Liquidity, Credit Spreads, and Monetary Policy Shocks: Evidence from the U.S. Corporate Bond Market

Giacomo Cattelan *and Yuki Sato†

Very preliminary draft. Latest version here

Abstract

This paper examines the interplay between corporate bond liquidity and monetary policy in determining credit spreads dynamics. Using intraday transaction-level data from the Trade Reporting and Compliance Engine (TRACE), we construct comprehensive liquidity measures—including bid-ask spreads and turnover ratios—to assess their contribution to credit spreads. Using high-frequency identified shocks for Gurkaynak et al. (2005) and Nakamura and Steinsson (2018), we document that the credit spread for less liquid bonds increases by more as a consequence of a monetary tightening. Hence we proceed to identifying the liquidity channel of monetary policy on corporate bond spread by adopting a two-step procedure: first we compute the responses of liquidity measures to the shocks, and then use the fitted values in a second local projection regression to compute the responses of credit spreads. Lastly, we show that the loading of the liquidity risk factor varies over time and strongly anti-correlates with the slope of the yield curve, suggesting a higher-order nonlinear effect of the liquidity channel.

*NYU

†Goethe University Frankfurt

1 Introduction

Liquidity in financial markets refers to the ease with which an asset can be traded. In the corporate bond market, liquidity is critical because bonds are often traded over-the-counter (OTC), making liquidity highly variable compared to equity markets. In fact, transactions in the corporate bond market is not as frequent and has to carried out by broker-dealers, that can charge a significant premium on the price. This lower trade frequency, combined with the market power exerted by dealers, contributes to the structural illiquidity of OTC markets.

In addition to this, the supply of money and money-like assets plays a pivotal role in amplifying or mitigating liquidity constraints, influencing the pricing of bonds and their response to economic shocks. At the same time, liquidity conditions shape how securities traded in OTC markets react to changes in monetary policy. Given these dynamics, understanding the interaction between liquidity and monetary policy is essential for a comprehensive analysis of credit market behavior.

This study explores the extent to which monetary policy and corporate bond liquidity jointly determine borrowing costs. Our first finding is that credit spreads reaction to monetary policy shocks crucially depend on a combination of default risk and liquidity risk of each bond. In particular, the spread of High-Yield securities increases by more when highly liquid, whereas high liquidity-Investment Grade bonds suffer the least from tightening monetary policy. This can be explained by different offloading pressure exerted by a higher interest rate environment on the two risk categories: where flight-to-safety episodes are more likely to happen (i.e. in the High-Yield segment) securities that are traded more frequently are more likely to be re-priced, and hence experience the largest swings in credit spreads.

The liquidity-dependent reaction of credit spreads to monetary shocks points to a very strong liquidity channel for monetary policy. To disentangle this channel from other, more conventional channels, we adopt a two-stage estimation procedure, leveraging on the exogeneity of the shocks and their effect. First, we estimate the impulse responses of liquidity measures to the shocks; hence, we computed the fitted values of our liquidity measures conditional on each shock level, generating the variation in liquidity conditions induced by monetary policy. Since this variation is a linear function of an exogenous shock, it is exogenous as well, hence we can regress the credit spreads on these fitted value to obtain the partial effect of monetary policy due to the liquidity channel. What we find is that a shock to the target rate has a meaningful effect on the credit spread through the liquidity channel, and this channel is stronger in the High-Yield segment than in the Investment Grade segment.

Additionally, we find that the sensitivity of corporate bond excess returns to liquidity risk—measured through bid-ask spreads and turnover ratios—varies with the level and slope of the yield curve, suggesting that investors incorporate both current and expected monetary policy stances into bond pricing decisions. This relationship is further reinforced by the observation that liquidity influences how corporate bond spreads react to monetary policy shocks, with less liquid bonds exhibiting a stronger response.

These findings underscore the importance of liquidity as a transmission channel for monetary policy and highlight its role in shaping credit market outcomes.

Understanding how monetary policy affects corporate borrowing costs is essential for both financial stability and macroeconomic policy formulation. By examining the interaction between liquidity and monetary policy, this study provides new insights into the mechanisms driving credit market dynamics and the pricing of corporate bonds.

1.1 Literature Review

1.1.1 On Liquidity

Empirical research has developed a range of proxies to measure liquidity in financial markets. Beyond traditional measures such as turnover ratios—the ratio of traded volume to outstanding securities—and bid-ask spreads, the literature has introduced more sophisticated metrics. Notable contributions include price impact measures Kyle (1985), the effective bid-ask spread Roll (1984), and the illiquidity measure of Amihud (2002), which captures the price impact of trading volume by computing the daily average return per dollar traded. Edwards et al. (2007) employ bid-ask spreads to assess direct trading costs, while Bao et al. (2011) introduce a market-adjusted liquidity measure, which accounts for transitory price movements to reflect varying trading conditions.

Early studies by Amihud and Mendelson (1986) and Amihud (2002) highlight the relationship between liquidity risk, asset prices, and required returns in equity markets. These empirical findings were later formalized in theoretical models such as those of Acharya and Pedersen (2005). In the context of corporate bonds, Chen et al. (2007) and Bao et al. (2011) confirm that liquidity accounts for a substantial share of the variation in corporate bond spreads. The importance of liquidity becomes even more pronounced during periods of financial distress, as illiquidity exacerbates credit spreads, particularly for bonds with higher default risk Lin et al. (2011). Liquidity shocks can also heighten refinancing risk and default probabilities, emphasizing the need for liquidity provisions during crises to prevent market disruptions He and Xiong (2012).

The liquidity of corporate bonds is shaped by multiple factors, including bond characteristics, market structure, and macroeconomic conditions. Empirical evidence suggests that bonds with lower credit ratings and longer maturities tend to be less liquid Houweling et al. (2005). Additionally, callable and structured bonds exhibit lower liquidity due to their complex valuation Helwege et al. (2014). The over-the-counter (OTC) nature of corporate bond trading also contributes to fragmented liquidity, distinguishing it from centralized equity exchanges Bessembinder et al. (2006). Macroeconomic conditions further influence liquidity, with studies showing that liquidity deteriorates and trading volumes decline during financial crises (see Acharya et al. (2013) and Dick-Nielsen et al. (2012)). These patterns were particularly evident during the Global Financial Crisis, when bond markets experienced a sharp contraction in liquidity.

