Increasing Corporate Bond Liquidity Premium and Post-Crisis Regulations *

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Abstract

I employ the liquidity premium measure to understand the important changes in corporate bond market liquidity from 2004 to 2019. I show that while commonly-used transaction cost measures such as the bid-ask spread have been declining, the corporate bond liquidity premium has actually increased since the financial crisis. For speculative bonds, about 30% of their yield spread now compensates for illiquidity compared to 15% before the crisis. I demonstrate that this increasing liquidity premium is due to investors facing longer trading delays as dealers have become less willing to provide immediacy, and develop a structural over-the-counter model to estimate the latent trading delays implied by the size of the liquidity premium. The estimation results suggest that bonds that took less than one day to sell before the financial crisis now take weeks to trade. Finally, I establish a causal relationship between the major post-crisis regulations and the variations in the corporate bond liquidity premium to uncover the potential cause of dealers' unwillingness to provide liquidity. I show that Basel II.5, by introducing the stressed value-at-risk and incremental risk charges for credit products, contributed the most to increasing the liquidity premium out of all regulatory changes examined. The longer trading delays and the impact of regulations are consistent with practitioners' descriptions of the post-crisis market and corroborate the relevance of using the liquidity premium to understand corporate bond market liquidity.

Keywords: Corporate Bond, Liquidity Premium, Trading Delays, Basel II.5

JEL classification: G10, G12, G18, G20

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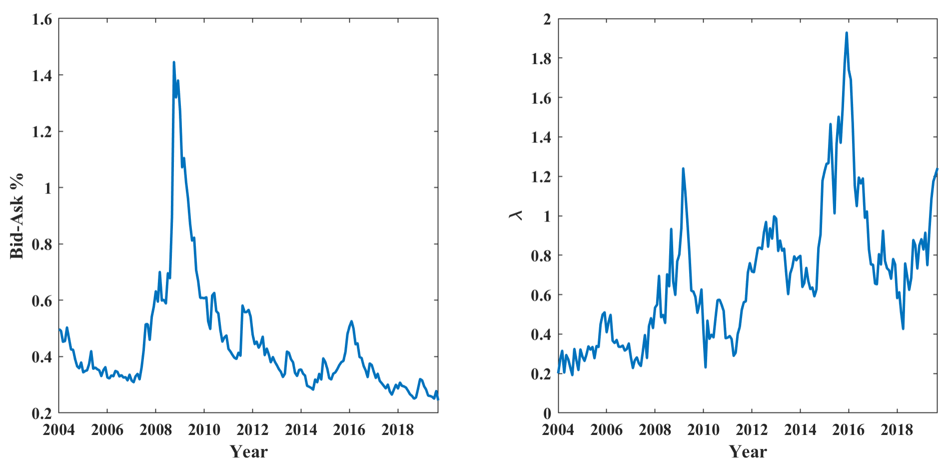
1 Introduction

Industry participants have been complaining about the lack of liquidity in the U.S. corporate bond market since the financial crisis. According to the Goldman Sachs, *"it isn't that they can't get trades done; it's that they can't get trades done as quickly [...] [T]rade that historically may have taken a day to get done now needs to [...] take a week or two to execute."*[1] However, such lack of liquidity fails to show up in the corporate bond transaction cost measured by the bid-ask spread, which has remained low since the crisis. When transaction costs no longer measure the true liquidity condition, investors are looking for new variables to better assess corporate bond market liquidity.[2] In this paper, I reconcile these two seemingly contradictory pictures of low transaction costs yet lack of liquidity claimed by practitioners, and provide a feasible alternative liquidity measure that better reflects corporate bond market liquidity: the liquidity premium.[3] I document that while the average corporate bond bid-ask spread is roughly the same as the pre-crisis level,[4] cross-sectional variation in the corporate bond yield spread has become more and more sensitive to the cross-sectional variation in the corporate bond bid-ask spread (Figure 1). The level of the corporate bond liquidity premium has also increased. The average liquidity component of the yield spread

Figure 1: Corporate Bond Bid-Ask Spread and Yield Spread Sensitivity to Bid-Ask Spread

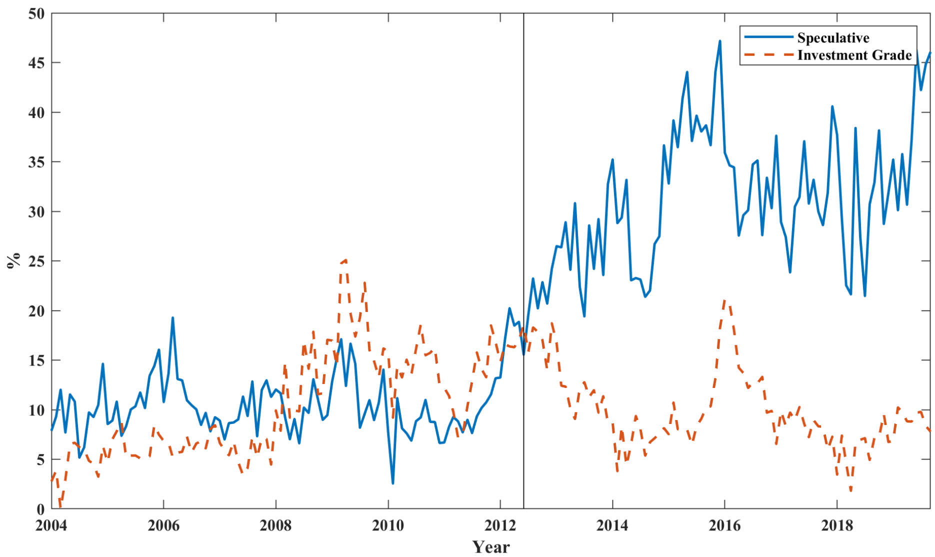


Notes: The left panel shows the aggregate bid-ask spread. The right panel shows the cross-sectional coefficient (λ) of regressing corporate bond yield spread on its bid-ask spread, controlling for credit risk.

[1]Global Investment Research: https://www.goldmansachs.com/insights/pages/macroeconomic-insights-folder/liquidy-top-of-mind/pdf.pdf.
[2]Source: https://www.markit.com/Company/Files/DownloadDocument?CMSID=3e73ade9d7c1461091776bd5afefa65d.
[3]I use the term "liquidity premium" to refer to the liquidity component of the corporate bond yield spread.
[4]By "bid-ask spread," I mean the difference between the prices at which dealers actually sell and buy the bond. This is not the "bid-ask *quote*" in the equity market, which is not available in the realized bond transaction data.

is currently higher than the pre-crisis level for all bonds rated below A. For BBB-rated bonds, the liquidity premium (as a fraction of the yield spread) is the same as the crisis level, while for speculative bonds, it is even more than twice the crisis level. Over 30% of the speculative bond yield spread now compensates for illiquidity (Figure 2). Therefore, even though the actual transaction

Figure 2: Liquidity Premium as a Fraction of Total Yield Spread



Notes: This figure presents the corporate bond liquidity premium as a fraction of the yield spread. For each month, I plot the median of $\lambda_t \times$ *Bid-Ask-Spread*$_{it}$/*Yield-Spread*$_{it}$ for investment grade and speculative bonds, where λ_t is the regression coefficient from the cross-sectional regression (1) of yield spread on the bid ask spread, run on both investment grade and speculative bond samples. The vertical line is June 2012 when Basel II.5 was implemented.

cost may have dropped since the crisis, the implied post-crisis cost of borrowing that is due to illiquidity has actually increased.

The high liquidity premium does not contradict the low bid-ask spread after the financial crisis. Recent studies (Schultz 2017, Choi and Huh 2019, Goldstein and Hotchkiss 2020) suggest that corporate bond dealers can act both as market makers that use inventory to provide immediacy, and as brokers that simply match customers without holding the bonds on their balance sheets. As balance sheet costs increase and holding inventory becomes more costly due to regulations, dealers will increasingly function as brokers rather than as true market makers to avoid incurring inventory costs. The bid-ask spread charged by brokers, however, is low.[5] Hence, a higher inventory cost

[5]The natural analogy is that apartment seekers and renters can contact real estate agents by paying an intermediation fee, or they can search on Craigslist and contact each other directly without any intermediation fees.

can result in a lower average bid-ask spread because a larger fraction of the total transactions are the brokered trades with low bid-ask spreads (Choi and Huh 2019). However, a low bid-ask spread does not mean that the liquidity premium is low. On the contrary, higher inventory costs will lead to a decline in immediacy provision and longer trading delays, and so investors will require a larger liquidity premium despite the low bid-ask spread. I develop a structural over-the-counter model based on Lagos and Rocheteau (2009) that can reconcile the time series patterns of the higher liquidity premium yet a lower bid-ask spread, and generate the increasing cross-sectional sensitivity of corporate bond yield spread to bid-ask spread over time. Moreover, the model suggests that illiquidity can be interpreted as a product of transaction costs times trading delays, which previous studies have overlooked because trading delays are not directly observable in the data.

However, if investors face rising illiquidity in terms of longer trading delays that are not observable, they should require a higher premium, which can be measured. This intrinsic link between trading delays and the liquidity premium allows me to use my structural model to estimate the latent trading delays implied by the magnitude of the liquidity premium. The estimates suggest that trading delays after the financial crisis have increased more than fivefold relative to the pre-crisis level. While it took less than one day to sell an average BBB-rated bond before the crisis, now it takes nearly a week. For speculative bonds, the post-crisis trading delay is roughly 2-3 weeks. The estimation results are consistent with practitioners' descriptions of the post-crisis market liquidity.[6]

To demonstrate that this liquidity premium is indeed due to dealers being less willing to buy and hold inventory from investors, I decompose the corporate bond bid-ask spread into the spread components that compensate for the inventory cost and the search cost respectively, and compare the magnitudes of the liquidity premia computed from the two costs. The spread that compensates for the inventory cost is the spread measure introduced in Randall (2015) and Choi and Huh (2019), while the spread that compensates for the search cost is measured by the price spread between the immediately matched customer buy and sell trades that happen within one minute and with the same quantity (Feldhütter 2012, Green, Hollifield, and Schürhoff 2007). I show that

[6]Realistically, the results suggest that it now takes weeks to fully execute the trades, for instance, by splitting large trades into smaller pieces over the longer delay horizon as dealers' inventory capacity shrinks. According to Goldman Sachs, *"one $10 million trade that historically may have taken a day to get done now needs to be split into 20 $500,000 trades that take a week or two to execute."* Source: `https://www.goldmansachs.com/insights/pages/macroeconomic-insights-folder/liquidy-top-of-mind/pdf.pdf`.

the resulting inventory premium is 10 times as large as the associated search premium. Moreover, while the search premium remains at the pre-crisis level, the inventory premium has significantly increased since the financial crisis. This result suggests that investors have increased the required compensation for holding illiquid bonds after the crisis because dealers have become increasingly reluctant to use inventory to provide immediacy to investors.

