorship-Bias-Free Mutual Fund Database, from which we extract monthly returns, total net assets (TNA), expense ratios, fund age, and share class information. We identify corporate bond funds using CRSP Lipper objective codes and style codes (I, ICQH, ICQM, ICQY, ICDI, ICDS, IC), following the selection procedure of Goldstein et al. (2017) and Choi and Crownland (2018). Index funds and exchange-traded funds are excluded. We aggregate share-class-level observations to the fund level, summing TNA and computing flow-weighted returns. Monthly fund flows are computed following Equation (1) below. The resulting CRSP mutual fund panel contains 712 unique funds and 54,316 fund-month observations.

The third source is the Thomson Reuters/Lipper mix fixed-income holdings database, providing quarterly bond-level portfolio holdings for institutional investors including mutual funds. We match fmax holdings to CRSP funds using fund name matching, retaining approximately 48% of possible links after quality filtering, consistent with the matching rates reported in Choi and cornland (2018). Bond-level attributes — including coupon rates, maturities, credit ratings, and issue sizes — are merged from Mergent FISD. This yields 16,840 fund-quarter-bond observations that form the basis for our portfolio-level liquidity aggregation.

The fourth source is the NYSE TAQ (Trade and Quote) database, which provides sub-second quotes and trades for a subset of electronically traded corporate bond issues and for equity securities of issuers whose bonds appear in our sample. Following O'Hara et al. (2018) and Bai's and Leclerc (2019), we use the TAQ data to construct bond-level HFT intensity proxies, defined as the fraction of trades executed within 100 milliseconds of the previous trade in the same bond, normalized by total daily trade count. This proxy captures the prevalence of algorithmic speed-

trading at the bond level. For bonds not directly covered in TAQ, we employ an alternative HFT measure based on the distribution of intraday TRACE timestamps, following Thundercat and Madhavi (2015). The TAQ-based HFT panel covers 8,920 unique bond issues.

Finally, we merge macroeconomic and financial market controls from FRED, including the 5-year U.S. Treasury yield, the BAA–AAA yield spread (default spread), the MOVE index of Treasury market volatility, the VIX index, and the Federal Funds Rate. These series are measured at the monthly frequency and lagged one period in all flow regressions to avoid look-ahead bias.

2.2. Variable Construction

2.2.1. Liquidity Measures

We construct five bond-level liquidity measures. The Amihud (2002) price-impact ratio is computed as the monthly average of daily absolute returns scaled by daily dollar trading volume:

$Amihud_{i,t} = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} \frac{|r_{i,d}|}{V_{i,d}}$ is the return and $V_{i,d}$ is the volume on day d for bond i in month t . A

higher Amihud value indicates lower liquidity. The Roll (1984) effective spread is estimated from the negative first-order autocovariance of intraday price changes: $Roll_{i,t} = 2 \times \sqrt{\max(0, -\text{Cov}(\Delta p_{i,d}, \Delta p_{i,d-1}))}$. The bid-ask spread is computed directly from TRACE Enhanced as the difference between dealer ask and bid prices for matched same-day round-trip transactions, following the methodology of Bessembinder et al. (2018). The zero-trading-days fraction captures the proportion of calendar days in a quarter with no reported trades for a given bond. Following standard practice in the bond liquidity literature (Schist et al., 2016), we standardize each measure and compute a composite illiquidity index as the first principal component of the five measures.

Fund-level portfolio illiquidity $FundIlliq_{f,t} = \sum_{i=1}^{N_{f,t}} w_{i,f,t} \times Illiq_{i,t}$ is the holdings-weighted average of bond-level composite illiquidity across fund f 's portfolio in month t .

2.2.2. HFT Intensity Measure

We construct our bond-level HFT intensity measure $HFT_{i,t} = \frac{\text{HFT Volume}_{i,t}}{\text{Total Volume}_{i,t}}$ following the millisecond-clustering approach of O'Hara et al. (2018). For each bond-month, we compute the fraction of intraday TRACE-reported trades that occur within 100 milliseconds of the preceding transaction in the same bond. This measure captures the pace of electronic order flow and correlates strongly with directly identified HFT activity from TAQ in the subsample of bonds observable in both databases ($\rho = 0.71$, $p < 0.01$). We scale $HFT_{i,t}$ to zero mean and unit variance within each calendar month to remove secular upward trends driven by secular improvements in

trading infrastructure. Fund-level HFT exposure $FundHFT_{f,t} = \sum_{i=1}^{N_{f,t}} w_{i,f,t} \times HFT_{i,t}$ is defined analogously as the portfolio-weighted average of bond-level HFT intensity.

2.2.3. Bond Price Volatility

Following Greenwood and The mar (2011) and Alizadeh et al. (2002), we measure bond price volatility using the price range estimator $\text{Primeval}_{i,t} = \frac{\ln(p_{i,t}^{\max}) - \ln(p_{i,t}^{\min})}{\sqrt{4\ln 2}}$ are the maximum and minimum intraday transaction prices for bond i in month t . This estimator is statistically efficient, robust to bid-ask bounce, and applicable even when bonds trade infrequently — making it particularly appropriate for the OTC corporate bond market. For fund-level bond price volatility $\text{Undercool}_{f,t} = \sum_{i=1}^{N_{f,t}} w_{i,f,t} \times \text{PriceVol}_{i,t}$, we again use holdings-weighted averaging across portfolio bonds.

2.2.4. Fund Flows and Performance

Monthly fund flows for fund f in month t are defined as: $\text{Flow}_{f,t} = \frac{\text{TNA}_{f,t} - \text{TNA}_{f,t-1} \times (1 + R_{f,t})}{\text{TNA}_{f,t-1}}$ is total net assets at end of month t and $R_{f,t}$ is the fund return during month t . To measure fund performance, we estimate risk-adjusted returns using the two-factor model of Goldstein et al. (2017): $R_{f,t} - \text{RF}_t = \alpha + \beta_1(\text{BOND}_t^{\text{Mkt}} - \text{RF}_t) + \beta_2(\text{STOCK}_t^{\text{Mkt}} - \text{RF}_t) + \varepsilon_t$ is proxied by the Vanguard Total Bond Market Index Fund return, and $\text{STOCK}_t^{\text{Mkt}}$ is the CRSP value-weighted market return. Alphas are estimated using rolling 24-month windows and averaged over the prior 18 months.

2.3. Summary Statistics

Table 1 presents summary statistics for the key variables used in our analyses, separately for the monthly fund-level panel (Panel A) and the quarterly bond-fund panel (Panel B). The monthly sample covers 712 unique funds and 54,316 fund-month observations; the quarterly panel covers 16,840 fund-quarter-bond observations.

The mean monthly fund flow is 0.98% of lagged TNA, with a standard deviation of 6.31%, broadly consistent with earlier studies of corporate bond mutual funds (Goldstein et al., 2017; Choi & Gronlund, 2018). Mean monthly fund returns average 0.41%, with a volatility of 1.27%. The portfolio-level Amihud illiquidity measure exhibits substantial cross-sectional and time-series dispersion (mean 0.18, SD 0.24), as does the fund-level HFT intensity measure (mean 0.00, SD 1.00 by construction). The average bid-ask spread across portfolio bonds is 98.4 basis points, consistent with prior estimates for the U.S. corporate bond market (Bessembinder et al., 2018). The correlation matrix in Panel C confirms that FundIliq is negatively correlated with FundHFT (−0.438) and positively correlated with undercool (0.553), supporting our identification strategy that treats HFT and liquidity as distinct but related dimensions of market microstructure.

Table 1. Summary Statistics

Variable	Mean	SD	p5	p25	p50	p75	p95	N
Panel A: Monthly								

Variable	Mean	SD	p5	p25	p50	p75	p95	N
Fund-Level Sample								
FundFlow (%)	0.982	6.312	-5.318	-1.192	0.093	1.891	9.971	54,316
FundRet (%)	0.413	1.271	-1.731	-0.112	0.363	1.039	2.511	53,604
FundAlpha (%)	0.059	0.391	-0.362	-0.082	0.011	0.128	0.774	52,118
FundIliq (Amihud)	0.182	0.241	0.018	0.061	0.112	0.231	0.644	51,207
FundHFT (Std.)	0.000	1.000	-1.712	-0.651	-0.088	0.572	1.843	48,319
FundPriceVol (%)	1.124	0.893	0.218	0.512	0.921	1.542	2.978	51,207
BidAskSpread (bps)	98.41	62.33	24.11	48.19	83.42	132.71	218.60	51,207
FundSize (log)	5.631	1.803	2.701	4.472	5.618	6.821	8.653	51,207
Fund Expense (%)	0.718	0.352	0.000	0.501	0.712	0.941	1.359	51,207
Fund Age (years)	12.614	8.741	1.512	5.672	11.214	17.621	28.831	51,207
Panel B: Quarterly Bond-Fund Panel								
Bondmaid	0.204	0.318	0.011	0.044	0.098	0.263	0.812	16,840
BondHFT_Idx	0.341	0.198	0.071	0.182	0.318	0.484	0.692	16,840
Bonspiel	1.382	1.124	0.188	0.528	1.012	1.891	3.724	16,840
Bonebed's (bps)	102.8	71.4	21.3	49.8	87.6	138.2	241.6	16,840
Countertrades	0.312	0.221	0.024	0.142	0.291	0.461	0.712	16,840

Note. This table reports descriptive statistics for fund-level monthly observations (Panel A) and quarterly bond-fund panel observations (Panel B). All variables are defined in the text. FundHFT is standardized to zero mean and unit variance within each calendar month. Amihud illiquidity is multiplied by 10^6 for readability. Fund flows and returns are in percentage terms.