1.1.2 On Monetary Policy and Asset Prices

Monetary policy shocks play a critical role in shaping asset prices and returns by influencing interest rates, risk premia, and expectations about future economic conditions. Classic asset pricing theories suggest that monetary policy primarily affects risk-free rates, which serve as a discounting mechanism for valuing financial assets. However, empirical research has shown that monetary shocks have broader effects on risk premia and asset valuation, often through unexpected changes in central bank policy decisions. Bernanke and Kuttner (2005) develop an identification strategy to isolate unanticipated monetary policy shocks using expectation revisions, showing that asset prices respond almost immediately to policy changes. Similarly, Gertler and Karadi (2015) provide evidence that contractionary monetary shocks lead to declines in equity prices, driven by increases in the cost of capital and deteriorating expectations about future earnings. Rigobon and Sack (2004) find that monetary policy surprises result in significant declines in stock indices, adopting an identification strategy based on the heteroskedasticity of policy shocks.

Gurkaynak et al. (2005) use high-frequency data around FOMC announcements to isolate demonstrate that financial markets respond to both current policy rates and central bank communication about the future trajectory of interest rate. This is confirmed by Nakamura and Steinsson (2018) who introduce a method to identify monetary policy news shocks using high-frequency movements in interest rates around FOMC announcements, controlling for information effects.

Monetary policy also affects bond liquidity. Krishnamurthy and Vissing-Jorgensen (2011) argue that higher interest rates can reduce liquidity by increasing holding costs, while quantitative easing (QE) programs improve liquidity by reducing spreads and stimulating trading activity. The risk-taking channel of monetary policy further influences market liquidity and risk appetite Borio and Zhu (2012). Monetary tightening leads to wider credit spreads, reflecting higher default risk and liquidity constraints Hanson and Stein (2014).

2 Data

The TRACE database provides detailed trade-level information essential for analyzing corporate bond market dynamics. Each transaction is uniquely identified by its CUSIP code, which links the bond to its issuer and characteristics. The dataset also records the trade date and time in Eastern Standard Time (EST), facilitating an analysis of intraday liquidity fluctuations. In addition to trade timestamps, TRACE specifies the counterparty type, indicating whether the transaction occurred between two dealers or between a dealer and a customer, and the counterparty side, which denotes whether the trade represented a purchase or a sale for the reporting dealer.

The dataset further includes key pricing and volume measures. The trade price represents the transaction price per $100 face value, while the yield-to-maturity (YTM) is computed based on the bond's trade price, coupon payments, and time to maturity. The trade volume captures the total par value exchanged in a given trade, with large transactions subject to dissemination caps to limit market impact.

To enrich the dataset with firm-level characteristics, we merge TRACE with the Mergent-FISD database, which provides bond issuance details, including the credit rating at the time of trade and the total amount of outstanding debt for each issuer. Additionally, we integrate financial statement data from COMPUSTAT, focusing on variables related to profitability, liquidity, and leverage. Specifically, we consider operating margin (before depreciation), return on assets, cash ratio, current ratio, debt-to-capital ratio, and debt-to-EBITDA ratio, ensuring a comprehensive view of firm-specific determinants of bond spreads.

We use three different types of high frequency monetary policy shocks. First, we use the *target* and *path* shocks introduced by Gurkaynak et al. (2005) (henceforth, GSS). Target shocks refer to unexpected changes in the federal funds rate itself, capturing surprises in the immediate policy decision. In contrast, path shocks reflect changes in market expectations about the future path of policy, measured by movements in longer-term interest rates that are not explained by the current rate change. On top of these, we also use the monetary policy news shocks introduced by Nakamura and Steinsson (2018), henceforth NS shocks.

2.1 Liquidity Measures

The main empirical section of the paper will use the turnover ratio $\mathcal{T}$ and the bid-ask spread Δ^{ba} as a liquidity proxies. Such variable is defined as the volume of trading activity normalized by outstanding bonds in circulation at the time of the trade:

$$\mathcal{T}_{it} = \frac{1}{N_{it}} \sum_{hh \in t} \frac{\mathcal{V}_{i,hh}}{\mathcal{O}_{it}} \tag{1}$$

where $\mathcal{V}_{i,hh}$ represents the traded volume of bond i in transaction hh, and $\mathcal{O}_{it}$ denotes the total outstanding amount of the bond. Clearly, higher daily turnover implies a much more liquid bond, since it is easier for market participants to transact large fractions of bonds in circulation.

On the other hand, the bid-ask spread is a proxy for the *illiquidity* of the bond, as it increases with dealers' market power and lower trading frequency. Hence, higher bid-ask spreads imply stronger dependence on dealers and, therefore, more illiquid bonds. First, we compute the bid price as the average daily sell price from dealer to customer for a specific bond i during day t. In formulas:

$$\text{Bid}_{it} = \frac{1}{N} \sum_{hh \in t} P_{i,hh}(S, D \to C) \tag{2}$$

where $P_{i,hh}$ represents the price for bond i in transaction hh classified as a dealer-to-customer sale $(S, D \to C)$. The ask price, on the other hand, corresponds to the average daily transaction price for customer-to-dealer purchases, given by:

$$\text{Ask}_{it} = \frac{1}{N} \sum_{hh \in t} P_{i,hh}(B, C \to D) \tag{3}$$

The bid-ask spread is then computed as the normalized difference between bid and ask prices:

$$\Delta_{it}^{ba} = 2 \times \frac{\text{Bid}_{it} - \text{Ask}_{it}}{\text{Bid}_{it} + \text{Ask}_{it}} \tag{4}$$

Turnover captures the quantity dimension of liquidity, whereas bid-ask spreads capture movement the price dimension. To add on the robustness checks, and to make sure that we use all the available information contained in quantity and price, we compute a synthetic measure of liquidity identified as the first principal component of these two variables.