To uncover the potential cause of the dealers' unwillingness to provide liquidity to investors, I examine the impacts of different post-crisis regulations on the corporate bond liquidity premium. I find that the liquidity premium of BBB-rated and speculative bonds significantly increased following Basel II.5, while the liquidity premium of investment grade bonds significantly decreased during the Basel III period. The Volcker Rule increased the liquidity premium of the speculative bonds. Furthermore, I find that changes in the aggregate dealer value-at-risk (VaR) can predict changes in the corporate bond liquidity premium. A 0.1 tightening of the aggregate dealer VaR Granger causes the liquidity premium (as a fraction of the total yield spread) to increase by over 10 percentage points, or equivalently almost six days in terms of the estimated trading delays. I then employ a difference-in-differences framework to establish a causal relationship between the post-crisis regulations and the variations in the liquidity premium. I find that Basel II.5, which introduced the stressed value-at-risk (SVaR) and incremental risk capital charge (IRC) in 2012, led to a 15 percentage point difference in the average liquidity premium (as a fraction of the yield spread) between the bonds at the top and bottom of the risk charge distributions. The liquidity coverage ratio (LCR) introduced under Basel III in 2013, on the other hand, includes investment grade corporate bonds issued by non-financial firms as high-quality liquid assets (HQLA), which decreased the average liquidity premium (as a fraction of the yield spread) of these bonds by 2.5 percentage points compared to the investment grade bonds issued by financial firms. Furthermore, by assuming that the lead underwriters of corporate bonds are likely to be the dealers (Dick-Nielsen, Feldhütter, and Lando 2012), I find that the average liquidity premium (as a fraction of the yield spread) of the speculative bonds whose lead underwriters are more likely to be the Volcker-affected dealers increased by 4 percentage points compared to the liquidity premium of the speculative bonds whose lead underwriters are less likely to be regulated by the Volcker Rule. All these results are robust if I use alternative credit risk controls or transaction cost measures to extract the corporate bond liquidity premium.[7]

This paper contributes to the following areas of the literature. First, it extends early studies that examine the liquidity component of the yield spread during the financial crisis. Dick-Nielsen, Feldhütter, and Lando (2012) find that the liquidity premium increased dramatically during the financial crisis. Friewald, Jankowitsch, and Subrahmanyam (2012) find that liquidity is more important in explaining changes in the yield spread for bonds with high credit risk during the crisis. My results confirm their findings for the crisis period and I extend their analyses to the post-crisis period. Furthermore, I show that during the financial crisis period, it is mainly systematic liquidity risk that drives the liquidity premium (Pástor and Stambaugh 2003), while afterwards the liquidity premium increases mainly as a compensation for the higher corporate bond illiquidity level (Amihud and Mendelson 1986), as new regulations have made it more costly for dealers to hold corporate bonds on their balance sheets to provide liquidity to investors.

Second, a number of studies decompose the corporate bond bid-ask spreads into components that compensate for different frictions. Ederington, Guan, and Yadav (2014) and Choi and Huh (2019) measure the bid-ask spread components that compensate for dealers' dual roles as brokers and market makers. Few studies have looked at the extent to which each of these spread components explains cross-sectional variation in the corporate bond yield spreads. I show that the spread component that is compensation for liquidity provision and inventory costs explains more cross-sectional variation in yield spreads than the spread component that is compensation for search costs. More broadly, this paper contributes to the large literature on corporate bond liquidity and asset pricing (e.g., Collin-Dufresne, Goldstein, and Martin 2001, Longstaff, Mithal, and Neis 2005, Chen, Lesmond, and Wei 2007, Bongaerts, de Jong, and Driessen 2017, Friewald and Nagler 2019, and He, Khorrami, and Song 2019). While these papers establish the existence of the liquidity premium in the corporate bond yields and returns, I take a further step and show how the liquidity premium varies across different times and is affected by the regulatory changes in the corporate

[7]The robustness of my results using the alternative credit risk controls means that composition changes within the credit ratings are unlikely to drive the results.

bond market.[8]

Third, my paper contributes to the studies that model the over-the-counter (OTC) market based on the seminal search framework in Duffie, Gârleanu, and Pedersen (2005). While most studies take trading delays as fixed, ranging from days (Pagnotta and Philippon 2018) to weeks (He and Milbradt 2014) in their calibrations, my study brings an important time series perspective on the evolution of these trading delays and their potential drivers. Moreover, I am the first to propose the use of the liquidity premium as an important model moment to calibrate the search intensities and estimate trading delays in the corporate bond market. Previous studies typically rely on bid-ask spreads (Feldhütter 2012) or various trading activity variables (Hugonnier, Lester, and Weill 2019) that are usually laborious to compute or require proprietary data to identify the search intensity parameters. These models have to be complicated enough to reflect various microstructure minutiae and the changing dealer/customer dynamics in the market. My model, on the other hand, is fairly stylized and the liquidity premium is easy to measure empirically. It generates longer trading delays that are consistent with practitioners' descriptions of the post-crisis corporate bond market reality.

Finally, I demonstrate the potential usefulness of *asset pricing-based* liquidity measures such as the liquidity premium by weighing in on the debate over the impact of post-crisis banking regulations on market liquidity. Whether the post-crisis regulations affect *transaction cost-based* liquidity measures such as the bid-ask spread or price impact is debatable as different authors have reached different conclusions (Trebbi and Xiao 2019, Bao, O'Hara, and Zhou 2018). Most of these studies have to rely on natural experiments during stressful times to quantify the impact (Dick-Nielsen and Rossi 2018, Bao, O'Hara, and Zhou 2018). During normal market conditions, there is very little evidence suggesting that new regulations have worsened corporate bond transaction cost measures (Anderson and Stulz 2017). By contrast, I find that post-crisis regulations have had sizeable impacts on the liquidity component of the yield spread. Furthermore, while previous

[8] In a recent working paper, Li and Yu (2020) attribute the cross-sectional sensitivity of the corporate bond yield spread to the bid-ask spread to the declining risk-free rate and changes in the investor composition as short-term investors (mutual funds) reach for yield and provide liquidity in the bond market. Other changes in the composition of corporate bond investors have come about due to the introduction of corporate bond ETFs and the gradual adoptions of electronic trading platforms (O'Hara and Zhou 2021). These innovations *improve* liquidity, as a *consequence* of the worsened bond market liquidity due to the new regulatory rules. I focus on the dealers liquidity supply and the associated rising trading delays and liquidity premium. My results suggest that these innovations have not fully made up for the loss of liquidity provided by dealers, because market participants complain about the longer trading delays and have increased the liquidity premium, *despite* these innovations that improve liquidity. Indeed according to PwC, *"the collective impacts of these three developments [...] is not likely, in the short- to medium term, to be sufficient to fully replace the [...] loss of market-making capacity [...] from dealers."* Source: https://www.pwc.com/gx/en/financial-services/publications/assets/global-financial-market-liquidity-study.pdf.

studies focus on the impact of the Volcker Rule on corporate bond liquidity (Bessembinder et al. 2018, Bao, O'Hara, and Zhou 2018), I conduct a comprehensive study of the major post-crisis regulations and examine the impact of each regulation on the liquidity premium. I find that Basel II.5 is primarily responsible for the increase in the average liquidity premium since the financial crisis and drives the huge difference in the average liquidity premium between the investment grade and speculative corporate bonds in the post-crisis period. The results are consistent with an informal survey of market participants by the Committee on the Global Financial System (CGFS 2016), which suggested that Basel II.5 had the largest impact on corporate bond liquidity out of all regulations.

Traditional transaction cost-based liquidity measures no longer offer a full picture of the true liquidity conditions of the corporate bond market because regulations have prompted dealers to change their business models and operate more as brokers that charge low bid-ask spreads. The illiquidity that industry participants are experiencing manifests as a loss of immediacy and longer trading delays, which are almost impossible to observe or measure.[9] My study is motivated by the simple yet compelling intuition that if corporate bond liquidity conditions have deteriorated and resulted in longer trading delays, then investors will require a higher compensation for holding the illiquid bonds and the liquidity premium should become higher. In the words of Dick-Nielsen and Rossi (2018): *"Discouraging air travel might well lower the actual realized cost of transportation (taking the bus is cheaper) [...] Traveling from Los Angeles to New York in 3 days by bus is not the same as completing the trip in 5 hours by plane."* While previous studies all choose to quantify travel inconvenience by looking at the costs of the rare and infrequent emergency events of air travel when, for instance, travelers have to attend wedding ceremonies the very next day, I essentially uncover the duration of travel, which is a more natural and continuous indicator of travel inconvenience during normal times, through the lens of travelers' required compensation for travel inconvenience. Using a structural OTC model, I am able to show for the first time in the literature that trading delays have increased since the financial crisis and it now takes more than a week or two to fully execute corporate bond trades.

[9] Adrian, Boyarchenko, and Shachar (2017) rely on regulatory data and detailed dealer-level information to show the decline in liquidity after the financial crisis. Chernenko and Sunderam (2020) use mutual fund data and show that the liquidity perceived by the funds has declined, particularly for speculative bonds. Hendershott et al. (2020) use proprietary auction data that accounts for the failed attempts to trade to measure the true cost of immediacy. By contrast, my study only requires publicly available data.

2 Data

I use the Bond Returns database readily available from Wharton Research Data Services (WRDS) for my study. It is a cleaned version of the TRACE database merged with the Mergent Fixed Income Securities Database (FISD) by WRDS. The data are easily accessible and compiled on a monthly basis. The database also contains monthly returns and bid-ask spreads. I focus on senior corporate debentures in the United States that have not defaulted and have a principal amount equal to 1000 USD. Table A1 of Appendix A.1 provides the step-by-step data filtering and cleaning procedures. I compute additional microstructure statistics from the Enhanced TRACE database and merge those statistics with the WRDS Bond Returns database.[10]

The sample period is from January 2004 to in September 2019. Following Bao, O'Hara, and Zhou (2018) and Choi and Huh (2019), I divide the sample period into six subperiods to study the impact of the financial crisis and regulations: the pre-crisis period (January 2004 - June 2007), the crisis period (July 2007 - April 2009), the post-crisis period (May 2009 - May 2012), the Basel II.5 period (June 2012 - June 2013), the Basel III period (July 2013 - March 2014), and the post-Volcker period (April 2014 - September 2019).[11]

Table 1 provides the summary statistics. For each subperiod, I report the (sub)sample mean and median (in parentheses). The average credit rating of each subperiod is around BBB. Bid-ask spreads and yield-to-maturity increase sharply during the financial crisis period. While the average bid-ask spread keeps declining after the crisis, the yield-to-maturity has increased slightly since mid-2013. Bond prices, on the other hand, dropped substantially during the financial crisis before recovering after the crisis. Similarly, bond returns are cut by half on average during the financial crisis before making a fivefold rebound during the post-crisis period.

[Table 1]

[10]Following Bai, Bali, and Wen (2019), I require each bond to be present in the sample for at least 24 months to avoid infrequently traded bonds. Following Dick-Nielsen, Feldhütter, and Lando (2012), all variables are winsorized at 0.5%. All the thresholds are standard in the literature. The results are robust to alternative thresholds.

[11]Appendix A.2 provides a summary of the post-crisis regulations.

2.1 Empirical Methodology

I use the methodology established in Dick-Nielsen, Feldhütter, and Lando (2012) to calculate the liquidity component of the corporate bond yield spread. For each month, I run the following cross-sectional regression:

$$\begin{aligned} \textit{Yield-Spread}_{it} = \beta_{0t} + \lambda_t \textit{Bid-Ask-Spread}_{it} + \beta_{1t} \textit{Bond-Age}_{it} + \beta_{2t} \log(\textit{Amount-Issued}_{it}) \\ + \beta_{3t} \textit{Coupon}_{it} + \beta_{4t} \textit{Time-to-Maturity}_{it} + \beta_{5t} \textit{Rating-Dummy}_{it} + \epsilon_{it}. \end{aligned} \tag{1}$$

The dependent variable, *Yield-Spread*, is the monthly corporate bond yield spread to the Treasury yield of equivalent maturity. I include bond age, offering amount, coupon, time to maturity, and bond rating dummies to control for bond characteristics and credit risk. The same specification has been used extensively by Friewald, Jankowitsch, and Subrahmanyam (2012), Schwert (2017), and many others. In Appendix A.4, I also consider alternative cross-sectional regression specifications using firm-level accounting variables to control for credit risk.