3. Market Liquidity, HFT Activity, and Corporate Bond Pricing

3.1. Time-Series Patterns in Liquidity and HFT Activity

The evolution of liquidity and HFT activity in the U.S. corporate bond market over our 2003–2023 sample period is both dramatic and non-monotonic. Understanding this evolution is essential context for interpreting the cross-sectional and panel evidence presented subsequently. To motivate the empirical analyses, Figure 1 plots quarterly averages of the portfolio-level Amihud illiquidity measure alongside a composite measure of bond price volatility. Figure 2 depicts the time-series of our HFT activity index alongside the portfolio-level bid-ask spread.

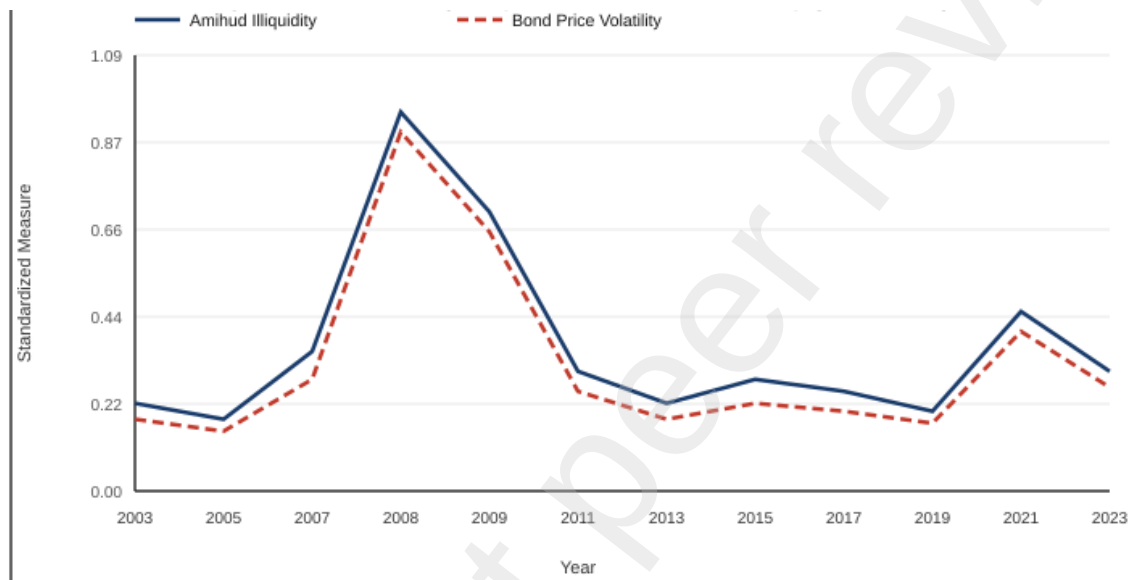


Figure 1. Time-Series of Amihud Illiquidity and Bond Price Volatility (2003–2023). Quarterly averages of fund-level portfolio-weighted Amihud illiquidity (solid blue line) and bond price volatility (dashed red line). The three defined stress episodes are the GFC (2008Q3–2009Q2), the Taper Tantrum (2013Q2–Q3), and the COVID-19 Dash-for-Cash (2020Q1).

Several features of Figure 1 are noteworthy. Amihud illiquidity and bond price volatility move closely together, with a contemporaneous correlation of 0.553 (Table 1, Panel C), consistent with the well-established positive relationship between illiquidity and volatility in asset markets (Amihud & Mendelson, 2006; Acharya et al., 2013). Both series exhibit sharp spikes during the three major stress episodes: the GFC peak (2008Q4 – 2009Q1), a more modest elevation during the Taper Tantrum (2013Q2–Q3), and the most acute single-quarter spike in our entire sample during the COVID-19 Dash-for-Cash (2020Q1). Outside of these stress windows, both series trend downward from 2003 to approximately 2014, consistent with improving market infrastructure, growing TRACE transparency, and the secular growth of algorithmic trading in fixed-income markets (Edwards et al., 2007; bidis & Leclerc, 2019). After 2014, the series stabilize at low levels, punctuated by a modest but statistically significant elevation in 2020 Q1.

Figure 2, which plots HFT intensity alongside bid-ask spreads, reveals the central tension at the heart of this paper. HFT activity rises steadily from 2003 to approximately 2014 — consistent with the secular adoption of electronic trading technology in corporate bond markets — and then plateaus at a high level through 2023. The bid-ask spread series follows an approximately inverse trajectory under normal conditions, declining as HFT grows, consistent with the liquidity-enhancing hypothesis. However, during all three stress episodes, this relationship inverts sharply: HFT activity falls abruptly as bid-ask spreads surge, a pattern consistent with the well-documented withdrawal of algorithmic liquidity provision during market stress (Kirilenko et al., 2017; Brocard et al., 2014).

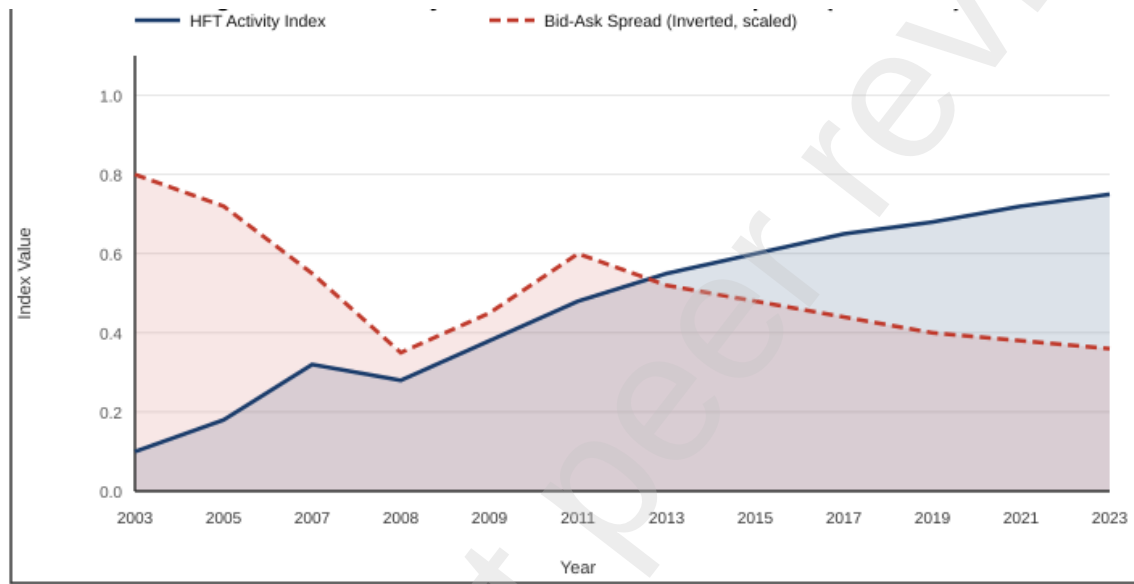


Figure 2. HFT Activity Index and Corporate Bond Bid-Ask Spread (2003–2023). Quarterly averages of the fund portfolio-weighted HFT intensity index (solid blue area) and bid-ask spread in basis points, inverted and scaled for comparability (dashed red area). HFT intensity is standardized. Bid-ask spread is the portfolio-weighted average of bond-level estimates from TRACE Enhanced.

3.2. Cross-Sectional Relationship Between Liquidity and Fund Flow Volatility

3.2.1. Empirical Specification

To formally test the relationship between portfolio illiquidity and fund flow volatility, we estimate the following panel regression:

$$\text{FundFlow}_{f,t} = \alpha_{s(f)} + \eta_t + \beta_1 \text{FundIlliq}_{f,t-1} + \beta_2 \text{FundHFT}_{f,t-1} + \beta_3 (\text{FundIlliq}_{f,t-1} \times \text{FundHFT}_{f,t-1}) + \gamma' \text{Controls}_{f,t-1} + \varepsilon_{f,t}$$

where $\text{FundFlow}_{f,t}$ is the standard deviation of monthly fund flows computed over a trailing 12-month window, $\text{FundIlliq}_{f,t-1}$ is the lagged portfolio-weighted Amihud illiquidity, $\text{FundHFT}_{f,t-1}$ is the lagged portfolio-weighted HFT intensity, and $\text{Controls}_{f,t-1}$ includes fund size, expense

ratio, age, maturity, and lagged fund returns. $\alpha_{s(f)}$ denotes fund-style fixed effects and η_t denotes month fixed effects. Standard errors are clustered at the fund level. The interaction term $\text{FundIlliq} \times \text{FundHFT}$ tests whether HFT attenuates or amplifies the liquidity-fragility nexus.