2.2 Credit Spreads

To compute credit spreads, we estimate the risk-free yield curve using the model in Nelson and Siegel (1987). For each day t, the risk-free yield at maturity τ is given by:

$$y_t^{rf}(\tau) = \theta_{1,t} + \theta_{2,t} \left(\frac{1 - \exp(-\lambda_t \tau)}{\lambda_t \tau} \right) + \theta_{3,t} \left(\frac{1 - \exp(-\lambda_t \tau)}{\lambda_t \tau} - \exp(-\lambda_t \tau) \right) \tag{5}$$

where the parameters $(\lambda_t, \theta_{1,t}, \theta_{2,t}, \theta_{3,t})$ are estimated using daily yield curve data. The daily credit spread for bond i is then calculated as the difference between the bond's yield and the estimated risk-free yield at the same maturity:

$$\text{cs}_{it} = \text{YTM}_{it} - y_t^{rf}(\text{TTM}_{it}) \tag{6}$$

where YTM_{it} and TTM_{it} denote the bond's yield to maturity and time to maturity, respectively.

2.3 Summary Statistics

Table 1 reports summary statistics for bond-level credit spreads, bid-ask spreads, and turnover, separately for investment-grade and high-yield bonds. Credit spreads and bid-ask spreads are, on average, higher for high-yield bonds, reflecting their greater credit and liquidity risk. Both measures also exhibit

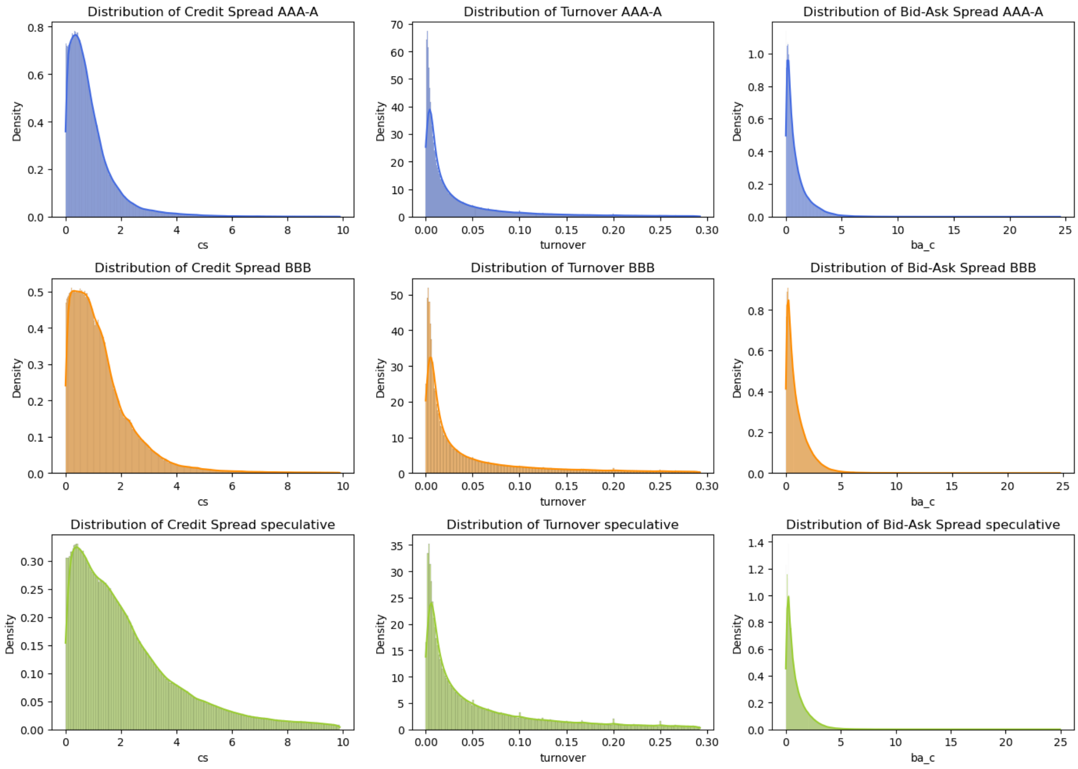

Figure 1: Distribution of credit spreads, $-\log$ Turnover, and log bid-ask spreads across different corporate bond rating categories.

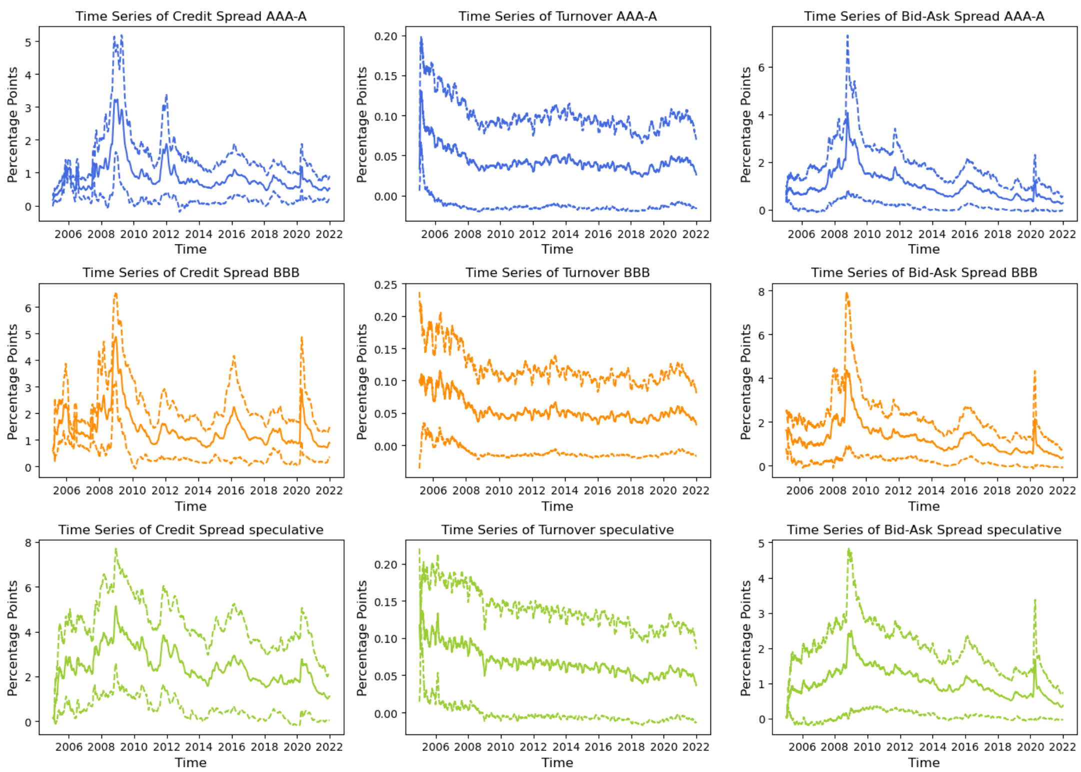

Figure 2: Time series of daily average credit spreads, turnover, and bid-ask spreads across different corporate bond rating categories. Bands represent 1 standard deviation above and below average.