The cross-sectional regression coefficient of transaction costs, λ_t, measures how much the yield spread will change given the per unit change in corporate bond transaction costs. I use the bid-ask spread measure in the WRDS Bond Returns database as my measure of corporate bond transaction costs, which is calculated as follows. First, at daily level, proportional bid-ask spreads are calculated as the difference between the volume-weighted dealer-sell and dealer-buy trade prices, divided by the volume-weighted average of these trade prices. Second, the monthly bid-ask spreads are taken as the simple average of the daily bid-ask spreads of that month. This measure of bid-ask spreads is also employed by Hong and Warga (2000) and many others. There are alternative measures of bid-ask spreads and corporate bond transaction costs in general. Schestag, Schuster, and Uhrig-Homburg (2016) show that all high-frequency corporate bond transaction costs are over 90% correlated in time series and cross-sectionally. So how bid-ask spreads or general corporate bond transaction costs are calculated in the transaction-level data is not likely to be a concern.[12] In Appendix A.5, I also use alternative corporate bond transaction cost measures as robustness checks.

[12] The fact that the bid-ask spread is not a good indicator of corporate bond liquidity in the *time series* does not mean that bid-ask spread is not a good measure of the corporate bond transaction costs. *Cross-sectionally*, a higher bid-ask spread is associated with a liquidity premium. See Subsection 4.1 for a theoretical justification of using transaction costs such as the bid-ask spread to extract the liquidity premium of corporate bonds.

3 Increasing Corporate Bond Liquidity Premium

Figure 1 (page 2) presents one of my major findings. In the left panel, I plot the median bid-ask spread for each month. In the right panel, I plot the cross-sectional transaction cost coefficient λ from the cross-sectional regression (1). The figure shows that while the aggregate bid-ask spread has generally been declining since the financial crisis, cross-sectional variation in the corporate bond yield spread has become more and more sensitive to the cross-sectional variation in the corporate bond bid-ask spread. Excluding the financial crisis period, the figure shows that the cross-sectional regression coefficient of transaction costs has increased since the financial crisis and is higher than the pre-crisis level as of September 2019. To see whether this increasing λ holds for all types of bonds, I split the sample into investment grade bonds (credit rating BBB- and above) and speculative bonds (credit rating below BBB-). In Figure 3, I plot the cross-sectional transaction cost coefficient λ for each subsample. For both investment grade and speculative bonds, the cross-sectional transaction cost coefficient λ has increased and remained larger than the pre-crisis level. For investment grade bonds, their post-2016 λ is nearly twice (0.4) as large as the pre-crisis level (0.2). The pattern is particularly striking for speculative bonds. Their λ has been steadily increasing, even reaching more than twice as large as the financial crisis level (3 vs. 1.5).

[Figure 3]

3.1 Variations in λ

To study the time series variations in the cross-sectional transaction cost coefficient λ more closely, I split the sample into three rating groups: A- and above-rated bonds, BBB-rated bonds, and speculative bonds. Within each group, I run the cross-sectional regression (1) and compute the time series average of λ_t in each subperiod using the following regression:

$$\begin{aligned}\lambda_t = {} & \lambda_{\text{Pre-Crisis}} \mathbb{1}_{\{t \in \text{Pre-Crisis}\}} + \lambda_{\text{Crisis}} \mathbb{1}_{\{t \in \text{Crisis}\}} + \lambda_{\text{Post-Crisis}} \mathbb{1}_{\{t \in \text{Post-Crisis}\}} \\ & + \lambda_{\text{Basel II.5}} \mathbb{1}_{\{t \in \text{Basel II.5}\}} + \lambda_{\text{Basel III}} \mathbb{1}_{\{t \in \text{Basel III}\}} + \lambda_{\text{Post-Volcker}} \mathbb{1}_{\{t \in \text{Post-Volcker}\}} + \epsilon_t.\end{aligned} \tag{2}$$

I follow Fama and MacBeth (1973) and report Newey and West (1987) standard errors with four lags. I also test the differences between the average λ of the different subperiods to understand how λ varies across different regulatory regimes.

[Table 2]

Table 2 shows that the average λ is significantly positive at the 1% level for all rating groups and for all subperiods. The differences in the average λ between the pre-crisis and the crisis periods are significant. The increase is most noticeable for A- and above-rated bonds, as their average λ nearly quintuples (from 0.110 to 0.505) during the crisis period, while it only doubles at best for BBB-rated and speculative bonds. After the financial crisis, different regulatory regimes all have non-trivial impacts on the cross-sectional transaction cost coefficient λ. The λs of BBB-rated and speculative bonds increase significantly during the Basel II.5 period. Compared to the previous post-crisis level, the average λ of the Basel II.5 period increases by over 25% for BBB-rated bonds (from 0.405 to 0.553) and by more than 100% for speculative bonds (from 0.981 to 2.021). On the other hand, the cross-sectional transaction cost coefficient λ of the investment grade corporate bonds decreases during the Basel III period compared to the previous Basel II.5 level. For A- and above-rated bonds, the average λ decreases by over 40% (from 0.365 to 0.206). For BBB-rated bonds, it decreases by nearly 20% (from 0.553 to 0.453). Finally, the Volcker Rule appears to have mainly affected the cross-sectional transaction cost coefficient of the speculative bonds. Compared to the previous Basel III level, the average λ during the post-Volcker period increases by over 30% (from 1.989 to 2.665) for speculative bonds, while the differences in the average λ are not significant for investment grade bonds. One thing is for sure however. Compared to the pre-crisis level, the average post-Volcker λ is significantly higher for all rating groups. The increase is modest for A- and above-rated bonds, while the increase is more than four times for speculative bonds (0.645 vs. 2.665).[13] Even compared to the financial crisis level, the average λ of the speculative bonds has more than doubled (from 1.155 to 2.665) following Basel II.5 and the Volcker Rule.

I conduct a few robustness checks to examine more closely the increasing cross-sectional transaction cost coefficient λ and its variations across the different post-crisis regulatory episodes. To control for changes in the market conditions, following Bessembinder et al. (2018) I add controls for the market-wide stock (S&P 500 Index) and bond (Barclays Capital U.S. Corporate

[13] The spikes at the end of 2015 might be attributed to the Federal Reserve hiking the interest rate, the U.S. gas and oil industry defaults, or the Chinese stock market crash (Goldberg and Nozawa 2021). However, the spikes are temporary and do not appear to affect my analysis of the average trends.

Bond Index) returns, the changes in the stock market volatility index (VIX) and the three-month LIBOR in the time series regression (2). I also add the changes in the aggregate outstanding amount and the aggregate corporate bond mutual bond flows to account for the growth in the market size and transaction demand throughout the sample. Appendix Table A2 in Appendix A.3 presents the results. To address the concerns about rating inflations after the financial crisis, I follow Blume, Lim, and Mackinlay (1998) and use firm-level accounting variables (3-month equity volatility, operating income, leverage, long-term debt, and pretax interest coverage) instead of rating dummies to control for credit risk. I also use the 5-year probability of default to control for credit risk.[14] Appendix Tables A3 and A4 present the regression results. Finally, instead of using the bid-ask spread in the WRDS Bond Returns database in the cross-sectional regression (1), I use the absolute bid-ask difference, as well as the equally-weighted average of the standardized bid-ask spread, the Roll measure (Roll 1984, Bao, Pan, and Wang 2011), and the Amihud (2002) measure, which is essentially the first principal component (PC1) of some of the widely-used transaction cost and trading activity variables in the literature (e.g., Dick-Nielsen, Feldhütter, and Lando 2012, Friewald, Jankowitsch, and Subrahmanyam 2012, Schwert 2017).[15] Figure 4 shows that the increasing trend of λ is not affected if I use alternative measures of corporate bond transaction costs. The regression results are shown in Appendix Tables A5 and A8.

[Figure 4]

In all cases, cross-sectional variation in the yield spread has become more and more sensitive to the cross-sectional variation in the corporate bond transaction costs after the financial crisis, regardless of how the credit risk is controlled for or which corporate bond transaction cost measure is used. Moreover, in all robustness checks, post-crisis regulations have non-trivial impacts on the cross-sectional transaction cost coefficient λ. While the λ of BBB-rated and speculative bonds increased during the Basel II.5 episode, the λ of investment grade bonds declined following Basel III, and the

[14]The results are similar if I use the Altman (1968) Z-score, the Merton (1974) distance-to-default, or the firm fixed effect to control for credit risk. The absolute magnitude of λ might depend on credit risk controls. However, the increasing trend of λ is robust.

[15]In addition to the first principal component (PC1), I also add the equally-weighted average of the standardized turnover and trade size in the cross-sectional regression (1). This is essentially the second principal component (PC2) of some of the widely-used transaction cost and trading activity variables. These trading activity variables have been declining since the financial crisis. However, Adrian et al. (2017) notice that the declining turnover comes with the increasing debt issues and therefore it is not clear whether the decline in turnover means a decline in liquidity.

Volcker Rule increased the cross-sectional transaction cost coefficient of the speculative bonds.

The increasing λ could suggest an increase in price of liquidity. Alternatively, the increasing λ could be due to an unobserved increase in the corporate bond illiquidity level, which has not been captured by the transaction cost measures computed from the TRACE data where only the realized transactions are recorded. Dealers may reject large orders and so customers have to wait longer for their trades to be fully executed. In fact, in Subsection 4.2 I show that the increasing λ actually represents an increase in the illiquidity level in terms of longer trading delays. Regardless of the sources of the increasing λ, it is important to see whether the liquidity premium (=price of liquidity $\times$ illiquidity level=$\lambda \times$ transaction cost) has also increased.

3.2 Size of Liquidity Premium

I define the liquidity premium of each bond as the yield spread component that compensates for illiquidity: $\lambda_t \times \textit{Bid-Ask-Spread}_{it}$. In Figure 2 (page 3), I plot the median liquidity premium (as a fraction of the total yield spread) of the investment grade and speculative corporate bonds for each month. The figure shows that prior to the financial crisis, the liquidity premium is around 5%-10% of the investment grade bond yield spread and around 10%-15% of the speculative bond yield spread. During the financial crisis, liquidity can explain nearly 25% of the investment grade bond yield spread. Consistent with Dick-Nielsen, Feldhütter, and Lando (2012), the liquidity premium of the investment grade bonds spiked and persisted until after the financial crisis in 2010. On the other hand, even if the average λ of the speculative bonds increased by nearly 100% during the financial crisis, the overall liquidity premium as a fraction of the speculative bond yield spread remained steady during the crisis, perhaps due to the disproportional increase in the speculative yield spread relative to the bid-ask spread as there was substantial credit deterioration in this segment of the market during the crisis. After the crisis however, while the liquidity premium of the investment grade bonds is generally declining, the liquidity premium of the speculative bonds steadily increases and makes up about 30% of the total yield spread in the post-crisis period.