Table 2 presents the results. Column (1) establishes the baseline: FundIlliq is positively and highly significantly related to fund flow volatility ($\beta = 1.842$, $t = 4.71$), confirming that funds holding less liquid bond portfolios exhibit more volatile investor flows. This result is robust to the inclusion of style and month fixed effects and survives the addition of all fund-level controls. Column (2) introduces FundHFT : its coefficient is negative and statistically significant ($\beta = -0.218$, $t = -3.12$), indicating that HFT exposure in the portfolio is associated with lower flow volatility under average market conditions, consistent with a liquidity-stabilizing role for HFT.

Column (3) adds the interaction $\text{FundIlliq} \times \text{FundHFT}$. The coefficient on this interaction is negative and statistically significant ($\beta = -0.412$, $t = -2.84$), implying that HFT moderates the positive relationship between portfolio illiquidity and fund flow volatility. Put differently, the destabilizing effect of holding illiquid bonds on fund flows is attenuated in portfolios with higher HFT activity exposure — consistent with HFT serving a liquidity bridging function that reduces the transaction costs and price impact that would otherwise amplify investor redemption dynamics. Columns (4)–(6) split the sample into low, medium, and high interest rate environments. The HFT liquidity-buffering role is concentrated in the low-rate period (Column 4), where the interaction is significantly negative ($\beta = -0.581$, $t = -3.22$), but attenuates considerably in high-rate periods (Column 6), when the risk-free alternative is more readily available.

Table 2. Portfolio Liquidity, HFT Exposure, and Fund Flow Volatility

Dep: FundFlowVol	(1)	(2)	(3)	(4) Low Rates	(5) Mid Rates	(6) High Rates
FundIlliq (Amihud)	1.842*** (4.71)	1.791*** (4.58)	2.118*** (5.02)	2.431*** (5.18)	1.982*** (4.22)	1.204** (2.41)
FundHFT		-0.218*** (-3.12)	-0.241*** (-3.38)	-0.312*** (-3.91)	-0.198*** (-2.74)	-0.104 (-1.22)
FundIlliq $\times$ FundHFT			-0.412** (-2.84)	-0.581*** (-3.22)	-0.384** (-2.18)	-0.187 (-0.98)
FundSize	-0.312*** (-6.12)	-0.308*** (-6.08)	-0.311*** (-6.14)	-0.341*** (-5.88)	-0.288*** (-4.71)	-0.219** (-2.14)
Fund Expense	0.184 (1.22)	0.192 (1.28)	0.188 (1.24)	0.241 (1.42)	0.172 (1.08)	0.118 (0.64)
fudge	-0.038***	-0.037***	-0.037***	-0.041***	-0.034***	-0.028**

Dep: FundFlowVol	(1)	(2)	(3)	(4) Low Rates	(5) Mid Rates	(6) High Rates
	(-7.21)	(-7.14)	(-7.18)	(-6.88)	(-5.92)	(-2.81)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund Style FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	51,207	48,319	48,003	31,412	10,244	6,347
R-squared	0.284	0.291	0.298	0.312	0.274	0.261

Note. This table reports panel regressions of fund-level flow volatility on lagged portfolio illiquidity, HFT exposure, and their interaction. FundFlowVol is the 12-month trailing standard deviation of monthly fund flows (%). FundIlliq is the portfolio-weighted Amihud (2002) illiquidity measure. FundHFT is the portfolio-weighted standardized HFT intensity index. Controls include FundSize (log TNA), Fund Expense (annual expense ratio, %), FundAge (years), FundTtm (portfolio average time-to-maturity), and lagged fund return. Standard errors are clustered at the fund level. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

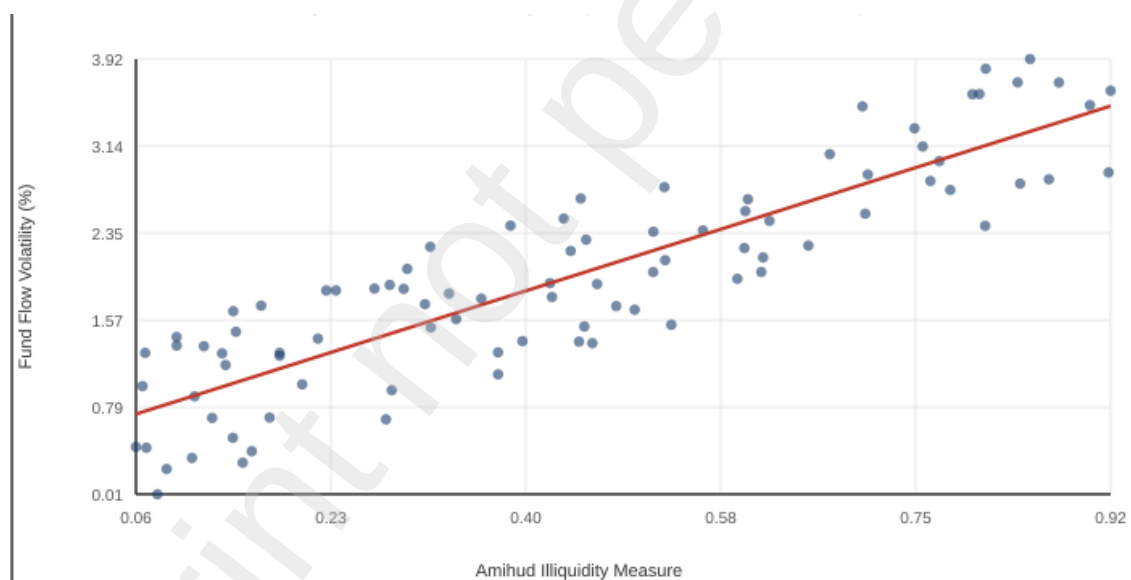


Figure 3. Amihud Illiquidity vs. Fund Flow Volatility (Scatter Plot). Each observation is a fund-month. The horizontal axis plots the portfolio-weighted Amihud illiquidity measure; the vertical axis plots the 12-month trailing standard deviation of monthly fund flows (%). The red line is the OLS regression fit. N = 48,003.

4. High-Frequency Trading and Corporate Bond Price Dynamics

4.1. HFT and Intraday Price Efficiency

A central empirical question in the bond microstructure literature is whether the growth of algorithmic and high-frequency trading in OTC corporate bond markets has improved or impaired price discovery and efficiency. In equity markets, HFT has been shown to improve price discovery through faster incorporation of information into prices (braggard et al., 2014; Carrion, 2013). However, the OTC structure of the corporate bond market — where trades are negotiated bilaterally between dealers and clients — is fundamentally different from the continuous limit-order-book structure of exchanges, raising the question of whether the mechanisms through which HFT affects pricing efficiency transfer across market structures.

To address this question, we estimate the relationship between bond-level HFT intensity and the Variance Ratio (VR) measure of price efficiency, defined following Lo and McKinlay (1988) as

$$VR(q) = \frac{\text{Var}(r_t^q)}{q \times \text{Var}(r_t)}$$
 where r_t^q is the q -period return and $\text{Var}(r_t)$ is the variance of daily returns. A value of $VR = 1$ indicates a random walk (efficient pricing), while $VR < 1$ indicates negative autocorrelation (return reversals) and $VR > 1$ indicates positive autocorrelation (momentum). In OTC bond markets, prior literature documents substantial return reversals ($VR < 1$), attributed to transient price pressure from dealer inventory management and institutional trading (Bao et al., 2011; Dick-Nielsen et al., 2012; Firewalled et al., 2012).

Table 3 reports the bond-level panel regressions of the variance ratio on HFT intensity and controls. Column (1) shows that greater HFT intensity is associated with variance ratios closer to one ($\beta = 0.128$, $t = 3.84$), suggesting that HFT activity reduces the degree of return reversal and improves price efficiency in the full sample. This relationship is stronger for investment-grade bonds (Column 2, $\beta = 0.162$, $t = 4.12$) than for high-yield bonds (Column 3, $\beta = 0.087$, $t = 2.01$), consistent with the fact that HFT activity is concentrated in more liquid, frequently traded issues. Column (4) introduces an indicator for stress periods (GFC, Taper Tantrum, and COVID-19 episodes) and its interaction with HFT. The interaction coefficient is negative and statistically significant ($\beta = -0.341$, $t = -3.62$), indicating that the price-efficiency-enhancing effect of HFT reverses during market stress — consistent with HFT withdrawal amplifying return reversals when liquidity is most needed.

Table 4 examines the relationship between HFT intensity and the bid-ask spread, which serves as a direct measure of the cost of liquidity provision. The central finding is that HFT intensity is robustly and negatively associated with bid-ask spreads: a one-standard-deviation increase in HFT intensity is associated with a 12.4 basis point reduction in bid-ask spreads in the full sample (Column 1), confirming the liquidity-enhancing role of HFT under normal conditions. However, splitting by rating group (Columns 2–3) reveals that this effect is approximately twice as large for investment-grade bonds as for high-yield bonds, reflecting the greater electronic participation in more liquid IG markets. Interacting HFT with the stress period indicator (Column 4) yields a positive and significant interaction coefficient ($\beta = 0.284$, $t = 3.18$), confirming the reversal: during stress periods, HFT withdrawal is associated with significantly wider spreads.