Table 1: Summary statistics by risk class

Variable	Statistic	Investment Grade	High Yield
Credit spread	Mean	1.02	1.39
	Standard Deviation	1.05	1.23
	Q1	0.360	0.54
	Median	0.73	1.1
	Q3	1.30	1.86
	Kurtosis	12.98	7.02
	Skewness	2.90	2.11
Bid-Ask spread	Mean	1.08	1.09
	Standard Deviation	1.29	1.17
	Q1	0.26	0.31
	Median	0.65	0.73
	Q3	1.44	1.50
	Kurtosis	24.17	24.07
	Skewness	3.45	3.30
Turnover	Mean	0.05	0.06
	Standard Deviation	0.08	0.10
	Q1	0.00	0.01
	Median	0.02	0.02
	Q3	0.05	0.07
	Kurtosis	8.90	5.08
	Skewness	2.86	2.29

significant right skewness and excess kurtosis, indicating the presence of extreme values. Turnover is slightly higher for high-yield bonds, with similar distributional asymmetries. These statistics highlight systematic differences in market characteristics across credit risk classes.

Figure 1 shows the distribution of credit spreads, turnover and bid-ask spreads, across different corporate bond rating categories: AAA-A, BBB, and speculative-grade bonds. As expected, speculative-grade bonds exhibit fatter right tail in credit spreads distribution, indicating a higher mean and greater dispersion compared to investment-grade bonds, reflecting their greater default risk. BBB-rated bonds have a slightly fatter right tail compared to AAA-A but less than speculative-grade bonds. Similarly, the distribution of liquidity measures for speculative bonds is seems to first-order stochastically dominate the other two, suggesting lower liquidity.

Figure 2, on the other hand, displays the time series of the daily average of the variable of interest, and the bands within 1 standard deviation from the Mean. A clear cyclical pattern emerges, with spikes in credit spreads and bid-ask spreads during periods of financial distress, most notably around the 2008 Global Financial Crisis and the 2020 COVID-19 market shock. Turnover also exhibits cyclical variations, with declining liquidity during stress periods, particularly for lower-rated bonds. Additionally, speculative-grade bonds show a consistently higher and more volatile credit spread compared to investment-grade bonds, reinforcing the notion that riskier bonds face greater borrowing costs and more pronounced liquidity fluctuations in response to market conditions. The overall trends highlight the strong relationship between market liquidity, bond risk premia, and macroeconomic conditions over time.

3 Response to Monetary Policy Shocks

First, we are interested in assessing whether bonds with different degrees of liquidity are affected differently by monetary policy shocks. To this end, we split bonds into 4 portfolios, sorted by credit rating (Investment Grade vs. High Yield) and liquidity (Low, High). We estimate the following regression separately for each portfolio:

$$\text{cs}_{i,t+h} = \alpha_p(h) + \beta_p(h)\varepsilon_t^{mp} + \gamma_{0,p}(h)'\mathbf{x}_t^{agg} + \gamma_{1,p}(h)'\mathbf{x}_{i,t}^{fs} + \epsilon_{it} \qquad i \in p \tag{7}$$

where ε_t^{mp} represents the high-frequency identified monetary policy shock and $\mathbf{x}^{agg}, \mathbf{x}^{fs}$ are aggregate and firm specific controls. p indexes the four risk-liquidity portfolios:

$$p \in \{\text{HY-low}, \text{HY-high}, \text{IG-low}, \text{IG-high}\}$$

According to the local projection methodology introduced by Jordà (2005), the impulse response function of a shock at horizon h is the coefficient associated to the shock itself in Equation 7. Hence, this framework allows us to quantify how monetary policy differentially affects credit spreads based on liquidity and risk exposure, providing insights into the transmission mechanisms of monetary policy in corporate bond markets.

Figure 3 shows the IRF generated by Equation 7. A shock to the current policy rate target (i.e., a "GSS target" shock) leads to an increase in the credit spread of high-yield (HY) bonds by up to 10 basis points, with no statistically significant heterogeneity across liquidity tiers. Investment-grade (IG) bonds with low liquidity exhibit a similar response, mirroring the dynamics observed for HY bonds. In contrast, highly liquid IG bonds are considerably less sensitive to the shock. This suggests that, in the face of immediate monetary policy tightening, investors prioritize liquidating HY and illiquid securities, accepting greater price concessions in the process.

A more nuanced pattern emerges in response to shocks to the expected path of future short-term interest rates (i.e., "GSS path" shocks). Among HY bonds, those with high liquidity experience a sharper rise in credit spreads—exceeding 14 basis points—compared to approximately 10 basis points for their less liquid counterparts. The opposite pattern holds for IG bonds: low-liquidity IG bonds experience a larger increase in spreads (approximately 8 basis points), while highly liquid IG bonds display a more muted and short-lived response (approximately 6 basis points). A similar configuration is observed in response to monetary policy news shocks (NS). These results indicate a hierarchy in investors' sell-off behavior during persistent monetary tightening: they first shed HY securities, particularly those that are easier to trade, reflecting concerns over default risk amid deteriorating macroeconomic conditions. Conversely, demand for IG bonds remains relatively stable, and their more liquid variants are less likely to be offloaded, thus exhibiting smaller spread adjustments.

This evidence highlights an important interaction between credit risk and market liquidity in shaping the pricing dynamics of corporate bonds. Due to their long maturities, corporate bonds are particularly sensitive to revisions in the expected interest rate path. Portfolios concentrated in higher-risk debt are more susceptible to flight-to-safety behavior, amplifying the pressure to liquidate and driving larger repricing—especially for securities that are more easily traded. In contrast, portfolios with lower exposure to credit risk face less investor aversion during tightening episodes; within these, liquid bonds experience relatively milder price corrections, consistent with sustained demand.