[Table 3]

To quantify the liquidity premium as a fraction of the yield spread, I perform a pooled regression of $\lambda_t \times$ *Bid-Ask-Spread*$_{it}$/ *Yield-Spread*$_{it}$ for each rating class and subperiod, and test their differences between different subperiods. I follow Driscoll and Kraay (1998) and report standard errors with five lags to account for heteroskedasticity and temporal autocorrelations. The results in Table 3 are consistent with Figure 2. The average liquidity premium (as a fraction of the yield spread) of A- and above-rated bonds increased substantially by over 14 percentage points during the financial crisis, while the liquidity premium of the speculative bonds remained at 15% of the total yield spread during the pre-crisis and the crisis periods. After the financial crisis, there are nontrivial variations in the liquidity premium (as a fraction of the yield spread) in each regulatory regime as before. The average liquidity component of the yield spread of the BBB-rated and speculative bonds increased following Basel II.5. The increase is most noticeable for speculative bonds as their liquidity premium (as a fraction of the yield spread) doubled by over 14 percentage points compared to the post-crisis level. The average liquidity component of the yield spread of the investment grade bonds decreased following Basel III. For BBB-rated bonds, their liquidity premium (as a fraction of the yield spread) decreased by nearly 3 percentage points while for A- and above-rated bonds, the decrease is more than 8 percentage points following Basel III. Finally, the Volcker Rule increased the average liquidity component of the speculative bond yield spread by almost 5 percentage points, at the 10% significance level. Compared to the pre-crisis level, the liquidity premium (as a fraction of the yield spread) has increased for all bonds rated below A.[16] For speculative bonds, over 30% of their yield spread is now compensation for illiquidity.

[Table 4]

Finally, Table 4 reports the pooled averages of the absolute liquidity premium: $\lambda_t \times$ *Bid-Ask-Spread*$_{it}$, as well as the default premium, defined as the rest of the yield spread: *Default Premium*$_{it}$ = *Yield-Spread*$_{it}$ $- \lambda_t \times$ *Bid-Ask-Spread*$_{it}$. I compare the post-Volcker and the pre-crisis levels to see how the liquidity and default premia have evolved. The results show that the financial crisis increased both components of the yield spread and the impact is larger for bonds with poorer ratings, consistent with findings in Friewald, Jankowitsch, and Subrahmanyam (2012). After the financial crisis, the absolute liquidity premium for A- and above-rated bonds

[16]See Footnote 34 for a potential explanation for why the λ of A-rated bonds has increased while their liquidity premium remained at the pre-crisis level.

reverted to the pre-crisis level at around 6-7 basis points. For BBB-rated and speculative bonds, on the other hand, the absolute liquidity premium is now significantly larger than their pre-crisis level and for speculative bonds, the absolute liquidity premium is now more than 140 basis points. Notice that the change in the speculative bond default premium is negligible between the post-Volcker and the pre-crisis periods. Therefore, the entire increase in the speculative bond yield spread from 2004 to 2019 is likely due to illiquidity. On the other hand, the average default premium of investment grade bonds increased by more than 15 basis points from 2004 to 2019. This evidence supports the anecdotal claims of rating inflations in recent years that has made investment grade bonds, especially the BBB-rated ones, riskier than before.[17]

These results suggest that corporate bond liquidity premia, both in terms of the fraction of the yield spread and the absolute size, are now on average significantly higher than the pre-crisis level for BBB-rated and speculative bonds. Investors now require higher illiquidity compensation for holding these bonds. While the actual transaction cost to trade corporate bonds might be low after the financial crisis, the cost of borrowing that is due to illiquidity has increased for firms with ratings below A. For firms with speculative ratings, more than 30% of their cost of borrowing is now paying for liquidity.[18]

4 Low Transaction Cost vs. High Liquidity Premium: A Model

The decline in the bid-ask spread does not contradict that the liquidity premium has increased since the financial crisis. In this section, I present a structural OTC model based on the framework developed in Lagos and Rocheteau (2009) to reconcile these two seemingly contradictory patterns. In the model, customers can execute trades both with dealers who provide immediacy by charging a positive bid-ask spread, and with each other via the customer-broker service that charges zero spreads and simply passes prices from buyers to sellers. This is a natural modeling assumption. Ederington, Guan, and Yadav (2014), Schultz (2017), and Choi and Huh (2019) highlight the dual capacity of corporate bond dealers: as market makers who use inventory to provide liquidity and

[17]Edward Altman finds that many BBB-rated corporate bonds have the potential to move to speculative junk status. Source: https://fortune.com/2020/01/27/investors-near-junk-corporate-bonds-bbb/.

[18]Relatedly, Goldstein, Hotchkiss, and Pedersen (2019) find that secondary market trading activities affect the corporate bond yield spread at issuance.

immediacy to investors, and as broker agents who merely match the market participants without taking the bonds into their inventory. Furthermore, these authors find that the spread charged by brokers is lower than the spread charged by dealers who use inventory to provide immediacy.

To be specific, in the model time is continuous with discount rate r and there is a bond with fixed supply of A. There are customers with a total measure of 1 and dealers with measure v, which is a function of the dealer flow cost k. So the dealer cost directly affects the amount of dealership in the economy, that is, the amount of immediacy that dealers are ready to provide. Customer i with bond holding a has a linear utility function $c_i a$ with $c_L < c_H$.[19] So a customer of high type H enjoys a higher periodic cashflow from holding the bond than a customer of low type L. There is a liquidity shock that happens at the Poisson rate of δ. Conditional on the shock, customer H switches to the low type L with probability π_L or remains at the high type H with probability $\pi_H = 1 - \pi_L$. In addition, the bond matures at the Poisson rate of λ_T, upon which customer i collects the value F_i per unit of his bond holdings.[20] Similarly, the bond defaults at the Poisson rate of λ_D.[21] The matured and defaulted bonds are immediately reissued so the amount-outstanding of the bond is fixed at A.

In the setting, there is a competitive asset market. Customers can trade in the asset market by contacting dealers at the Poisson rate of $\alpha(v)$.[22] Upon contact, customers and dealers will negotiate trade quantities and an intermediation fee ϕ. Alternatively, customers can access the competitive asset market via the broker services that simply match customers directly at the Poisson rate β.

[19] In Appendix A.6, I consider this linear utility as the limiting case of $\frac{a^{1-\gamma}}{1-\gamma}$ when $\gamma \to 0$.

[20] As in $c_L < c_H$, we also have $F_L < F_H$. One can think of c_H as the coupon of the bond, and F_H as the face value. Duffie, Gârleanu, and Pedersen (2005) suggest that the difference between the H and L type customers' valuations of the asset may stem from liquidity or hedging reasons.

[21] Customer i can also be allowed to get the "recovered" value $(1-f)F_i$ per unit of bond holdings when the bond defaults, where $1-f$ is the recovery rate. However, this addition does not change my theoretical analysis nor the structural estimation. I therefore just assume the zero recovery rate: $1-f=0$.

[22] I follow the literature and assume that $\alpha(\cdot)$ is continuous differentiable with $\alpha(v)$ strictly increasing and $\alpha(v)/v$ decreasing in v, and $\alpha(0)=0$, $\alpha(\infty)=\infty$ and $\alpha(\infty)/\infty = 0$. For instance, $\alpha(v) = \alpha v^{\theta}$ where $0 < \theta \leq 1$.

Brokers do not charge intermediation fees.[23]

Consider a stationary equilibrium with asset price p in the competitive asset market. The value function of customer $i \in \{H, L\}$ with asset holding a satisfies the following Hamilton-Jacobi-Bellman (HJB) equation:

$$\begin{aligned} rV_i(a) = c_i a + \delta\pi_j\big(V_j(a) - V_i(a)\big) + \lambda_T\big(V_i(0) + F_i a - V_i(a)\big) + \lambda_D\big(V_i(0) - V_i(a)\big) \\ + \alpha(v)\big(V_i(a_i) - V_i(a) - p(a_i - a) - \phi_i(a)\big) + \beta\big(V_i(a_i) - V_i(a) - p(a_i - a)\big), \end{aligned} \tag{3}$$

where $j \neq i$. The value function is intuitive. For customer of type i, he enjoys the periodic cashflow $c_i a$ from his bond holdings each time until a liquidity shock arrives at rate $\delta\pi_j$, in which case he becomes a customer of type j. The bond matures (defaults) at the rate λ_T (λ_D), upon which his asset holdings are destroyed. When the bond matures, customer i is able to collect the terminal cashflow $F_i a$ from his bond holdings. Finally, customer i contacts a dealer at rate $\alpha(v)$, upon which he trades $a_i - a$ at price p to achieve his optimal asset holding a_i, and pays an intermediation fee $\phi_i(a)$. Alternatively, customer i can trade $a_i - a$ in the competitive market via the broker service without paying any intermediation fee at rate β. Trades with dealers are determined by Nash bargaining: $(a_i, \phi_i) = \text{argmax}\big[V_i(a_i) - V_i(a) - p(a_i - a) - \phi_i\big]^{(1-\eta)}\phi_i^{\eta}$, where η is the dealer's bargaining power. Finally, the market clears: $\sum_{i,j} n_{ij} a_i = A$, where n_{ij} denotes the measure of customers with asset holding a_i and preference type j.

Following the calculations in Appendix A.6, I show that the bond price satisfies:

$$p = \frac{1}{r + \lambda_T + \lambda_D}\left\{\frac{\big(r + \lambda_T + \lambda_D + \sigma(v)\big)\epsilon_H + \delta\bar{\epsilon}}{r + \lambda_T + \lambda_D + \sigma(v) + \delta}\right\}, \tag{4}$$

where $\epsilon_i = c_i + \lambda_T F_i$, $\bar{\epsilon} = \pi_L\epsilon_L + \pi_H\epsilon_H$ and $\sigma(v) = \alpha(v)(1 - \eta) + \beta$. Thus, as the trading friction vanishes: $\sigma(v) \to \infty$, $p \to \frac{\epsilon_H}{r+\lambda_T+\lambda_D}$, the discounted promised cashflow of the bond. The yield-to-

[23] In Duffie, Gârleanu, and Pedersen (2005), dealers do not hold inventory, and customers can trade with each other directly. I alter their interpretations that in the former case dealers are indeed providing immediacy while in the latter case of direct customer-customer trades, customers are actually paired up by the broker service to be able to trade with each other. This interpretation fits more naturally the corporate bond market. The competitive asset market can be seen as the active interdealer market, which allows all dealers to unwind their inventory positions and end up with the even position of zero. However, even if dealers end up holding zero positions, they still incur a flow cost k, which can be readily seen as the dealer inventory cost because it directly affects the amount of immediacy that dealers are ready to provide. Similarly, customer-customer trading can be viewed as customers being paired up by brokers in between that simply pass the price from buyers to sellers without charging an intermediation fee or bid-ask spread.

maturity of the bond, y, equates the present value of the bond's promised cashflow to its price: $p = \mathbb{E}\big[\int_0^T e^{-yt} c_H dt + e^{-yT} F_H\big]$, where the expectation $\mathbb{E}$ is with respect to the random maturity date T, which is exponentially distributed with parameter λ_T:

$$y - r = \underbrace{\frac{\delta \pi_L (\epsilon_H - \epsilon_L)(r + \lambda_T + \lambda_D)}{\big(r + \lambda_T + \lambda_D + \sigma(v)\big)\epsilon_H + \delta\bar{\epsilon}}}_{LP} + \lambda_D.$$

The credit yield spread $y - r$ therefore can be decomposed into two components: the default premium λ_D and the liquidity premium:[24]

$$LP = \frac{\delta \pi_L (\epsilon_H - \epsilon_L)(r + \lambda_T + \lambda_D)}{\big(r + \lambda_T + \lambda_D + \sigma(v)\big)\epsilon_H + \delta\bar{\epsilon}}. \tag{5}$$

Notice that as the trading friction vanishes, $\sigma(v) \to \infty$, $LP \to 0$ and the credit yield spread becomes solely a compensation for the default intensity.