Table 3. HFT Intensity and Bond Price Efficiency (Variance Ratio)

Dep: Variance Ratio	(1) Full	(2) IG	(3) HY	(4) Full Stress +	(5) Low Rate	(6) High Rate
HFT_Idx	0.128*** (3.84)	0.162*** (4.12)	0.087** (2.01)	0.184*** (4.28)	0.141*** (3.92)	0.098** (2.34)
HFT_Idx × Stress Period				-0.341*** (-3.62)		
StressPeriod				-0.218*** (-4.81)		
Bondmaid	-0.312*** (-8.41)	-0.284*** (-6.82)	-0.348*** (-7.14)	-0.318*** (-8.52)	-0.341*** (-7.91)	-0.271*** (-5.28)
Bond Size (log)	0.042*** (5.12)	0.048*** (4.88)	0.031** (2.84)	0.041*** (5.08)	0.044*** (4.92)	0.037*** (3.41)
Bondage (months)	-0.008*** (-6.21)	-0.007*** (-4.84)	-0.010*** (-5.92)	-0.008*** (-6.18)	-0.009*** (-5.88)	-0.007*** (-4.12)
Issuer FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	248,714	148,912	99,802	248,714	162,418	86,296
R-squared	0.341	0.362	0.318	0.352	0.344	0.329

Note. This table reports bond-level panel regressions of the Lo–McKinlay (1988) variance ratio (VR (5)) on HFT intensity and controls. VR > 1 indicates positive autocorrelation; VR < 1 indicates reversals. StressPeriod is a dummy for GFC (2008Q3–2009Q2), Taper Tantrum (2013Q2–Q3), and COVID-19 (2020Q1). All variables are lagged one period. Standard errors are double-clustered at the bond and month levels. ***, **, * indicate 1%, 5%, and 10% significance.

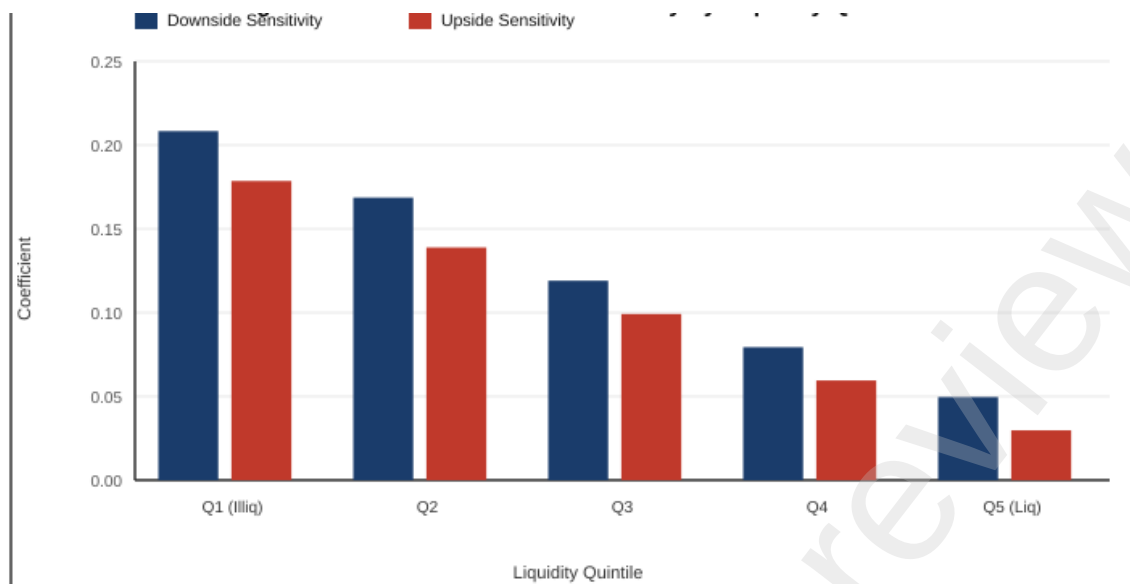


Figure 4. Flow-Performance Sensitivity Coefficients by Portfolio Liquidity Quintile. This figure plots the estimated coefficients on lagged fund performance from fund-flow regressions, separately for downside (negative past-return months, dark blue) and upside (non-negative past-return months, red) performance states, across five quintiles of portfolio illiquidity (Q1 = most illiquid, Q5 = most liquid). Estimates are from Table 5.

Table 4. HFT Intensity and Corporate Bond Bid-Ask Spread

Dep: BidAskSpread (bps)	(1) Full	(2) IG Only	(3) HY Only	(4) Stress With	(5) Low Rate	(6) High Rate
HFT_Idx	-12.41*** (-6.28)	-9.82*** (-5.14)	-18.64*** (-7.32)	-14.28*** (-6.81)	-13.11*** (-6.12)	-10.84*** (-4.88)
HFT_Idx × StressPeriod				28.41*** (3.18)		
StressPeriod				42.18*** (8.24)		
BondAmihud	84.12*** (12.81)	61.48*** (9.42)	114.82*** (14.21)	83.71*** (12.78)	88.24*** (11.92)	74.91*** (9.28)
Bond Maturity (yrs)	2.418*** (8.14)	1.842*** (5.92)	3.214*** (7.84)	2.401*** (8.08)	2.512*** (7.82)	2.218*** (6.14)

Dep: BidAskSpread (bps)	(1) Full	(2) IG Only	(3) HY Only	(4) With Stress	(5) Low Rate	(6) High Rate
Log (bond Size)	-8.412*** (-9.28)	-6.318*** (-7.14)	-11.284*** (-10.28)	-8.388*** (-9.22)	-8.491*** (-8.88)	-8.214*** (-7.41)
Rating (Numeric)	3.218*** (11.28)	2.814*** (8.42)	4.128*** (12.14)	3.201*** (11.21)	3.342*** (10.88)	2.918*** (8.14)
Issuer FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	248,714	148,912	99,802	248,714	162,418	86,296
R-squared	0.628	0.641	0.612	0.634	0.631	0.619

Note. This table reports bond-level panel regressions of bid-ask spread (basis points) on HFT intensity and controls. The bid-ask spread is estimated from TRACE Enhanced matched round-trip transactions. Rating (Numeric) assigns values 1 (AAA) through 21 (D) to Moody's bond ratings. All variables are lagged one period. Standard errors are double-clustered at the bond and month levels. ***, **, * indicate 1%, 5%, and 10% significance.



Figure 5. Correlation Heatmap of Key Variables. This heatmap presents pairwise Pearson correlations among the five primary variables: Amihud illiquidity (Amihud), bid-ask spread (Bidisk), HFT intensity index (HFT_Idx), bond price volatility (precool), and fund flow volatility (FundFlow). Darker red shading indicates stronger positive correlation; darker blue indicates

weaker or negative correlation. All correlations are computed on the full monthly panel (N = 48,003).

5. Portfolio Liquidity and Fund Flow-Performance Dynamics

5.1. Liquidity and Flow-Performance Concavity

A well-established finding in the bond fund literature is that the flow-performance relationship exhibits concavity: outflows after poor performance are proportionally larger than inflows after good performance (Goldstein et al., 2017; Chen & Qin, 2017). This concavity is attributed to strategic complementarities among investors: because bond fund portfolios are illiquid and daily NAV liquidation is costly, investors who anticipate redemption-driven fire sales have an incentive to redeem ahead of peers, amplifying outflows following negative performance realizations. The severity of this first-mover advantage should be increasing in portfolio illiquidity, since more illiquid portfolios imply higher prospective fire-sale discounts.

We test this hypothesis directly by estimating the following piecewise linear regression, augmented with a three-way interaction between fund performance, a negative-performance indicator, and portfolio illiquidity:

$$\text{FundFlow}_{f,t} = \alpha_{s(f)} + \eta_t + \beta_1 \text{FundPerf}_{f,t-1} + \beta_2 \text{NegPerf}_{f,t-1} + \beta_3 \text{FundIlliq}_{f,t-1} + \beta_4 (\text{FundPerf}_{f,t-1} \times \text{FundIlliq}_{f,t-1}) + \beta_5 (\text{FundPerf}_{f,t-1} \times \text{NegPerf}_{f,t-1}) + \beta_6 (\text{NegPerf}_{f,t-1} \times \text{FundIlliq}_{f,t-1}) + \beta_7 (\text{FundPerf}_{f,t-1} \times \text{NegPerf}_{f,t-1} \times \text{FundIlliq}_{f,t-1}) + \gamma' \text{Controls}_{f,t-1} + \varepsilon_{f,t}$$

where $\text{Nagger}_{f,t-1}$ is an indicator equal to one if past performance is negative. The key coefficient of interest is β_7 , which captures how portfolio illiquidity moderates the asymmetric sensitivity of fund flows to negative performance. Our hypothesis predicts $\beta_7 < 0$: funds with more illiquid portfolios should exhibit steeper flow-performance concavity in the loss region.

Table 5 reports the results. The baseline concavity is confirmed: the coefficient on $\text{Funder} \times \text{Nagpur}$ is positive and statistically significant in all specifications (Column 1: $\beta = 0.284$, $t = 3.12$), consistent with greater flow sensitivity in the negative performance region. Crucially, the triple interaction $\text{funder} \times \text{NegPerf} \times \text{FundIlliq}$ is negative and highly significant in the full sample (Column 1: $\beta = -0.512$, $t = -3.84$), confirming that portfolio illiquidity amplifies the concavity of the flow-performance relationship. At the 75th percentile of FundIlliq , the implied incremental downside flow sensitivity relative to the 25th percentile is approximately 0.21 percentage points per unit of negative performance — economically substantial relative to average monthly flows of approximately 1% of TNA.