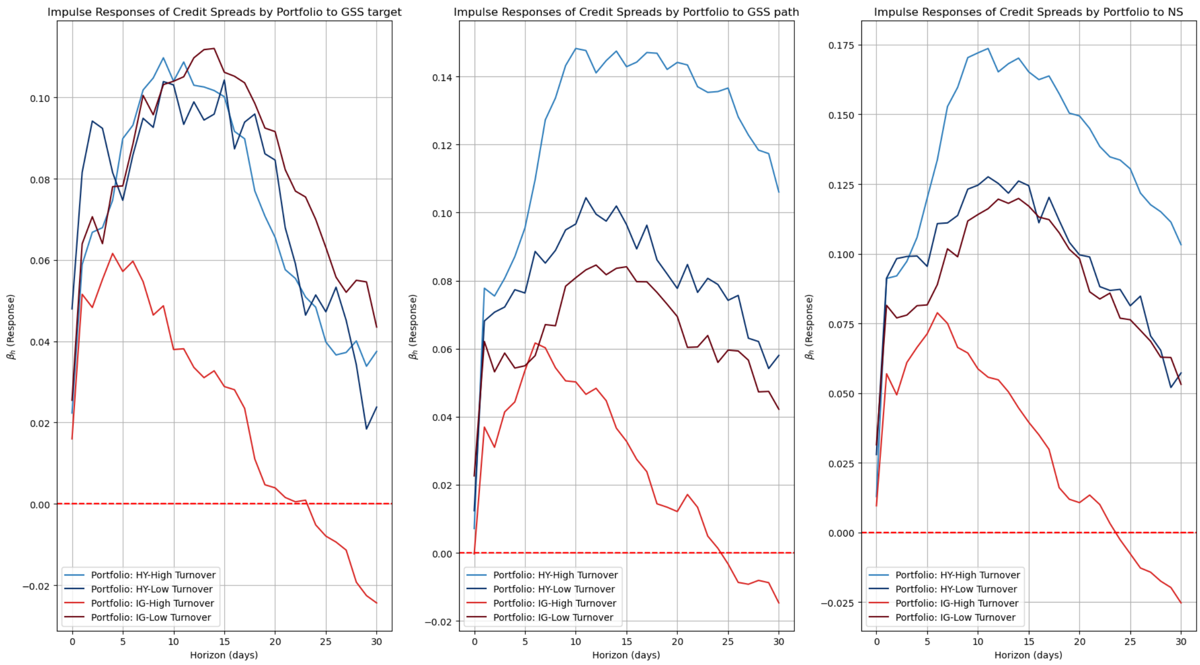

Figure 3: Impulse responses of credit spreads to monetary policy shocks. Bonds are divided in portfolios sorted by liquidity and risk.

3.1 Liquidity Channel of Monetary Policy

Monetary shocks may impact the liquidity of bonds and affect credit spreads through the liquidity channel. That is, if cs_{it+h} is a function of both the monetary policy shock and liquidity measures, we have:

$$\frac{\mathrm{dcs}_{it+h}}{\mathrm{d}\varepsilon_t^{mp}} = \frac{\partial \mathrm{cs}_{it+h}}{\partial \varepsilon_t^{mp}} + \frac{\partial \mathrm{cs}_{it+h}}{\partial \ell_{it+h}} \frac{\partial \ell_{it+h}}{\partial \varepsilon_t^{mp}} \qquad \ell \in \{\mathcal{T}, \Delta^{ba}\}$$

To identify $\frac{\partial \mathrm{cs}_{it+h}}{\partial \ell_{it+h}} \frac{\partial \ell_{it+h}}{\partial \varepsilon_t^{mp}}$, we proceed in two steps. First, we apply the same local projection methodology introduced in the previous paragraph to estimate the partial effect of the monetary policy shock on liquidity. Hence, we first estimate:

$$\ell_{i,t+h} = \alpha_r(h) + \beta_r(h)\varepsilon_t^{mp} + \gamma_{0,r}(h)'\mathbf{x}_t^{agg} + \epsilon_{it} \qquad r \in \{\text{HY, IG}\} \tag{8}$$

Then, we fit the above equation and find the variation of liquidity generated by the monetary policy shock, $\widehat{\ell}_{i,t+h}$. Given the exogenous nature of the shock, the variable does not present endogeneity concerns that arises when estimating $\frac{\partial \text{cs}}{\partial \ell}$. Therefore, we can use OLS to estimate:

$$\text{cs}_{i,t+h} = \alpha_r + \beta_r(h)\varepsilon_t^{mp} + \beta_r^{\ell}(h)\widehat{\ell}_{i,t+h} + \gamma_{0,r}(h)'\mathbf{x}_t^{agg} + \gamma_{r,1}(h)'\mathbf{x}_{i,t}^{fs} + \epsilon_{it} \tag{9}$$

Hence, the liquidity channel of monetary policy shocks can be estimated combining the OLS estimator for $\beta_r(h)$ from Equation 8 and the OLS estimator for $\beta_r^{\ell}(h)$ from Equation 9.

Figure 4 presents the impulse response functions estimated from Equation 8. While the effects of monetary policy shocks on turnover seem to be moderately positive, the responses of bid-ask spreads indicate a deterioration in liquidity conditions, in particular for IG bonds. News shocks and target shocks exhibit the strongest immediate impact, whereas path shocks display a more gradual but still significant effect.

Figure 5, presents the plot of $\beta^{\ell}(h)$.

4 Higher-order liquidity channel of monetary policy

We document that another way in which monetary policy affect credit spreads through the liquidity channel is by changing the liquidity risk factor loading. To this end, we define two liquidity risk factors, $lrf^{\mathcal{T}} = -\log \mathcal{T}$ and $lrf^{\Delta} = \log \Delta^{ba}$, since they capture the risk associated to trading frictions incurred by investors.

4.1 Liquidity Risk factor Loading

To assess the time varying nature of the relationship between liquidity risk and credit spreads, for each month t_m we estimate the following panel regression model:

$$\text{cs}_{i,t} = \alpha_{t_m}^R + \beta_{t_m} lrf_{it} + \gamma_{t_m,0}'\mathbf{x}_t^{agg} + \gamma_{t_m,1}'\mathbf{x}_{i,t}^{fr} + \epsilon_{it} \qquad t \in t_m \tag{10}$$

where lrf_{it} represents a liquidity risk factor, and $\mathbf{x}_t^{agg}$ and $\mathbf{x}_{i,t}^{fr}$. denote aggregate and firm-specific control variables, respectively. Aggregate controls include the level and slope of the yield curve, the VIX index, and the ICE-BofA spread between high-yield and investment-grade bonds. Firm-specific controls capture profitability, liquidity leverage.