Finally, dealers collect intermediation fees but incur a flow cost k. The intermediation fees satisfy $\phi_L(0) = \phi_H(0) = \phi_H(a_L) = 0$, and $\phi_L(a_H) = \frac{\eta(\epsilon_H - \epsilon_L)}{r + \lambda_T + \lambda_D + \sigma(v) + \delta} a_H$. So the ask price is $P_a = p$ and the bid price is $P_b = p - \frac{\eta(\epsilon_H - \epsilon_L)}{r + \lambda_T + \lambda_D + \sigma(v) + \delta}$. The dealer's bid-ask spread is therefore just $P_a - P_b = \frac{\eta(\epsilon_H - \epsilon_L)}{r + \lambda_T + \lambda_D + \delta + \sigma(v)}$, or as a proportion of the asset price: $\frac{P_a - P_b}{p} = \frac{\eta(\epsilon_H - \epsilon_L)(r + \lambda_T + \lambda_D)}{(r + \lambda_T + \lambda_D + \sigma(v))\epsilon_H + \delta\bar{\epsilon}}$. The free-entry of dealers suggests that dealer's profit must be zero: $\frac{\alpha(v)}{v} \sum_{i,j} \phi_i(a_j) n_{ji} - k = 0$, which simplifies to:

$$\frac{\alpha(v)}{v} \frac{\eta A \delta \pi_L (\epsilon_H - \epsilon_L)}{(r + \lambda_T + \lambda_D + \alpha(v)(1 - \eta) + \beta + \delta)(\alpha(v) + \beta + \lambda_T + \lambda_D + \delta)} = k. \tag{6}$$

Assume that $\alpha(v)$ is strictly increasing and $\alpha(v)/v$ strictly decreasing in v. The left-hand side of the above equation is thus strictly decreasing in v. Therefore when the dealer's cost k goes up, dealers will provide less liquidity ($\frac{\partial v}{\partial k} < 0$) and so customers will contact dealers less frequently at the rate $\alpha(v)$.[25] As a consequence, the fraction of the brokered trades, $\frac{\beta}{\alpha(v) + \beta}$, will go up, and

[24] The absolute illiquidity discount, defined as the difference between the frictionless price and the traded price, is: $\Delta P = \frac{\epsilon_H}{r + \lambda_T + \lambda_D} - p = \frac{1}{r + \lambda_T + \lambda_D} \frac{\delta(\epsilon_H - \epsilon_L)}{r + \lambda_T + \lambda_D + \sigma(v) + \delta}$. Therefore, we have $\frac{\Delta P}{p} = \frac{1}{r + \lambda_T + \lambda_D} LP$, where $\frac{1}{r + \lambda_T + \lambda_D}$ is the duration of the bond.

[25] One should interpret the lower $\alpha(v)$ as dealers' reduction of liquidity supply. A lower trading frequency with dealers is isomorphic to a shrinking market making capacity of dealers in the model: whether to trade 3 trillions of bond altogether on the third day or to trade only 1 trillion every day for 3 days are identical in an economic sense as both represent a trading delay of 3 days.

customers will experience longer trading delays, $\frac{1}{\alpha(v)+\beta}$, as the dealer's cost increases. The bid-ask spread charged by the dealers, also known as the cost of immediacy, $\frac{P_a-P_b}{p} = \frac{\eta(\epsilon_H-\epsilon_L)(r+\lambda_T+\lambda_D)}{(r+\lambda_T+\lambda_D+\sigma(v))\epsilon_H+\delta\bar{\epsilon}}$, will rise as the dealer's cost increases. However, the cost of immediacy is not easily measurable by econometricians as it is hard to distinguish who conducts the trades. The empirically feasible average bid-ask spread, observed by econometricians, therefore is:

$$\frac{BA}{p} = \frac{1}{p}\Big\{\frac{\alpha(v)}{\alpha(v)+\beta}(P_a-P_b)+\frac{\beta}{\alpha(v)+\beta}(p-p)\Big\} = \Big\{\frac{\alpha(v)}{\alpha(v)+\beta}\Big\}\Big\{\frac{\eta(\epsilon_H-\epsilon_L)(r+\lambda_T+\lambda_D)}{\big(r+\lambda_T+\lambda_D+\sigma(v)\big)\epsilon_H+\delta\bar{\epsilon}}\Big\}. \tag{7}$$

Since the fraction of dealer trades $\frac{\alpha(v)}{\alpha(v)+\beta}$ decreases as the dealer's cost goes up, the observable bid-ask spread (either as the absolute difference or as a proportion of the asset price) may not increase or even decrease. However even if the average bid-ask spread may be low, the liquidity component of the credit yield spread, or the liquidity premium, is higher, because customers now experience longer trading delays than before. Indeed, equation (5) suggests that the liquidity premium indisputably increases as the dealer's cost goes up:

$$\frac{\partial LP}{\partial k} = \frac{\partial LP}{\partial v}\frac{\partial v}{\partial k} > 0. \tag{8}$$

In Proposition 1, I summarize the time series patterns of the model statistics when the dealer's cost goes up.

PROPOSITION 1. *All else equal, when the dealer's cost k goes up, dealers will provide less immediacy as $\alpha(v)$ declines. Therefore:*
1) the fraction of the brokered trades, $\frac{\beta}{\alpha(v)+\beta}$, and the trading delay, $\frac{1}{\alpha(v)+\beta}$, will increase;
2) the average bid-ask spread, $\Big\{\frac{\alpha(v)}{\alpha(v)+\beta}\Big\}\frac{\eta(\epsilon_H-\epsilon_L)(r+\lambda_T+\lambda_D)}{\big(r+\lambda_T+\lambda_D+\alpha(v)(1-\eta)+\beta\big)\epsilon_H+\delta\bar{\epsilon}}$, may not increase;
3) the liquidity premium, $LP = \frac{\delta\pi_L(\epsilon_H-\epsilon_L)(r+\lambda_T+\lambda_D)}{\big(r+\lambda_T+\lambda_D+\alpha(v)(1-\eta)+\beta\big)\epsilon_H+\delta\bar{\epsilon}}$, and the liquidity premium as a fraction of the total credit yield spread, $\frac{LP}{LP+\lambda_D}$, will increase.

Figure 5 shows the model generated statistics as a function of the dealer's cost. As the dealer's cost increases, dealership will become more costly and dealers will execute less trades. This is consistent with empirical studies that suggest more trades are being brokered after the financial crisis (Schultz 2017, Choi and Huh 2019, Goldstein and Hotchkiss 2020). The cost of immediacy or the bid-ask spread charged by dealers (dashed blue line) increases as the dealer's cost goes up. However, this happens less frequently because more trades are being brokered than being processed by dealers. This is why many previous studies relied on natural experiments during stressful times when customers do request for immediacy to be able to measure the cost of immediacy. On the other hand, the observable average bid-ask spread (solid red line) can decrease as more trades are just brokered with zero bid-ask spreads. However, a low average bid-ask spread does not mean that the liquidity premium is low. On the contrary, the decline in immediacy provision by dealers means that the liquidity premium, both in terms of the absolute size and in terms of a fraction of the total credit yield spread, can actually be higher because customers have to wait longer for trades to be fully executed.

[Figure 5]

4.1 Cross-sectional Regression Coefficient of Transaction Cost

To give a theoretical foundation for the cross-sectional regression (1), I introduce bond heterogeneity to the model. Suppose there are $m = 1, 2, ..., M$ assets, which differ in their cashflows ϵ_i^m, default intensities λ_D^m, maturity intensities λ_T^m, as well as the corresponding riskless yield r^m. From equation (5), the liquidity premium of bond m is: $LP^m = \frac{\delta\pi_L(\epsilon_H^m - \epsilon_L^m)(r^m+\lambda_T^m+\lambda_D^m)}{\left(r^m+\lambda_T^m+\lambda_D^m+\sigma(v)\right)\epsilon_H^m+\delta\bar{\epsilon}^m}$. From equation (7), the observable average bid-ask spread (as a proportion of the price) of bond m is: $\frac{BA^m}{p^m} = \left(\frac{\alpha(v)}{\alpha(v)+\beta}\right)\frac{\eta(\epsilon_H^m - \epsilon_L^m)(r^m+\lambda_T^m+\lambda_D^m)}{\left(r^m+\lambda_T^m+\lambda_D^m+\sigma(v)\right)\epsilon_H^m+\delta\bar{\epsilon}^m}$. Therefore, I can write the liquidity premium as a linear function of the bid-ask spread: $LP^m = \lambda\frac{BA^m}{p^m}$, or in terms of the total credit spread:

$$y^m - r^m = \lambda\frac{BA^m}{p^m} + \lambda_D^m, \tag{9}$$

where the cross-sectional transaction cost coefficient λ is independent of bond heterogeneity m:

$$\lambda = \frac{\delta\pi_L}{\eta}\left\{1 + \frac{\beta}{\alpha(v)}\right\}. \tag{10}$$

Doing so I exactly map the cross-sectional regression (1) into my model: after controlling for credit risk λ_D^m, the cross-sectional regression of the credit yield spread $y^m - r^m$ on the bid-ask spread $\frac{BA^m}{p^m}$ will result in a positive λ that increases over time as the dealer's cost goes up ($\frac{\partial \lambda}{\partial k} = \frac{\partial \lambda}{\partial v}\frac{\partial v}{\partial k} > 0$). Figure 6 presents this cross-sectional relationship between the model generated liquidity premium and the bid-ask spread. The slope coefficient (λ) increases as the dealer's cost rises.

[Figure 6]

Moreover, the result suggests that illiquidity (in terms of liquidity premium), can be interpreted a product of transaction-cost × trading delay:

$$LP^m = \frac{BA^m}{p^m} \times \lambda : \textit{Transaction-Cost} \times \textit{Delay}. \tag{11}$$

The increasing cross-sectional transaction cost coefficient λ found previously in Figure 1 therefore essentially represents the latent increasing trading delays.[26]

4.2 Estimation of Trading Delays

Trading delays are not generally observable in the transaction-level TRACE data. However, if investors experience longer trading delays, they should require a higher compensation for holding the illiquid corporate bonds. The intrinsic link between the trading delay and the liquidity premium allows me to estimate the trading delays implied by the size of the corporate bond liquidity premium using my structural model. Specifically, let LP_t^m denote the liquidity premium of bond m at time t calculated from the data using the cross-sectional regression (1).[27] Let $\widehat{LP^m}_t$ be the corresponding model-implied liquidity premium from equation (5) by substituting in the corresponding cashflow ϵ_{Ht}^m, default intensity λ_{Dt}^m, maturity intensity λ_{Tt}^m, and riskless yield r_t^m of bond m in month t. I

[26] To be more precise, $(1 + \frac{\beta}{\alpha(v)})$ is an increasing function in trading delays as they both increase in the dealer's cost k. In the absence of credit risk, the yield spread just compensates for illiquidity (*Transaction-Cost*×*Delay*). Since trading delay is not observable, one can only regress yield spreads on transaction costs: *Yield-Spread*=β× (*Transaction-Cost*×*Delay*)=λ×*Transaction-Cost*. Therefore, λ increases if trading delay increases: $\lambda = \beta \times$*Delay*. *Transaction-Cost*×*Delay* can be interpreted as the total transaction costs as market participants are likely to split large trades into smaller pieces over the longer delay horizons as dealers' capacity shrinks instead of waiting idly.