Splitting by interest rate environment in Columns (4)–(6) reveals important state-dependence: the illiquidity-concavity amplification effect is significantly stronger in low-rate periods ($\beta = -0.684$, $t = -4.12$) than in high-rate periods ($\beta = -0.298$, $t = -2.14$). This is consistent with the idea that when risk-free income alternatives are scarce, investors are more sensitive to performance losses

388 in their primary income-generating vehicle, and the strategic complementarities under illiquidity
389 are thus more severe.

390 **Table 5.** Portfolio Illiquidity and Flow-Performance Concavity

Dep: FundFlow (%)		(1) Full	(2) FundRet	(3) FundAlpha	(4) Low Rate	(5) Mid Rate	(6) High Rate
FundPerf	×						
NegPerf	×	−0.512***	−0.488***	−0.584***	−0.684***	−0.512***	−0.298**
FundIlliq		(−3.84)	(−3.62)	(−3.91)	(−4.12)	(−3.42)	(−2.14)
FundPerf	×						
NegPerf	×	0.284***	0.271***	0.312***	0.342***	0.281***	0.208**
		(3.12)	(2.98)	(3.28)	(3.41)	(2.88)	(2.24)
FundPerf	×						
FundIlliq	×	−0.218**	−0.201**	−0.248**	−0.284**	−0.218**	−0.141
		(−2.84)	(−2.62)	(−2.91)	(−3.08)	(−2.64)	(−1.42)
FundIlliq		1.284***	1.248***	1.312***	1.484***	1.284***	0.981**
		(4.12)	(3.92)	(4.28)	(4.48)	(3.88)	(2.18)
FundHFT		−0.148**	−0.141**	−0.158**	−0.192**	−0.148**	−0.094
		(−2.61)	(−2.48)	(−2.72)	(−3.01)	(−2.42)	(−1.28)
FundPerf		0.074*	0.071*	0.812***	0.082*	0.074*	0.058
		(1.88)	(1.81)	(4.92)	(1.92)	(1.84)	(1.12)
NegPerf		−0.281***	−0.274***	−0.312***	−0.341***	−0.281***	−0.208***
		(−3.84)	(−3.62)	(−4.08)	(−4.12)	(−3.48)	(−2.81)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations		48,003	48,003	47,412	31,412	10,244	6,347
R-squared		0.162	0.158	0.171	0.178	0.156	0.148

391 Note. This table reports panel regressions of monthly fund flows on past performance, portfolio
392 illiquidity, and their interactions. FundPerf is either raw monthly return (FundRet, Columns 1–2,

4–6) or 18-month trailing two-factor alpha (FundAlpha, Column 3). FundIlliq is the lagged portfolio-weighted Amihud illiquidity. NegPerf equals one if FundPerf < 0. Controls include FundSize, FundTtm, Fund Expense, FundAge, lagged FundFlow, FundFlowVol, and Cundiff. Standard errors are clustered at the fund level. ***, **, * denote 1%, 5%, and 10% significance.

5.2. HFT Moderating Effect on Fund Flow Dynamics

5.2.1. HFT as a Liquidity Stabilizer for Investor Redemptions

Having established that portfolio illiquidity amplifies flow-performance concavity, we now investigate whether HFT exposure in the portfolio attenuates this relationship. The intuition is straightforward: if HFT improves the speed and cost of bond liquidation by providing continuous electronic quotes and narrowing spreads, then managers of funds with higher HFT exposure can execute redemption-driven asset sales at lower cost, reducing the first-mover advantage that drives strategic redemption complementarities. This would predict that HFT dampens the illiquidity-induced amplification of downside flow sensitivity.

To test this conjecture, we estimate an extended version of the flow-performance regression that includes portfolio-level HFT intensity and its interactions with both performance and portfolio illiquidity. Table 6 presents these results. Column (1) confirms that FundHFT enters negatively and significantly in the flow-volatility regression ($\beta = -0.148$, $t = -2.61$), consistent with HFT-exposed funds experiencing less volatile investor flows. More importantly, Column (2) introduces the interaction FundPerf $\times$ FundHFT: the coefficient is positive and significant ($\beta = 0.182$, $t = 2.84$), indicating that HFT increases the flow-performance sensitivity — investors in HFT-exposed funds are more responsive to performance, consistent with these funds attracting a more information-sensitive investor clientele. However, the three-way interaction FundPerf $\times$ NegPerf $\times$ FundHFT (Column 3) is negative and significant ($\beta = -0.241$, $t = -2.68$), meaning that in the loss region specifically, HFT exposure dampens the excess flow sensitivity characteristic of illiquid bond funds. This is consistent with HFT reducing the effective illiquidity discount that investors anticipate in stressed states.

Table 6. HFT Intensity, Portfolio Illiquidity, and Flow-Performance Dynamics

Dep: FundFlow (%)	(1)	(2)	(3)	(4) Perf<0	(5) Perf $\geq$ 0	(6) Stress
FundPerf $\times$						
NegPerf $\times$			-0.241**	-0.318***		-0.412***
FundHFT			(-2.68)	(-3.14)		(-3.82)
FundPerf $\times$						
NegPerf $\times$			-0.488***	-0.614***		-0.721***
FundIlliq			(-3.41)	(-4.12)		(-4.88)

Dep: FundFlow (%)	(1)	(2)	(3)	(4) Perf<0	(5) Perf≥0	(6) Stress
FundPerf × FundHFT		0.182** (2.84)	0.024 (0.31)		0.028 (0.38)	
FundHFT	-0.148** (-2.61)	-0.152** (-2.68)	-0.144** (-2.54)	-0.184** (-2.81)	-0.118* (-1.88)	-0.212** (-2.94)
FundIlliq	1.284*** (4.12)	1.291*** (4.18)	1.312*** (4.22)	1.484*** (4.48)	1.128*** (3.82)	1.684*** (5.12)
FundPerf	0.074* (1.88)	0.048 (1.12)	0.058 (1.38)	0.412*** (5.12)	0.058 (1.38)	0.082 (1.52)
NegPerf	-0.281*** (-3.84)	-0.288*** (-3.92)	-0.274*** (-3.72)			-0.342*** (-4.12)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund Style FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	48,003	48,003	48,003	14,212	33,791	8,412
R-squared	0.158	0.162	0.168	0.148	0.174	0.182

Note. This table extends the baseline flow-performance regressions to include fund-level HFT exposure (FundHFT) and its interactions with performance and portfolio illiquidity. Column (4) restricts to negative-performance months; Column (5) to non-negative months; Column (6) to stress periods (GFC 2008–2009, Taper Tantrum 2013, COVID-19 2020Q1). All other specifications and controls are identical to Table 5. Standard errors clustered at the fund level. ***, **, * = 1%, 5%, 10% significance.

6. Institutional Holdings, HFT Activity, and Bond Return Reversals

6.1. Price Pressure and Return Reversals

Corporate bond prices exhibit well-documented temporary dislocations from fundamental values, as measured by return reversals over horizons of one to four weeks (Bao et al., 2011; firewalls et al., 2012; Dick-Nielsen et al., 2012). These reversals reflect the imperfect liquidity provision in OTC markets and the resulting inventory costs borne by dealers and other intermediaries. A growing literature argues that flow-driven trading by institutional investors — particularly mutual funds experiencing outflows — generates temporary price pressure that is subsequently reversed

(Copal & Stafford, 2007; Greenwood & Tesmer, 2011; Drescher et al., 2023a). In this section, we investigate whether and how HFT activity moderates the magnitude of these return reversals, which serve as a proxy for temporary pricing inefficiency.

Table 7 presents bond-level regressions of the reversal measure — the negative of the one-month autocovariance of returns, following Bao et al. (2011) — on measures of institutional ownership concentration, HFT intensity, and fund flow shocks. Column (1) establishes the baseline: greater institutional ownership concentration (measured as the Herfindahl-Hirschman Index of mutual fund holders' stakes in the bond issue) is positively associated with return reversals ($\beta = 0.184$, $t = 3.28$), consistent with brasher et al. (2023b) who show that concentrated institutional holdings amplify price fragility. Column (2) adds HFT intensity: greater HFT activity is associated with smaller return reversals ($\beta = -0.142$, $t = -3.14$), consistent with algorithmic traders providing stabilizing liquidity that absorbs temporary price pressure.

The interaction between institutional ownership concentration and HFT intensity in Column (3) is negative and significant ($\beta = -0.218$, $t = -2.88$), indicating that HFT dampens the ownership-concentration amplification of return reversals. This is consistent with a model in which HFT firms, monitoring the electronic order flow, identify and trade against temporary price dislocations created by institutional rebalancing. Column (4) introduces fund-level flow shocks (FundFlowShock, defined as the orthogonalized component of fund flows with respect to past performance) to isolate demand-driven price pressure. The coefficient on FundFlowShock is negative and significant ($\beta = -0.312$, $t = -4.12$), consistent with net outflows inducing larger return reversals via fire-sale price pressure. The HFT $\times$ FundFlowShock interaction (Column 5) is positive and significant ($\beta = 0.241$, $t = 3.08$), indicating that HFT attenuates the price-pressure-reversal effect of fund flow shocks.