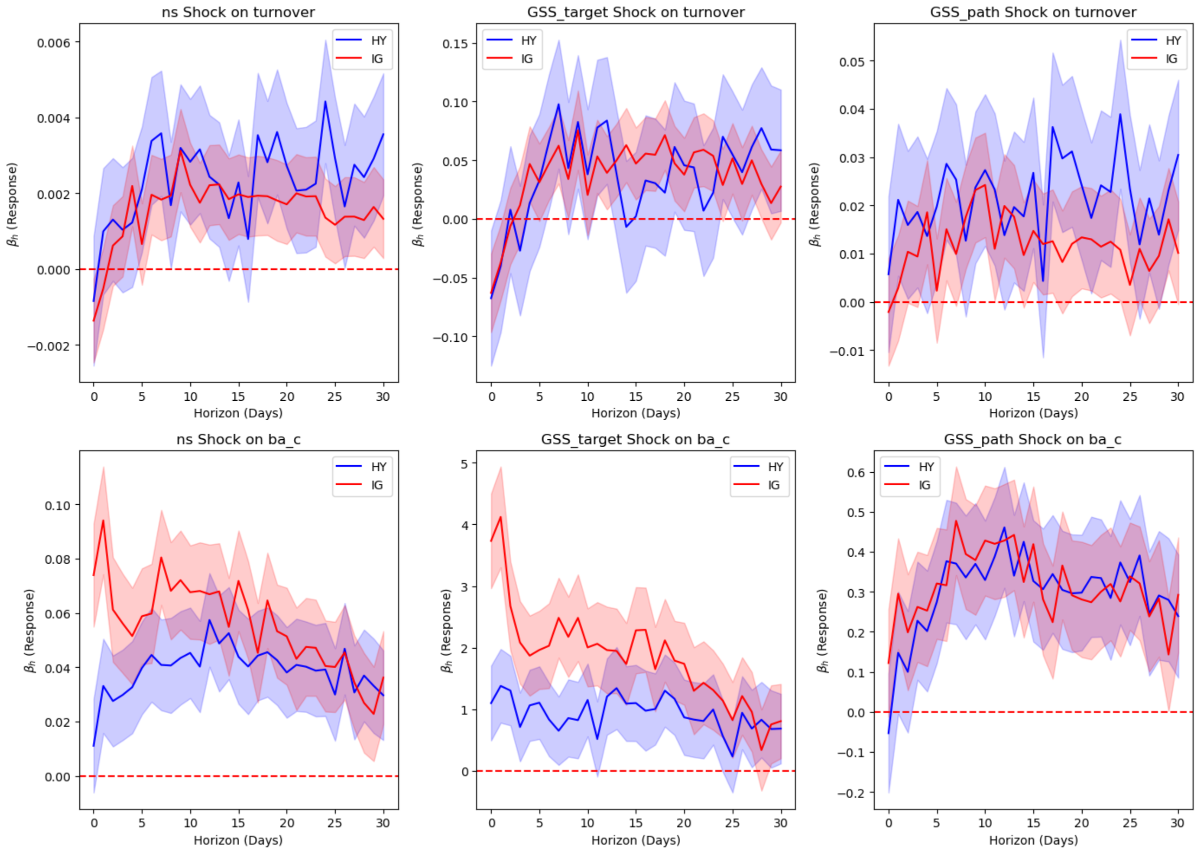

Figure 4: Impulse responses of credit spreads to monetary policy shocks, bonds are divided in low and high liquidity according to their turnover.

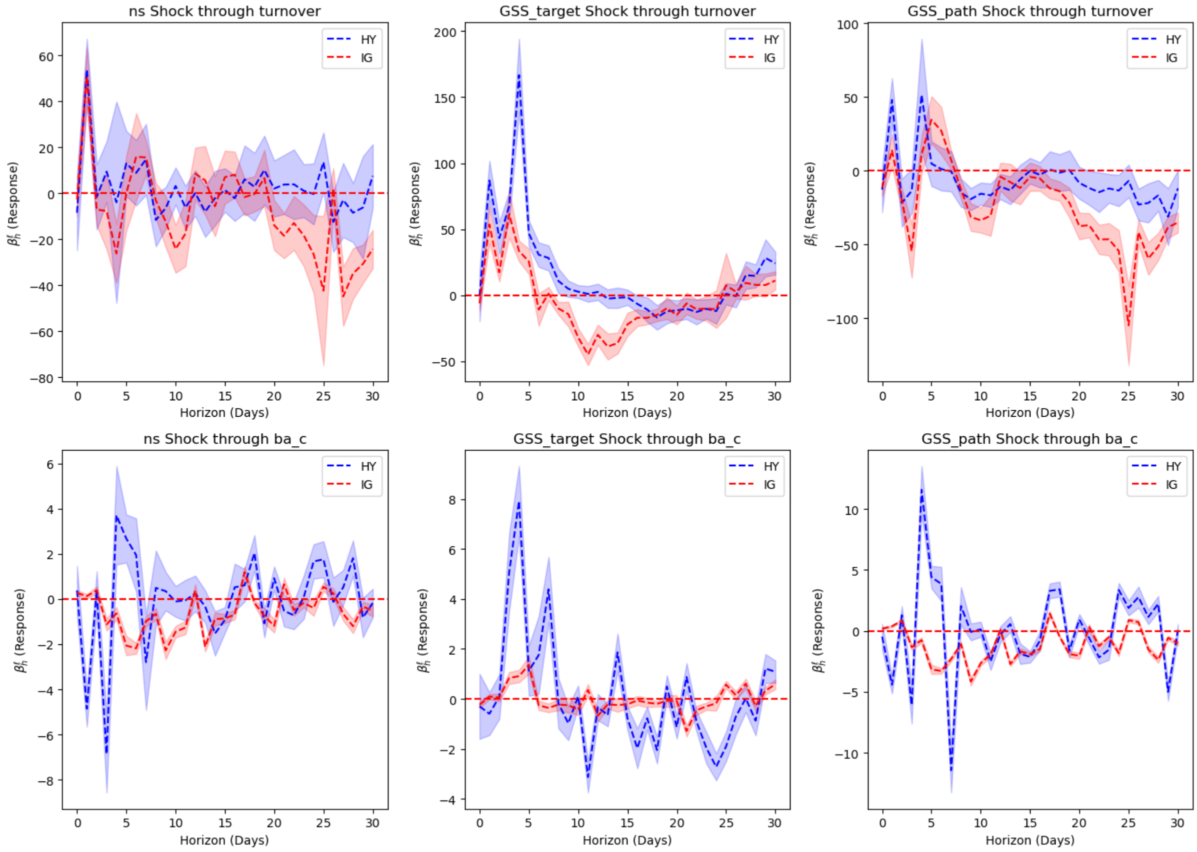

Figure 5: Coefficient β^{ℓ} showing the liquidity channel of monetary policy shocks.