[27] I here add accounting variables in the baseline regression (1). The estimation result is the same regardless of whether I use the absolute liquidity premium LP, or liquidity premium as a fraction of the total yield spread $\frac{LP}{LP+\lambda_D}$.

estimate the search intensity $\alpha(\cdot)$ and β every month by minimizing the following objective function:

$$\min_{\alpha_t,\beta_t} \sum_m \left[LP_t^m - \widehat{LP^m}_t\right]^2. \tag{12}$$

To separately identify α and β, I restrict $\frac{\beta}{\alpha+\beta}$ to match the average fraction of the brokered trades each month in the data.[28] In Appendix Table A9, I summarize the fraction of the total dealer-customer trade volumes that are immediately matched within one minute, which is a proxy of the brokered trades used widely in the literature such as Choi and Huh (2019). I rely on Feldhütter (2012) for the calibration of the remaining parameters: $\eta = 0.97$, $\delta = 3.58$, and $\pi_L = 0.33/3.58$. The author suggests that it is rare for corporate bond customers to be hit by a liquidity shock and become L type investors; it occurs on average once every three years. Once I estimate the search intensities α_t and β_t of month t, I can then compute the trading delay of that month as $\frac{1}{\alpha_t+\beta_t}$.[29]

Figure 7 shows the estimated trading delays, as well as the 95% confidence intervals, of executing investment grade and speculative bond trades, implied by the size of the liquidity premium. The figure shows that while the trading delays increased during the financial crisis, the impact was mostly temporary as they later quickly declined. However, there is a paradigm shift in the trading delays after the financial crisis as both the investment grade and speculative bonds subsequently require significantly longer execution time than they used to before the crisis. Moreover, the estimated trading delays closely resemble the cross-sectional transaction cost coefficient λ in Figure 3, suggesting that the increasing λ represents the increasing trading delays.

[Figure 7]

In Table 5, I summarize the estimated trading delays in each subsample. The results show that the trading delays estimated from the liquidity premium increased more than five times for BBB-rated and speculative bonds compared to the beginning of the sample period. While it used to take less than one day to sell an average BBB-rated bond before the crisis, now it takes nearly one week to be able to execute the trades. For speculative bonds, the trading delay after the financial crisis is roughly 2-3 weeks. On average, the trading delays increased the most following

[28] One can also use the parameter restriction from λ instead of the fraction of brokered trades. Appendix Table A10 shows that the estimated trading delays are robust.

[29] All parameters and the yield data are annualized. I convert trading delays into days.

the introduction of Basel II.5. The magnitude of the trading delays is within the range suggested by industry practices. According to Goldman Sachs, *"trade that historically may have taken a day to get done now needs to [...] take a week or two to execute."*[30]

[Table 5]

As a robustness check of my estimation results, I also estimate the trading delays implied by an alternative model by Longstaff (1995) that rely on different empirical inputs. In his model, security prices follow a geometric brownian motion: $dP = \mu P dt + \sigma P dW$, and investors are restricted from selling the security prior to some fixed time τ. The present value of the price discount due to the trading delay τ can be calculated in closed-form:

$$\Delta P(P,\tau) = P\big(2 + \frac{\sigma^2\tau}{2}\big)\text{Normal}\big(\frac{\sqrt{\sigma^2\tau}}{2}\big) + P\sqrt{\frac{\sigma^2\tau}{2\pi}}\exp\big(-\frac{\sigma^2\tau}{8}\big) - P, \tag{13}$$

where Normal$(\cdot)$ is the cumulative normal distribution. Notice the illiquidity discount depends on the product $\sigma^2\tau$, which again can be more generally interpreted as *Transaction-Cost* $\times$ *Delay* as in equation (11), since the volatility of asset fundamentals is closely related to the dealer bid-ask spread in the classical models of Stoll (1978) and Ho and Stoll (1981).[31] Figure A1 in Appendix A.8 shows the implied trading delays of executing investment grade and speculative bond trades, estimated from my structural model (solid blue line) and the model in Longstaff (1995) (dashed red line). The trading delays estimated from the two models are very close to each other, despite their distinct theoretical foundations and empirical inputs. The only apparent difference is perhaps during the financial crisis period, as Longstaff (1995) replies on return volatility, which overshoots during the crisis period, potentially underestimating the trading delays. After the crisis, however, the trading delays increased, regardless of which model the estimation is based on. The similarity of the estimation results demonstrates that it is really the moment of the liquidity premium that matters for trading delay estimations rather than the specific model one is using.

[30] Relatedly, Goldstein and Hotchkiss (2020) suggest that the average dealer non-overnight inventory holding period is 21 days. Notice that customers are likely to split large trades into smaller pieces over the longer delay horizons to facilitate executions as dealers' capacity shrinks. Source: `https://www.goldmansachs.com/insights/pages/macroeconomic-insights-folder/liquidy-top-of-mind/pdf.pdf`.

[31] One can estimate the trading delay τ from equation (13) by connecting the theoretical illiquidity discount (in terms of price) to the empirical liquidity premium (in terms of the yield) using a modified duration formula: $\frac{\Delta P(P,\tau)}{P} =$ Modified-Duration $\times$ $\big(\lambda \times \text{Bid-Ask}\big)$.

4.3 ETF? Electronic Trading?

The increasing presence of corporate bond exchange traded funds (ETF) and mutual funds, as well as the gradual electronification of the corporate bond market are important innovations in the corporate bond market. In the view of my model, these innovations can be summarized as a rising β. Indeed, ETFs allow investors to invest in the bond market without getting exposed to the underlying illiquidity. Electronic platforms allow customers to trade directly without employing traditional dealers. Holding dealer cost k constant and all else equal, a rising β can also generate an increasing cross-sectional transaction cost coefficient λ (equation 10), as well as a declining average bid-ask spread (equation 7). However, holding dealer cost constant, a rising β means that liquidity improves as trading delays decrease. Therefore, investors should require a *lower* liquidity premium (equation 5),[32] which is at odds with my evidence, as well as practitioners' complaints.[33] On the other hand, dealers' reduction in liquidity supply means that liquidity gets worsened, thus investors will require a *higher* premium for holding illiquid bonds. When dealers reduce their liquidity supply and customers adopt new technologies that aim to improve liquidity, the evidence of a higher liquidity premium suggests that these innovations have not fully replaced the loss of liquidity from dealers.[34] Indeed, according to PwC, *"the collective impacts of these three developments [...] is not likely, in the short- to medium term, to be sufficient to fully replace the [...] loss of market making capacity [...] from dealers."*[35] [36]

[32] From an equilibrium perspective, a higher β could affect dealer's zero profit condition. In Appendix A.7, I prove that the liquidity premium still decreases in β when it affects the free entry of dealers.

[33] Bai and Collin-Dufresne (2019) show that the CDS-bond basis has also become more negative after the financial crisis. Dannhauser and Hoseinzade (2021) show that corporate bond ETFs contribute to market fragility. However, this is an *ex post* consequence of ETF trading. *Ex ante*, ETFs increase the investment options available to investors and improve the liquidity of underlying assets. So investors should have required a *lower* liquidity premium.

[34] The rising technology and alternative trading arrangements may explain why the λ of A-rated bonds increased while their liquidity premium $LP = \lambda \frac{BA}{p}$ remained at the pre-crisis level. Indeed, the majority of corporate bond electronic trading and ETFs concentrate on the highly-rated, investment grade bonds, potentially improving the liquidity of this segment of the market. Source: https://www.ft.com/content/b08a7072-bd52-11e9-b350-db00d509634e and https://www.ft.com/content/9d6e520e-3ba8-11ea-b232-000f4477fbca

[35] Source: https://www.pwc.com/gx/en/financial-services/publications/assets/global-financial-market-liquidity-study.pdf

[36] The increasing liquidity premium does not seem to be driven by customer liquidity demand either. Appendix Table A11 shows that the customer liquidity preference intensity, δ, estimated jointly from the liquidity premium and turnover, did not increase over time.

5 Decompositions of Corporate Bond Liquidity Premium

The model suggests that the liquidity premium is primarily explained by dealers' bid-ask spread that compensates for immediacy provision and inventory costs. Thus, the explanatory power of the broker spread should be minimal. Moreover, the model successfully delivers liquidity premium without appealing to the systematic liquidity shocks. In this section, I show that the increasing liquidity premium is indeed driven by dealers' inventory costs and it compensates for the illiquidity level of individual corporate bonds.

5.1 Inventory vs. Search

The spread that dealers charge as brokers compensates for the search costs because brokers do not change their inventory positions and so do not face inventory risk. In the similar spirit of the imputed round-trip cost used in Feldhütter (2012) and the "immediate (customer) match" spread used in Green, Hollifield, and Schürhoff (2007), I take the matched customer buy and sell trades that take place within one minute and with the same quantity as the brokered trades. Randall (2015) shows that effects of dealers' inventory are much less significant on these matched brokered trades. I take the (relative) price difference of these immediately matched brokered trades as the spread that compensates for dealers' efforts to search for counterparties.[37] To arrive at the monthly spreads, I first take the volume-weighted average spread for each day and then use the equally-weighted average of all the daily spreads of that month. I also compute the spreads of the brokered trades that are immediately matched within 15 minutes.[38]

To measure the spreads that compensate for the dealers' role as market makers who use inventory to provide liquidity to investors, I follow Ederington, Guan, and Yadav (2014), Randall (2015), and Choi and Huh (2019). I first remove all the matched trades that happen within the 15 minutes,

[37]Here I take search costs *literally* as compensation for searching for counterparties. This should not be confused with the previous search model (Section 4) where the search friction should be taken as an economic language that endogenizes liquidity. Notice that even in my model (Figure 5), the underlying exogenous change is the dealer (inventory) cost and the liquidity premium varies in response.

[38]Dealers are required to report their transactions within 15 minutes. The results are essentially similar if I use the exact imputed round-trip costs in Feldhütter (2012) as the spread of the brokered trades. Since I do observe the buy/sell directions, my search spreads are closer to the "immediate match" spread in Green, Hollifield, and Schürhoff (2007), the original inspiration of the imputed round-trip costs.

and then compute the following spread measure:[39]

$$\text{CH} = 2Q \times \frac{\text{traded price} - \text{reference price}}{\text{reference price}}, \tag{14}$$

where $Q = 1(-1)$ refers to the customer's buy (sell) direction and reference price is the volume-weighted average of the interdealer price of the day. To get the monthly spread, I first calculate the spread at the bond-day level by taking the volume-weighted average of the trade-level spreads and then take the equally-weighted average of the daily spreads of the month. As a robustness check, I also use the 3-month bond return volatility as a proxy for the bid-ask spread that compensates for inventory costs. This proxy is inspired by the theoretical models of Stoll (1978) and Ho and Stoll (1981), where bid-ask spreads in the presence of inventory friction should be proportional to the volatility of the asset fundamentals.

Finally, I run the following regression to see how each type of the OTC frictions is priced in the cross-sectional yield spread:

$$\begin{aligned} \textit{Yield-Spread}_{it} = {} & \beta_{0t} + \lambda_t^{\text{Inventory}} \textit{Inventory-Spread}_{it} + \lambda_t^{\text{Search}} \textit{Search-Spread}_{it} \\ & + \beta_{1t} \textit{Bond-Age}_{it} + \beta_{2t} \log(\textit{Amount-Issued}_{it}) \\ & + \beta_{3t} \textit{Coupon}_{it} + \beta_{4t} \textit{Time-To-Maturity}_{it} + \beta_{5t} \textit{Rating-Dummy}_{it} + \epsilon_{it}, \end{aligned} \tag{15}$$

where the variable $\textit{Inventory-Spread}_{it}$ is either the spread in equation (14) (CH) or the bond return volatility (Vol), and the variable $\textit{Search-Spread}_{it}$ is the spread of the immediate matched trades that happen within one minute or 15 minutes. For each specification, I compare the magnitudes of the inventory premium ($\lambda_t^{\text{Inventory}} \times \textit{Inventory-Spread}_{it}$) and search premium ($\lambda_t^{\text{Search}} \times \textit{Search-Spread}_{it}$).