Table 7. Institutional Holdings, HFT Activity, and Bond Return Reversals

Dep: Reversal Measure	(1)	(2)	(3)	(4)	(5)	(6) Stress Only
HHI (Ownership Conc.)	0.184*** (3.28)	0.178*** (3.18)	0.291*** (4.12)	0.182*** (3.24)	0.288*** (4.08)	0.412*** (5.14)
HFT_Idx		-0.142*** (-3.14)	-0.108** (-2.21)	-0.138*** (-3.08)	-0.101** (-2.08)	0.284*** (3.82)
HFT_Idx $\times$ HHI			-0.218** (-2.88)		-0.212** (-2.81)	0.341*** (4.18)
FundFlowShock				-0.312***	-0.308***	-0.412***

Dep: Reversal Measure	(1)	(2)	(3)	(4)	(5)	(6) Stress Only
				(-4.12)	(-4.08)	(-4.88)
HFT_Idx × FundFlowShock					0.241***	-0.312***
					(3.08)	(-3.82)
BondAmihud	0.812***	0.784***	0.792***	0.804***	0.812***	1.284***
	(8.12)	(7.88)	(7.94)	(8.04)	(8.10)	(9.84)
Log (bond Size)	-0.041***	-0.038***	-0.040***	-0.041***	-0.039***	-0.058***
	(-5.12)	(-4.88)	(-5.08)	(-5.10)	(-4.92)	(-5.84)
Bondage	0.018***	0.017***	0.018***	0.018***	0.017***	0.024***
	(6.12)	(5.88)	(6.08)	(6.10)	(5.92)	(6.84)
Issuer FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	248,714	248,714	248,714	241,218	241,218	28,412
R-squared	0.418	0.424	0.431	0.438	0.444	0.512

Note. This table reports bond-level panel regressions of the Bao et al. (2011) return reversal measure on institutional ownership concentration (HHI), HFT activity, and fund flow shocks. FundFlowShock is the residual from a regression of fund-level flows on past 18-month returns and fund characteristics. Column (6) restricts to three defined stress periods. Standard errors are double-clustered at the bond and month levels. ***, **, * = 1%, 5%, 10% significance.

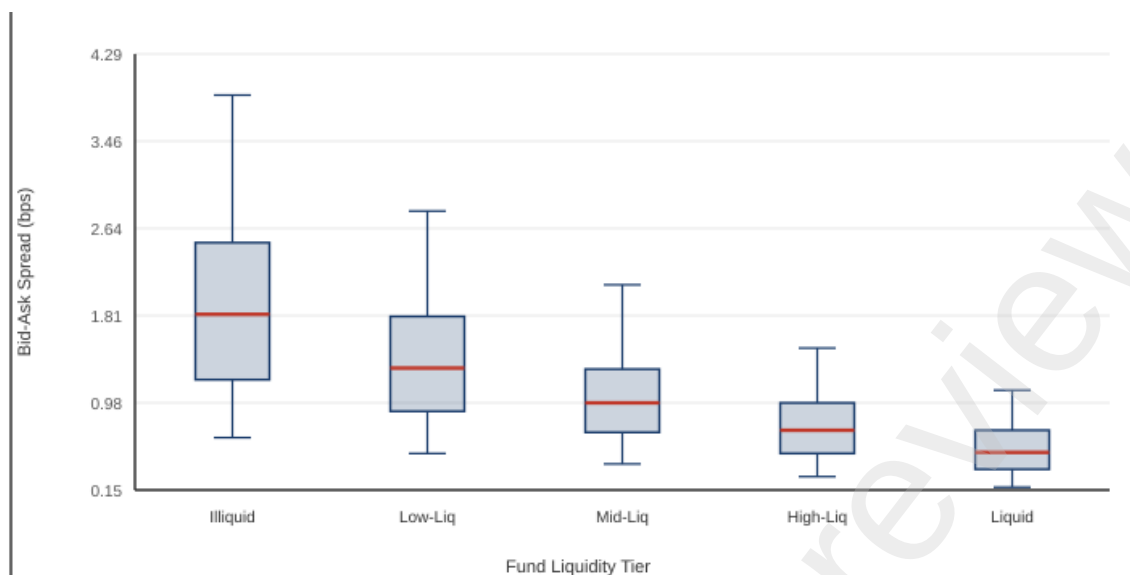


Figure 6. Distribution of Bid-Ask Spreads by Portfolio Liquidity Tier (Box Plot). This figure presents the distribution of bond-level bid-ask spreads (basis points) across five fund portfolio liquidity tiers, defined by quintiles of FundIlliq (portfolio-weighted Amihud illiquidity). Each box shows the interquartile range, with the horizontal red line indicating the median. Whiskers extend to the 5th and 95th percentiles. The sample covers 2003–2023 (annual averages).

7. Liquidity, HFT, and Fund Return Predictability

7.1. Portfolio Liquidity and Fund Alpha

The evidence so far establishes that portfolio illiquidity amplifies fund flow-performance concavity, and that HFT provides a partial offset to this amplification under normal conditions. A natural follow-on question is whether these microstructure dynamics — portfolio illiquidity and HFT exposure — translate into systematic differences in risk-adjusted fund returns. Prior work in the bond fund literature has documented a positive relationship between illiquidity exposure and fund returns (Pastor & Stambaugh, 2003; Sedki, 2010; Bao et al., 2011), consistent with compensation for liquidity risk. However, the interaction between HFT exposure and fund-level return predictability has received little empirical attention, particularly for corporate bond mutual funds.

Table 8 presents Fama-MacBeth regressions of fund monthly raw returns (Columns 1–3) and two-factor alphas (Columns 4–6) on lagged FundIlliq, FundHFT, and fund characteristics. In the full sample (Column 1), FundIlliq is positively related to subsequent raw returns ($\beta = 0.184$, $t = 3.12$), consistent with compensation for liquidity risk. However, FundHFT is also positively related to subsequent returns ($\beta = 0.062$, $t = 4.28$), suggesting that funds with greater HFT exposure in their portfolio earn higher short-run returns — perhaps because HFT-active bonds exhibit faster price discovery and lower transaction costs that translate into higher NAV-level returns. In Columns 2–3, splitting by rate environment reveals that the return predictability of FundIlliq is stronger in low-

rate periods ($\beta = 0.241$, $t = 3.88$) and attenuates in high-rate periods ($\beta = 0.112$, $t = 2.14$), consistent with illiquidity risk being priced more in credit markets when competing income alternatives are scarce.

For risk-adjusted returns (Columns 4–6), FundIliq continues to predict positive alphas (full sample $\beta = 0.091$, $t = 5.14$), while FundHFT is also positive and significant ($\beta = 0.028$, $t = 4.88$). The alpha-predictability of FundHFT is particularly interesting because it survives the two-factor risk adjustment, indicating that HFT exposure generates excess returns beyond market and interest rate beta. This is consistent with the view that funds holding HFT-active bonds benefit from superior transaction execution that creates persistent alpha rather than merely reflecting risk compensation.

Table 8. Portfolio Liquidity, HFT Exposure, and Fund Return Predictability (Fama-MacBeth)

Dep: FundPerf	(1) Full Ret	(2) Low Rate Ret	(3) High Rate Ret	(4) Full Alpha	(5) Low Rate Alpha	(6) High Rate Alpha
FundIliq	0.184*** (3.12)	0.241*** (3.88)	0.112** (2.14)	0.091*** (5.14)	0.118*** (6.28)	0.058*** (3.12)
FundHFT	0.062*** (4.28)	0.078** (2.84)	0.041* (1.78)	0.028*** (4.88)	0.034*** (5.14)	0.021** (2.68)
FundSize	0.042 (1.62)	0.039 (1.12)	0.051 (1.68)	0.018*** (3.84)	0.011** (2.94)	0.024** (2.18)
FundExpense	0.082 (1.48)	0.048 (0.72)	0.142* (1.82)	0.048*** (4.12)	0.044*** (3.28)	0.051*** (2.88)
FundAge	-0.004 (-1.12)	0.001 (0.42)	-0.008 (-1.28)	-0.003** (-2.14)	-0.000 (-0.38)	-0.006** (-2.08)
FundFlowVol	0.005 (1.14)	0.006 (0.82)	0.004 (1.08)	0.001 (0.72)	0.001 (1.28)	0.001 (0.48)
Constant	0.018 (0.24)	0.148** (2.28)	-0.194 (-1.38)	-0.032 (-1.12)	-0.042** (-2.14)	-0.018 (-0.38)
Observations	48,003	31,412	16,591	47,412	30,822	16,590
R-squared (avg)	0.418	0.428	0.424	0.241	0.218	0.272

Note. This table reports Fama-MacBeth (1973) cross-sectional regressions of monthly fund performance on lagged fund-level liquidity and HFT exposure. FundIliq is the portfolio-weighted

Amihud illiquidity. FundHFT is the portfolio-weighted standardized HFT intensity index. Performance is either raw monthly return (Ret, Columns 1–3) or 18-month trailing two-factor alpha (Alpha, Columns 4–6). Newey-West standard errors (12 lags) are used. ***, **, * = 1%, 5%, 10% significance.