Given potential endogeneity concerns, we employ an instrumental variable (IV) approach, using the average number of trades in the previous 30 days as an instrument for lrf_{it}. This variable is strongly correlated with liquidity but is exogenous to *current* credit spreads.

4.2 Results

Figure 6 and 7 show the dynamics of the coefficient β_{t_m} over time, plotted against major financial market events.

Figure 8 and 9, on the other hand, plot these two coefficient against the slope of the yield curve, measured as the spread between the 10 year Treasury yield and the 3 month Treasury rate. Both charts hints at a strong anti-correlation between the two variables. To quantify this relationship, we run the regression:

$$\beta_{t_m}^{\text{liq}} = \alpha + \phi_r r_{t_m}^{1\text{ mo}} + \phi_{slope}(r_{t_m}^{10\text{Y}} - r_{t_m}^{3\text{Mo}}) + \phi_{stock}\text{Stock}_{t_m} + \phi_{VIX} VIX_{t_m} + \nu_{t_m} \tag{11}$$

with $\text{liq} \in \{-\log \text{Turnover}, \log \text{Bid-Ask}\}$. The results are displayed in Table 2.

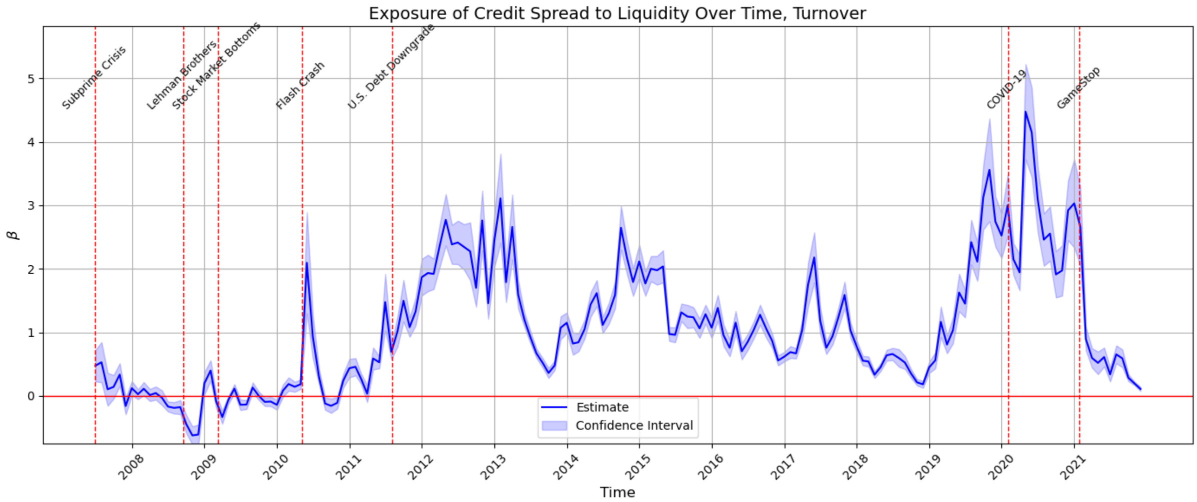

Figure 6: Time series of the coefficient $\{\beta_{t_m}\}_m$ from the rolling regression displayed in Equation 10, along with major financial market events. The liquidity measure employed is $-\log \mathcal{T}$.

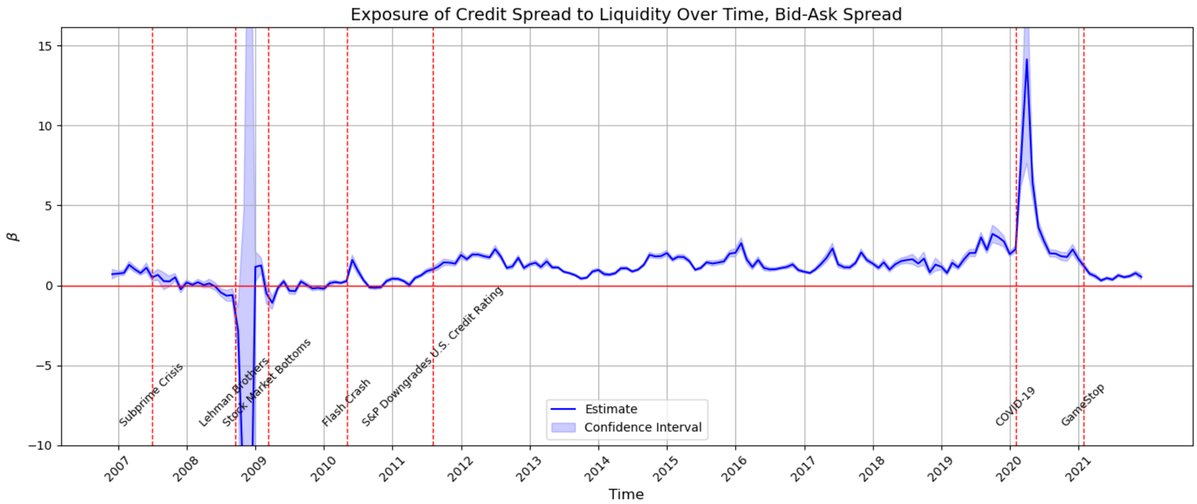

Figure 7: Time series of the coefficient $\{\beta_m\}_m$ from the rolling regression displayed in Equation 10, along with major financial market events. The liquidity measure employed is the $\log \Delta^{ba}$.