Table 6 presents the pooled averages of the inventory and search premia in each subperiod. The results show that both types of OTC premia are significantly positive. However, in all specifications, the average inventory premium is approximately 10 times as large as the average search premium in each subperiod. The results using the Choi and Huh (2019) spread (CH) and the 15-min "immediate match" spread (15min) suggest that the average inventory premium after the financial crisis is almost 1 percentage point while the average search premium is less than 10 basis points. In terms

[39] Choi and Huh (2019) demonstrate that this measure involves far fewer brokered trades, which are more likely to involve compensation for search costs of dealers as brokers.

of variations, the average inventory and the search premia increased nearly fourfold during the financial crisis. After the financial crisis, the average post-Volcker inventory premium is significantly higher than its pre-crisis level in all specifications and the difference is about 50 basis points. In the specification with the Choi and Huh (2019) measure (CH) as the inventory spread and the 15-min spread (15min) as the search spread, the average inventory premium increased from 44.3 basis points to 93.1 basis points, an increase of more than 100%. On the other hand, the average post-Volcker search premium is not significantly different from its pre-crisis level and remains at about 10 basis points. These results are consistent with my model and show that the increasing liquidity premium primarily represents the increase in the inventory premium while the magnitude of the search premium is minimal.

[Table 6]

5.2 Illiquidity Level vs. Liquidity Risk

I next examine whether the increasing liquidity premium compensates for individual corporate bond illiquidity level (Amihud and Mendelson 1986) or systematic liquidity risk (Pástor and Stambaugh 2003, Acharya and Pedersen 2005). I focus on corporate bond returns to separately study the pricing of these two liquidity effects as this type of analysis is traditionally conducted on returns, not yields. Following Bongaerts, de Jong, and Driessen (2017) and Reichenbacher and Schuster (2020), I examine the following two-stage asset pricing model. In the first stage, I run a 36-month rolling regression (24 months of observations are required) on the individual bond excess return:

$$r^e_{i,t} = \beta^0_i + \beta^M_i EMK_t + \beta^{\text{Shock}}_i SHOCK_t + \epsilon_{it}, \tag{16}$$

where EMK_t is the equity market excess return, and $SHOCK_t$ is the corporate bond liquidity shock, measured as the AR(2) residual of the equally-weighted corporate bond bid-ask spread. In the second stage, I run the cross-sectional regression on the bond's expected excess return:

$$\mathbb{E}_t r^e_{i,t+1} = \lambda_{0t} + \lambda^M_t \beta^M_i + \lambda^{\text{Shock}}_t \beta^{\text{Shock}}_i + \lambda^{\text{Level}}_t \textit{Bid-Ask-Spread}_{it} + \alpha_{it}. \tag{17}$$

I measure the corporate bond expected excess return as the following forward measure suggested by Campello, Chen, and Zhang (2008), Bongaerts, de Jong, and Driessen (2017) and many others:

$$\mathbb{E}_t r^e_{i,t+1} = (1 + y_{it})(1 - L\pi_{it})^{1/T_{it}} - (1 + y_{gt}),$$

where y_{it} denotes the yield-to-maturity of bond i, L denotes the loss given default assumed to be 60%, T_{it} denotes the duration, y_{gt} denotes the corresponding government bond yield with the same duration, and finally π_{it} denotes the cumulative default probability.[40]

One should expect that $\lambda^{\text{Level}} > 0$ because bonds with higher illiquidity levels compensate investors for higher returns (Amihud and Mendelson 1986). Also, one should expect that $\lambda^{\text{Shock}} < 0$ as investors require compensation for systematic liquidity risk and so more negative β^{shock} should lead to a higher expected corporate bond return. The above two-stage regression specification with the equity market risk serves as the baseline model. For alternative specifications, I also add the Fama and French (1993) three factors, as well as the four risk factors from Bai, Bali, and Wen (2019) (BBW)[41] in addition to the liquidity risk and level variables. I use Fama and MacBeth (1973) and calculate the time-series average of λ_t^{Level} and λ_t^{Shock} in each subperiod.

Table 7 presents the results. The signs are all as expected. During the financial crisis, liquidity risk is more strongly priced as the average absolute value of λ^{Shock} increased more than nine times (from 0.070 to 0.678) in the baseline model. However, once regulations came into effect, investors required higher compensation for bearing illiquidity level rather than liquidity risk, as the magnitude of λ^{Shock} declined in the post-crisis period. The differences between the average post-Volcker and pre-crisis λ^{Shock} are marginally significant at best. On the other hand, the average λ^{Level} almost tripled (from 0.393 to 0.997) in the baseline model. Therefore, the increase in the liquidity premium during the financial crisis documented in Dick-Nielsen, Feldhütter, and Lando (2012) and Friewald, Jankowitsch, and Subrahmanyam (2012) is largely compensation for corporate bonds' exposure to the systematic liquidity shock. The increase in the post-crisis liquidity premium documented in this paper, on the other hand, is about the increase in investors' required compensation for holding

[40] Following Reichenbacher and Schuster (2020), I use the firm-level default probability data from the Risk Management Institute of the University of Singapore, which provides monthly default probability up to five years. Assuming a flat curve beyond five years, I can calculate the default probability over the bond's entire duration.

[41] There are fewer observations when I use the BBW factors because these factors end in December 2016.

bonds whose secondary market liquidity was jeopardized by the increasing balance sheet costs that have made dealers averse to holding inventory and providing immediacy.

[Table 7]

6 Regulations and Corporate Bond Liquidity Premium

In this section, I employ the liquidity premium measure to examine the potential cause of dealers' unwillingness to provide liquidity. I demonstrate the potential usefulness of the liquidity premium measure by weighting in on the debate over the impact of the post-crisis regulations on market liquidity.

6.1 Aggregate Dealer Value-at-Risk

I first look at the relationship between the aggregate dealer value-at-risk (VaR) and the corporate bond liquidity premium. Dealer VaR measures the capital requirement of dealer banks and the tightness of dealers' regulatory constraints. Figure 8 shows the time series of the aggregate VaR of the top five dealer banks.[42] The figure shows that the aggregate dealer VaR has declined substantially since the financial crisis.

[Figure 8]

To quantify the relationship between the declining dealer VaR and the rising liquidity premium, I look at the following time series regressions:

$$\begin{aligned} \Delta\, VaR_t &= c_1 + a_1 \Delta\, VaR_{t-1} + a_2 \Delta\, VaR_{t-2} + b_1 \Delta Y_{t-1} + b_2 \Delta Y_{t-2} + \epsilon_t \\ \Delta Y_t &= \tilde{c}_1 + \tilde{a}_1 \Delta\, VaR_{t-1} + \tilde{a}_2 \Delta\, VaR_{t-2} + \tilde{b}_1 \Delta Y_{t-1} + \tilde{b_2} \Delta Y_{t-2} + \tilde{\epsilon}_t, \end{aligned} \tag{18}$$

where Y is either the cross-sectional transaction cost coefficient (λ), the liquidity premium as a fraction of the total yield spread (LP), or the implied trading delays ($Delay$). I use the first

[42] Following Adrian et al. (2017) and Anderson and Liu (2020), the aggregate VaR is computed as the sum of the VaRs of Bank of America, Citigroup, Morgan Stanley, J.P.Morgan and Goldman Sachs, scaled by the sum of their book equity. The VaR data are collected by Bloomberg from the banks' 10-Q filings, which report the VaR at either the 95% or 99% level. I scale the VaR to the 95% level using the Normal assumption.

difference in the regression because these variables are highly persistent.

Table 8 presents the time series regression results. The results show that changes in the aggregate dealer VaR Granger causes the changes in the cross-sectional transaction cost coefficient, the liquidity premium as a fraction of the yield spread, as well as the estimated trading delays implied by the size of the liquidity premium, but not the other way around. A tightening of the dealer VaR by a magnitude of 0.1 Granger causes the liquidity premium as a fraction of the total yield spread to increase by over 10 percentage points, or equivalently almost six days in terms of the trading delays.

[Table 8]

6.2 Impact of Basel II.5

The final rules for implementing Basel II.5 were announced on June 7, 2012. Compared to previous regulations, the incremental risk capital charge (IRC) and a stressed value-at-risk (SVaR) were introduced to supplement the VaR-based trading book framework. The incremental risk capital charge accounts for the default and migration risk of credit products. These additional risk charges could potentially increase the balance sheet costs of corporate bond dealers (Adrian et al. 2017).

I proxy the risk charges introduced by Basel II.5 using the volatility of daily bond yield changes. It is a standard input in the fixed-income VaR calculations.[43] In addition, industry practices often use bond yields to determine the market implied ratings (Breger, Goldberg, and Cheyette 2003). Therefore, higher volatility in yields represents higher rating migration risk. In Figure 9, I plot the average liquidity premium (as a fraction of the yield spread) of the bonds at the top 10% and bottom 90% of the yield change volatility in each month. The figure shows that the liquidity premia of the two groups only start to diverge in June 2012, the exact month when the final implementation of Basel II.5 was announced. While the bonds at the bottom 90% of the yield volatility have roughly 20% of their yield spread explained by liquidity, the liquidity premium (as a fraction of the yield spread) of the bonds at the top 10% of the yield volatility increased to around 40% since Basel II.5 came into effect. The diverging pattern in Figure 2 of the investment grade and speculative bond

[43]Suppose the yield changes follow a normal distribution with zero mean. Then adverse moves in yields by more than 2.33 × yield-change-volatility happen 1 percent of the time.

liquidity premia in the post-crisis period is indeed due to Basel II.5.

[Figure 9]

I employ the following difference-in-differences model to quantify the impact of Basel II.5:

$$\textit{Liquidity-Premium}_{it} = \eta^{\text{Basel II.5}} \textit{Post}_t^{\text{Basel II.5}} \times \textit{Treat}_{it}^{\text{Basel II.5}} + \alpha_i + \alpha_t + X_{it}'\gamma + u_{it}. \tag{19}$$

$\textit{Post}_t^{\text{Basel II.5}}$ is a dummy variable that equals 1 if the observation occurs after June 2012, the month when the final rule of Basel II.5 was announced; $\textit{Treat}_{it}^{\text{Basel II.5}}$ is a dummy variable that equals 1 if bond i is the in the top 10% of the risk charges proxied by yield change volatility at time t; α_i denotes the bond fixed effect and α_t denotes the monthly time fixed effect; X_{it} is a vector of controls that includes equity volatility, rating dummies, and time-to-maturity. The dependent variable is the liquidity premium as a fraction of the total yield spread: $\lambda_t \times \textit{Bid-Ask-Spread}_{it}/\textit{Yield-Spread}_{it}$. The sample period is from December 2011 to November 2012 to focus on Basel II.5 (June 2012). I separately run the regression with λ_t obtained from different credit risk controls and alternative corporate bond transaction cost measures. As a final robustness check, I also measure the credit migration risk by constructing a credit transition matrix and calculate the 12-month probability of ratings being downgraded to the speculative and default regimes.[44] Finally, the standard errors are clustered at the issuer-month level.

Table 9 presents the result. Compared to bonds at the bottom 90% of the calculated risk charges, since Basel II.5 came into effect, the liquidity premium (as a fraction of the yield spread) of the bonds at the top 10% of the risk charges has increased by around 15 percentage points. The results are robust to how credit risk is controlled for or which transaction cost measure is used, and to how Basel II.5 risk charges are measured.