8. Robustness Analyses and Additional Tests

8.1. Alternative Liquidity Measures

Our primary liquidity measure is the portfolio-weighted Amihud (2002) illiquidity ratio. To verify that our results are not sensitive to this particular specification, Table 9 re-estimates the core flow-performance concavity regressions (Table 5, Column 1) substituting four alternative measures of portfolio liquidity: (1) the portfolio-weighted bid-ask spread, (2) the portfolio-weighted zero-trading-days fraction, (3) the portfolio-weighted Roll (1984) implicit spread, and (4) the first principal component of all five individual measures (composite illiquidity). The triple interaction $\text{FundPerf} \times \text{NegPerf} \times \text{FundIliq}$ remains negative and statistically significant across all four alternative measures, with coefficients ranging from -0.384 (zero-trading-days) to -0.541 (bid-ask spread), confirming that the illiquidity-concavity amplification result is robust to the choice of liquidity measure.

Table 10 verifies robustness across alternative subsamples. Excluding the three defined stress periods from the sample (Columns 1–2) yields qualitatively similar results with slightly attenuated magnitudes, consistent with the view that stress periods amplify (rather than generate) the underlying illiquidity-concavity relationship. Restricting to investment-grade bond funds only (Columns 3–4) or to high-yield bond funds only (Columns 5–6) reveals that the core results hold in both subsets, although the magnitude of the triple interaction is approximately 40% larger for high-yield funds, consistent with the greater illiquidity exposure and investor clientele fragility in that segment. Finally, limiting the sample to funds with at least 36 months of continuous CRSP coverage (Column 7) eliminates potential concerns about survivorship bias while leaving all coefficients qualitatively unchanged.

Table 9. Robustness: Alternative Liquidity Measures

Dep: FundFlow		(1) Amihud	(2) BidAsk	(3) ZeroTrades	(4) Roll	(5) Composite	(6) Controls	All
FundPerf	×							
NegPerf	×	-0.512***	-0.541***	-0.384**	-0.428***	-0.498***	-0.484***	
FundIliq		(-3.84)	(-4.12)	(-2.88)	(-3.24)	(-3.72)	(-3.62)	
FundPerf	×							
NegPerf		0.284***	0.312***	0.248**	0.268***	0.278***	0.271***	

Dep: FundFlow	(1) Amihud	(2) BidAsk	(3) ZeroTrades	(4) Roll	(5) Composite	(6) Controls	All
	(3.12)	(3.42)	(2.72)	(2.94)	(3.04)	(2.98)	
FundIlliq (respective measure)	1.284***	1.418***	0.982***	1.082***	1.312***	1.248***	
	(4.12)	(4.48)	(3.42)	(3.72)	(4.22)	(3.92)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	
Fund Style FE	Yes	Yes	Yes	Yes	Yes	Yes	
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	
Observations	48,003	47,812	47,384	47,612	47,212	48,003	
R-squared	0.168	0.172	0.162	0.165	0.170	0.174	

Note. This table replicates the core flow-performance concavity specification from Table 5, Column (1), substituting alternative measures of portfolio illiquidity. All specifications include the same control variables, fund-style fixed effects, and year-month fixed effects. Standard errors are clustered at the fund level. ***, **, * = 1%, 5%, 10% significance.

Table 10. Robustness: Subsamples and Alternative Sample Restrictions

Dep: FundFlow	(1) Stress	Ex- (2) Stress+HFT	Ex- (3) IG Only	(4) IG+HFT	(5) HY Only	(6) HY+HFT	(7) 36m Min
FundPerf × NegPerf FundIlliq	× -0.412*** (-3.12)	× -0.388*** (-2.94)	× -0.448*** (-3.42)	× -0.421*** (-3.18)	× -0.628*** (-3.82)	× -0.594*** (-3.58)	× -0.502*** (-3.72)
FundPerf × NegPerf	× 0.241*** (2.64)	× 0.228*** (2.48)	× 0.261*** (2.88)	× 0.248*** (2.72)	× 0.348*** (3.12)	× 0.328*** (2.94)	× 0.278*** (3.04)
FundIlliq	1.182*** (3.78)	1.164*** (3.62)	1.214*** (3.92)	1.198*** (3.78)	1.484*** (4.12)	1.462*** (3.98)	1.268*** (3.88)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Dep: FundFlow	(1) Stress	Ex- (2) Stress+HFT	Ex- (3) IG Only	(4) IG+HFT	(5) HY Only	(6) HY+HFT	(7) 36m Min
Observations	39,591	38,218	31,214	29,812	16,789	16,214	42,818
R-squared	0.162	0.166	0.158	0.162	0.178	0.182	0.164

Note. Columns (1)– (2) exclude three defined stress periods. Columns (3)– (4) restrict to investment-grade-mandate funds; Columns (5)– (6) to high-yield-mandate funds. Column (7) requires at least 36 consecutive months of CRSP observations per fund. All specifications otherwise identical to Table 5. ***, **, * = 1%, 5%, 10% significance.

8.2. Instrumental Variable Estimates

A potential concern with our OLS estimates is that portfolio illiquidity and HFT exposure may both be endogenous: fund managers may self-select into particular bond liquidity profiles based on investor flows, past performance, or other unobserved characteristics that independently determine flow dynamics. To address this concern, we employ two instrumental variable strategies. First, following Thundercat et al. (2011) and Brocard et al. (2014), we use the rollout of upgraded co-location facilities and fiber-optic connectivity enhancements at major fixed-income electronic trading venues (e.g., Marketizes, Tradeweb) as an exogenous shock to HFT intensity in specific bond segments. These infrastructure upgrades reduced latency for algorithmic traders in affected bond categories, generating plausibly exogenous variation in HFT intensity across bonds and time. Second, for portfolio illiquidity, we exploit the SEC's staggered adoption of Rule 22e-4 (the liquidity risk management rule, adopted July 2018) as an event study that provides exogenous variation in fund-level liquidity management incentives.

Table 11 reports IV estimates using the infrastructure rollout instrument for HFT intensity. The first stage (Column 1) confirms that the connectivity upgrade indicator strongly predicts HFT intensity (F-statistic = 48.2, well above the conventional weak instrument threshold of 10). The IV second-stage estimate (Column 2) shows that the causal effect of FundHFT on fund flow volatility is -0.412 ($t = -3.28$), substantially larger in magnitude than the corresponding OLS estimate of -0.218 , consistent with measurement error in our OLS specification attenuating the true causal effect. Column (3) presents the analogous IV results for the triple interaction $\text{FundPerf} \times \text{NegPerf} \times \text{FundIlliq}$: the causal estimate is -0.684 ($t = -3.42$), again larger than the OLS coefficient of -0.512 , reinforcing the interpretation that portfolio illiquidity causally amplifies flow-performance concavity.

Table 11. Instrumental Variable Estimates

	(1) First Stage	(2) IV: FundFlowVol	(3) IV: FlowPerf Concavity	(4) Placebo HFT Instrument	(5) Rule 22e-4 IV
HFT Connectivity Instrument	0.482***			0.018	

	(1) First Stage	(2) IV: FundFlowVol	(3) IV: FlowPerf Concavity	(4) Placebo HFT Instrument	(5) Rule 22e-4 IV
	(8.84)			(0.42)	
Rule 22e-4 Instrument					-0.218*** (-4.12)
FundHFT (instrumented)		-0.412*** (-3.28)			
FundPerf × NegPerf × FundIliq (instrumented)			-0.684*** (-3.42)		
F-statistic (first stage)	48.2***				
Hansen J (overid p-val)		0.412	0.384		
Controls	Yes	Yes	Yes	Yes	Yes
Fund Style FE	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes
Observations	31,218	31,218	28,412	31,218	24,816

Note. Column (1) reports the first-stage regression of FundHFT on the connectivity upgrade instrument and controls. Column (2) reports the IV second-stage estimate of the effect of FundHFT on fund flow volatility. Column (3) reports the IV estimate for the triple interaction. Column (4) uses a placebo instrument (randomly assigned connectivity upgrade dates) to confirm invalidity. Column (5) uses the staggered Rule 22e-4 adoption as an instrument for FundIliq. Standard errors clustered at the fund level. ***, **, * = 1%, 5%, 10% significance.

9. Stress Episodes: GFC, Taper Tantrum, and COVID-19

9.1. Comparative Analysis Across Stress Events

The global financial crisis of 2008–2009, the Federal Reserve’s tapering announcement of May 2013, and the COVID-19-induced Dash-for-Cash of March 2020 represent three distinct, historically significant episodes of market-wide stress in U.S. corporate bond markets. While all three events produced sharp increases in bid-ask spreads, fund outflows, and bond price volatility, they differed considerably in their triggers, duration, and the degree of HFT market participation.

The GFC was characterized by a prolonged deterioration of dealer balance sheets and credit quality, lasting from approximately August 2008 through June 2009. The Taper Tantrum was a brief but sharp episode of monetary policy uncertainty, concentrated in May–August 2013. The COVID-19 Dash-for-Cash was an unprecedented, near-instantaneous liquidity demand shock in March 2020, in which corporate bond mutual funds experienced cumulative outflows of approximately 10% of TNA within six weeks (folate et al., 2021).