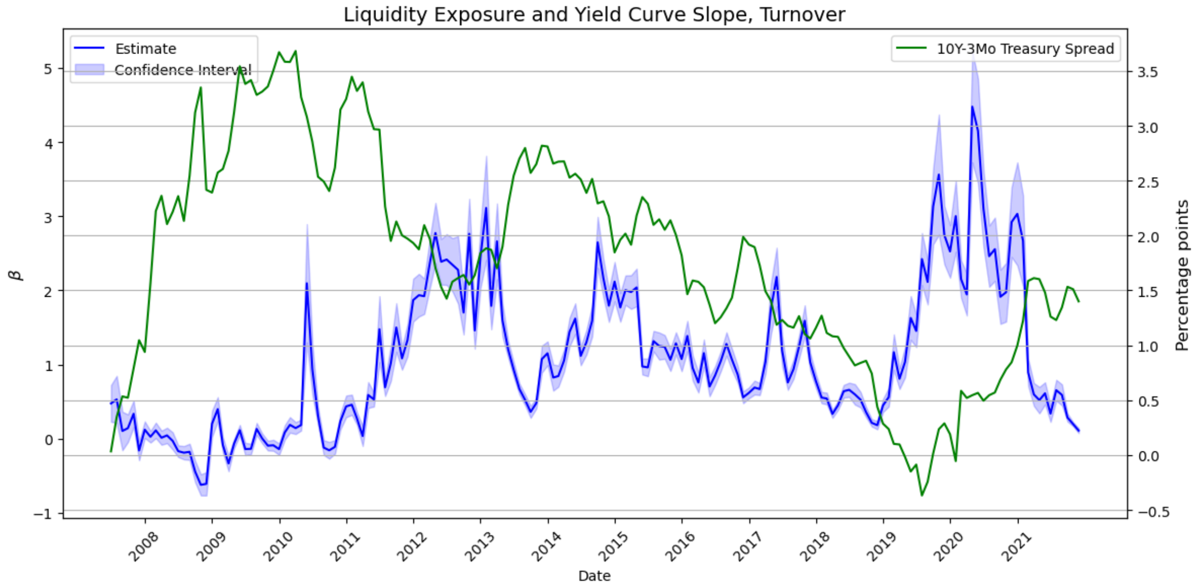

Figure 8: The loading on the liquidity risk factor plotted against the 10 year - 3 month spread highlights a comovement between the to variables. Liquidity is proxied by $-\log$ Turnover.

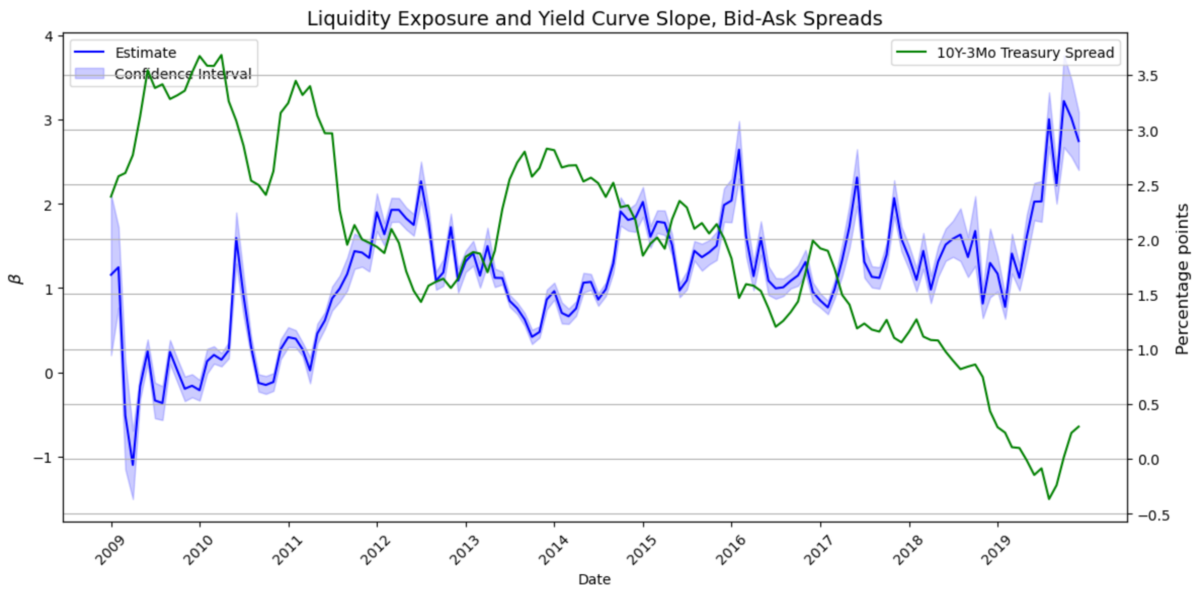

Figure 9: The loading on the liquidity risk factor plotted against the 10 year - 3 month spread highlights a negative comovement between the to variables. Liquidity is proxied by $\log \text{Bid-Ask}_{it}$. Only pre-Covid sample is displayed.

	Dependent variable: β^{liq}	
	$-\log \mathcal{T}$	$\log \Delta^{ba}$
const	3.135***	2.916***
	(0.029)	(0.210)
r^{1Mo}	-0.682***	-0.561***
	(0.007)	(0.102)
$r^{10\text{Y}} - r^{3\text{Mo}}$	-0.697***	-0.784***
	(0.011)	(0.074)
SP500	0.000	0.000*
	(0.000)	(0.000)
VIX	-0.022***	-0.007
	(0.001)	(0.006)
Observations	138	120
R^2	0.557	0.581
Adjusted R^2	0.544	0.567
Residual Standard Deviation. Error	0.557	0.449
F Statistic	41.832***	39.912***

Table 2: Results of OLS estimation of Equation 11. Note: *p<0.1; **p<0.05; ***p<0.01

5 Conclusion

This research highlights the crucial role of liquidity in determining how monetary policy shocks affect corporate credit spreads. The empirical results provide evidence that more liquid bonds display lower credit spreads all else equal, but they also experience smaller responses to monetary policy shocks. This suggests that liquidity dampens away the effects of rate hikes. These findings have implications for policymakers and market participants, emphasizing the need for liquidity considerations in financial stability assessments and monetary policy design.

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