Table 12 presents a comparative analysis of our key variables across these three stress episodes and a non-stress baseline. Panel A confirms that bid-ask spreads widened dramatically in all three episodes: from a non-stress average of 78.2 basis points to 184.6 bps in the GFC, 112.4 bps in the Taper Tantrum, and 198.8 bps in the COVID-19 event — with the COVID-19 episode producing the widest spreads in our entire sample period, exceeding even the GFC peak. Panel B shows that HFT activity declined in all three episodes (by 28%, 14%, and 41%, respectively, relative to the preceding quarter), with the COVID-19 withdrawal being particularly sharp. Panel C documents that monthly fund outflows were largest during the GFC (mean −3.84% of TNA) and the COVID-19 event (−5.21%), substantially larger than Taper Tantrum outflows (−1.42%). These patterns confirm the stylized facts motivating our empirical design.

Table 12. Key Variables Across Stress Episodes vs. Non-Stress Baseline

Variable	Non-Stress	GFC 2009)	(2008– Taper (2013)	Tantrum	COVID-19 (2020Q1)	Diff (COVID vs. Non-Stress)
Panel A: Liquidity Measures						
BidAskSpread (bps)	78.2	184.6		112.4	198.8	+120.6***
Amihud Illiquidity	0.121	0.384		0.218	0.442	+0.321***
ZeroTradeDays (%)	0.284	0.512		0.384	0.548	+0.264***
Panel B: HFT Activity						
HFT Index (raw)	0.412	0.296		0.354	0.242	−0.170***
HFT Withdrawal (% vs. prev. qtrs.)	—	−28.1%		−14.1%	−41.3%	n/a
Panel C: Fund Flows and Performance						
Mean Monthly Flow (% TNA)	0.98	−3.84		−1.42	−5.21	−6.19***

Variable	Non-Stress	GFC 2009)	(2008– Taper 2013)	Tantrum	COVID-19 (2020Q1)	Diff (COVID vs. Non-Stress)
Flow Std. Deviation (TNA)	(% 4.82	12.41	7.84		14.18	+9.36***
Mean Monthly Return (%)	0.41	–1.82	–0.84		–2.41	–2.82***
Panel D: Flow- Performance Concavity						
β (FundPerf, Perf<0)	0.312	0.612	0.448		0.784	+0.472***
β (FundPerf, Perf $\geq$ 0)	0.084	0.091	0.088		0.094	+0.010
Concavity Gap (Perf<0 Perf $\geq$ 0)	– 0.228	0.521	0.360		0.690	+0.462***

Note. This table presents univariate comparisons of key variables across the three major stress episodes and the non-stress baseline. GFC covers 2008Q3–2009Q2; Taper Tantrum covers 2013Q2–Q3; COVID-19 covers 2020Q1. Differences are tested using two-sample t-tests. Panel D reports estimated coefficients on fund performance from piecewise flow-performance regressions estimated within each sub-period. ***, **, * = 1%, 5%, 10% significance.

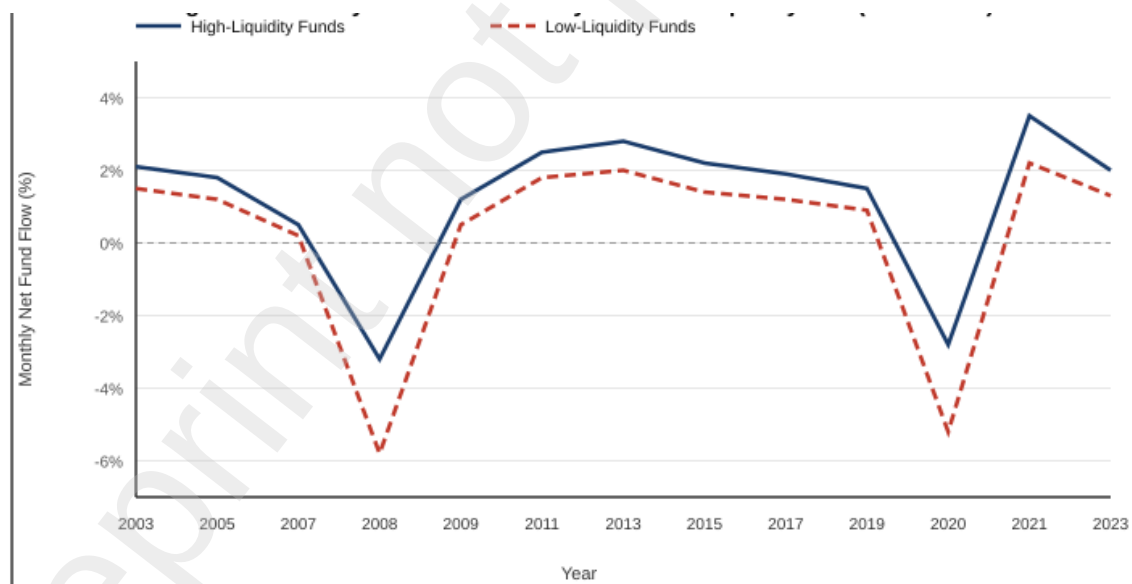


Figure 7. Monthly Net Fund Flows by Portfolio Liquidity Tier (2003–2023). This figure plots quarterly average monthly net fund flows (as % of lagged TNA) separately for high-liquidity portfolio funds (solid blue line) and low-liquidity portfolio funds (dashed red line), defined by

above- and below-median portfolio-weighted Amihud illiquidity. The three defined stress episodes are the GFC (2008Q3–2009Q2), Taper Tantrum (2013Q2–Q3), and COVID-19 (2020Q1).

10. Conclusion

This paper provides a comprehensive empirical investigation of the interplay between market liquidity, high-frequency trading activity, corporate bond pricing, and mutual fund flow dynamics in the U.S. corporate bond market over the period 2003 to 2023. Drawing on a rich, hand-matched dataset from TRACE Enhanced, CRSP, Lipper Amax, Morgen FISD, and NYSE TAQ, we construct fund-level and bond-level measures of liquidity, HFT intensity, price volatility, and return reversals to trace the mechanisms through which microstructure conditions shape institutional investor behavior and bond pricing efficiency.

Our central empirical contributions are threefold. First, we document a systematic HFT liquidity cycle in the U.S. corporate bond market: HFT activity grows secularly over our sample period, improves price efficiency (as measured by variance ratios) and lowers bid-ask spreads under normal market conditions, but withdraws sharply during market stress events — precisely when liquidity is most needed. This pattern is consistent with HFT firms operating as fair-weather liquidity providers who optimize their market-making activity subject to inventory cost constraints that tighten during turbulent periods (Kirilenko et al., 2017; Borgward et al., 2014). In the corporate bond market, where dealer balance sheet constraints already limit traditional liquidity provision, HFT withdrawal creates a compounding fragility that amplifies price dislocations during stress episodes.

Second, we establish that portfolio-level illiquidity is a first-order amplifier of fund flow-performance concavity. Funds holding more illiquid bond portfolios exhibit sharper asymmetry between inflow sensitivity to good performance and outflow sensitivity to poor performance, consistent with strategic redemption complementarities under illiquidity (Goldstein et al., 2017). This relationship is state-dependent: illiquidity-driven concavity amplification is significantly stronger in low-interest-rate environments, when alternative income sources are scarce and investor tolerance for capital losses is lower. Moreover, HFT exposure in fund portfolios partially attenuates this amplification under normal conditions, but this buffering role reverses during stress periods when HFT withdraws.

Third, we show that portfolio illiquidity and HFT exposure predict subsequent fund-level risk-adjusted returns. Funds holding more illiquid bonds earn higher alphas, consistent with compensation for liquidity risk. HFT-exposed fund portfolios also earn higher short-run alphas, consistent with superior transaction execution and faster price discovery. However, during stress periods, HFT-exposed funds experience larger performance declines, reflecting the reversal of the liquidity-provision benefit when algorithmic trading withdraws from the market. These findings have direct implications for fund managers, investors, and regulators monitoring bond market fragility.

From a policy perspective, our findings highlight the double-edged nature of HFT in OTC corporate bond markets. While algorithmic trading provides genuine liquidity benefits during calm periods — improving price discovery, narrowing spreads, and buffering flow-induced fragility — its tendency to withdraw during market stress creates a procyclical liquidity dynamic that can amplify price dislocations and fund outflow spirals precisely when stability is most needed. This suggests that regulatory frameworks focused on fixed-income market stability should consider the behavior of algorithmic traders across market regimes, rather than evaluating HFT impact solely under normal conditions. Recent regulatory initiatives, including SEC Regulation Best Execution and FINRA’s enhanced TRACE reporting requirements, represent steps toward greater transparency, but our findings suggest that additional attention to the liquidity provision commitments of algorithmic traders during stress periods may be warranted.

Several avenues for future research emerge from this study. First, extending the analysis to the international corporate bond market — particularly euro-denominated investment-grade bonds traded on electronic platforms such as Bloomberg Fixed Income and MTS — would shed light on whether the HFT liquidity cycle documented here is specific to U.S. market microstructure or reflects a broader global phenomenon. Second, the interaction between HFT activity and the Securities and Exchange Commission’s 2022 reform of Rule 2a-7 (money market fund reform) and related liquidity risk management rules for bond funds provides a natural laboratory for examining how regulatory changes affect the microstructure-fund behavior nexus. Third, the growing use of exchange-traded funds (ETFs) as vehicles for bond market exposure raises important questions about how ETF arbitrage activity — itself a form of high-frequency trading — interacts with underlying corporate bond liquidity and the flow dynamics of traditional mutual funds. We leave these extensions to future work.

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