[Table 9]

To translate the impact of Basel II.5 in terms of trading delays, in Figure 10 I plot the trading

[44] For instance, the migration risk of A-rated bonds between time t and time $t+12$ is simply the ratio of the number of A-rated bonds that are downgraded to the speculative or default regimes during the 12 months to the total number of A-rated bonds in the beginning: $\frac{N_{A\rightarrow\text{Speculative/Default}}(t+12)}{N_A(t)}$. For speculative bonds, I measure their migration risk as the probability of downgrading (within speculative ratings) or default.

delays and the associated 95% confidence intervals estimated from the bond samples at the top and bottom of the Basel II.5 risk charges. The figure shows that the confidence intervals of the estimated trading delays of the two samples coincide until the final implementation of Basel II.5 was announced. While the trading delays of the bonds at the bottom 90% of the yield volatility remained five days after June 2012, the trading delays of the bonds at the top 10% of the yield volatility increased significantly to around 15 days. The results suggest that the liquidity premium of the speculative bonds has increased substantially after the financial crisis because these bonds have been associated with higher balance sheet costs under Basel II.5.

[Figure 10]

6.3 Impact of Liquidity Coverage Ratio

The liquidity coverage ratio (LCR) was finalized in January 2013 by the Basel Committee.[45] It ensures that banks hold enough high-quality liquid assets (HQLA) that can be liquidated to cover 30 days of expected net cash outflows during a stress event. Investment grade corporate debt securities issued by non-financial sector corporations qualify as level 2B HQLA assets.[46] Therefore, the balance sheet costs of the bonds qualified as HQLA are likely to have decreased due to the liquidity coverage ratio. To quantify this impact of the LCR , I employ the following difference-in-differences model:

$$\textit{Liquidity-Premium}_{it} = \eta^{\text{LCR}} \textit{Post}_t^{\text{LCR}} \times \textit{Treat}_i^{\text{LCR}} + \alpha_i + \alpha_t + X_{it}'\gamma + u_{it}. \tag{20}$$

$\textit{Post}_t^{\text{LCR}}$ is a dummy variable that equals 1 if the observation occurs after January 2013, the month that the liquidity coverage ratio was finalized by the Basel Committee; $\textit{Treat}_i^{\text{LCR}}$ is a dummy variable that equals 1 if bond i is issued by a non-financial firm; α_i denotes the bond fixed effect and α_t denotes the monthly time fixed effect; X_{it} is a vector of controls that includes equity volatility, rating dummies and time-to-maturity. The sample period is from July 2012 to June 2013 to focus on the liquidity coverage ratio (January 2013). Finally, the standard errors are clustered at the issuer-month level. I conduct the analysis separately for investment grade and speculative bonds.

[45] Source: https://www.bis.org/publ/bcbs238.htm

[46] Source: https://www.federalregister.gov/documents/2014/10/10/2014-22520/liquidity-coverage-ratio-liquidity-risk-measurement-standards

One should expect the coefficient η^{LCR} to be significantly negative for the investment grade bond sample while to be insignificant for the speculative bond sample because only investment grade bonds issued by non-financial firms qualify as HQLA while there is no such distinction within speculative bonds.[47]

[Table 10]

Table 10 presents the results. As expected, once the liquidity coverage ratio has come into effect, the liquidity premium for the investment grade corporate bond (as a fraction of the yield spread) issued by non-financial firms declined by 2.5 percentage points on average, compared to the liquidity premium of the investment grade bonds issued by the financial firms, regardless of how credit risk is controlled for or which transaction cost measure is used. There is no such distinction within the speculative corporate bond sample between the bonds issued by financial and non-financial firms before and after the liquidity coverage ratio was implemented.[48]

6.4 Impact of the Volcker Rule

The Volcker Rule came into effect in April 2014, and full compliance was required by July 2015. The Volcker Rule prohibits dealer banks from engaging in proprietary trading. Since it is hard to distinguish market making from proprietary trading activities (Duffie 2012), the Volcker Rule is thought to have discouraged dealers from effectively providing liquidity when customers request immediacy. Tables 2 and 3 show that the Volcker Rule mainly affected the liquidity premium of speculative bonds. Part of the reason might be that the Volcker Rule has potentially increased the inventory costs of trading speculative bonds more than the inventory costs of the investment grade bonds.

[Figure 11]

In Figure 11, I plot the monthly interdealer dollar trading volume (as a fraction of the total dollar

[47] The distinction between investment grade and speculative bonds has to be based on their ratings. Of course, the Dodd-Frank Act forbids banks from using external ratings. The exact definition of "investment grade" class is vague and corresponds to "the issuer of a security has an adequate capacity to meet financial commitments under the security for the projected life of the asset or exposure." This definition is similar to the definitions used by the external rating agencies. Source: `https://www.govinfo.gov/content/pkg/CFR-2019-title12-vol1/xml/CFR-2019-title12-vol1-part1.xml`

[48] In Appendix Subsection A.9, I check the pre-trend using a dynamic difference-in-differences framework. Figure A2 shows that there is no pre-trend before 2013.

trading volume) of the A- and above-rated, BBB-rated, and the speculative bonds. The figure shows that after the full compliance of the Volcker Rule was required in July 2015, the fraction of interdealer trades reverted the downward trend and started to increase for all bonds, suggesting that dealers heavily relied on the interdealer market to manage their inventory positions. The effect appears to be larger for speculative bonds. Before the Volcker Rule was fully complied, the fraction of interdealar trades of the speculative bonds seems to be 10 percentage points lower than that of the investment grade bonds. After July 2015, the interdealer trades of the speculative bonds converged to the level of investment grade bonds.

To establish a causal link, I compare the liquidity premium of bonds whose dealers are likely to be affected by the Volcker Rule to the liquidity premium of the bonds whose dealers are not. Because I do not observe the dealer identity in my data, I cannot exactly identify which bonds are associated with the dealers affected by the Volcker Rule. Following Dick-Nielsen, Feldhütter, and Lando (2012) and Trebbi and Xiao (2019), I assume that the lead underwriters of the bonds are likely to make the market. I get the underwriter's information from the FISD and assign a bond to be affected by the Volcker Rule if all of its lead underwriters are associated with the Volcker-affected dealers identified in Wyman and SIFMA (2011). I use the following difference-in-differences model for the speculative high yield bonds:

$$\textit{Liquidity-Premium}_{it}^{HY} = \eta^{\text{Volcker}} \textit{Post}_t^{\text{Volcker}} \times \textit{Treat}_i^{\text{Volcker}} + \alpha_i + \alpha_t + X_{it}'\gamma + u_{it}. \tag{21}$$

$\textit{Post}_t^{\text{Volcker}}$ is a dummy variable that equals 1 if the observation occurs after April 2014, the month that the Volcker Rule went into effect; $Treat_i^{\text{Volcker}}$ is a dummy variable that equals 1 if all of bond i's lead underwriter are dealers affected by the Volcker Rule identified in Wyman and SIFMA (2011); α_i denotes the bond fixed effect and α_t denotes the monthly time fixed effect; X_{it} is a vector of controls that includes equity volatility, rating dummies, and time-to-maturity. The sample period is from January 2014 to December 2015, which covers both the finalization (April 2014) and the full compliance (July 2015) of the Volcker Rule. Finally, the standard errors are clustered at the issuer-month level.

The top panel of Table 11 presents the results. Within the speculative bond sample, since the

Volcker Rule came into effect in April 2014, the liquidity premium (as a fraction of the yield spread) of the corporate bonds whose lead underwriters are more likely to be regulated by the Volcker Rule increased by around 4 percentage points compared to the bonds whose lead underwriters are less likely to be affected by the Volcker Rule, regardless of how the credit risk is controlled for or which transaction cost measure is used. To check the pre-trend, I conduct a placebo test of the same regression before the finalization of the Volcker Rule. The bottom panel shows that there is no significant difference in the liquidity premium between the treatment and the control groups during the two years before the Volcker Rule was finalized.[49]

[Table 11]

In August 2019, the Federal Deposit Insurance Corp. (FDIC) approved a weakened version of the Volcker Rule that granted more exemptions for market making activities from the proprietary trading ban.[50] Although the regulation ease is mainly for small-sized banks, market watchers expect further steps towards easing the rule for large banks. However, the results in Tables 2 and 3 suggest that the liquidity premium, after the hypothetical repeal of the Volcker Rule, will still be higher than the pre-crisis level for BBB-rated and speculative bonds. For speculative bonds, liquidity premium already comprised 30% of the total yield spread before the Volcker Rule came into effect following Basel II.5. It is worth emphasizing that I do not observe the actual dealer identities in the data, nor are the Volcker-affected dealers identified in Wyman and SIFMA (2011) likely to be complete. Moreover, non-regulated broker-dealers require financing from the regulated dealers and their access to banks' balance sheet has also become more limited. Therefore, the impact of the Volcker Rule may spill over to the non-regulated broker-dealers as well.[51] The significance of my results suggests that the actual impact of the Volcker Rule is likely to be larger.

[49]In Appendix A.10, I also use a dynamic difference-in-differences regression framework and find that there is no pre-trend before 2014. However, dealers may have started to adjust to the Volcker Rule before the actual implementation date. For instance in 2011, Morgan Stanley announced the shutdown of its proprietary trading desk.

[50]Source: https://www.cnbc.com/2019/08/20/fdic-approves-volcker-rule-overhaul-eases-wall-street-trading-rules.html

[51]Practitioners have argued that regulators intended this so banks would not "transfer the outsize risk to the shadow banking area". Source: https://www.goldmansachs.com/insights/pages/macroeconomic-insights-folder/liquidy-top-of-mind/pdf.pdf

7 Conclusion

Traditional transaction cost-based liquidity measures such as the bid-ask spread tend to give a misleading picture of the liquidity condition in the corporate bond market after the financial crisis, as the other dimension of liquidity (trading delay) is not observable nor easily measured during normal market conditions. In this paper, I propose an alternative liquidity indicator that better reflects the post-crisis corporate bond market reality: the liquidity premium. It is based on the idea that if corporate bond liquidity deteriorates, investors should require a higher compensation for holding the illiquid bonds and the liquidity premium should be higher. I employ the asset pricing-based measure of liquidity to assess corporate bond liquidity conditions, uncover the latent trading delays, and provide important findings on the impact of the post-crisis regulations on market liquidity.

I show that the post-crisis regulations make liquidity more costly for firms to raise capital. For firms with speculative ratings, over 30% of their cost of borrowing is now paying for liquidity. My findings have important implications for the real economy. As of November 2019, there is $10 trillion outstanding corporate debt in the U.S., out of which over 50% are BBB-rated bonds, which are likely to be downgraded to speculative ratings. As Federal Reserve Chairman has pointed out, if the financial conditions were to deteriorate, overly indebted firms could face severe strains.[52] Some of the strain comes from the illiquidity in the market, as we see in the recent COVID-19 pandemic.[53] Understanding post-crisis corporate bond liquidity and liquidity risk premia, as well as the impact of different regulations is therefore important for policy design and financial stability.

[52]Source: `https://www.federalreserve.gov/newsevents/speech/powell20190520a.htm`

[53]A brief examination of the corporate bond liquidity during the initial COVID-19 pandemic through the lens of the liquidity premium is presented in Appendix A.11. However, the COVID pandemic is a *crisis* and so traditional transaction costs should reflect well the increase in illiquidity as investors request for immediacy. This paper, however, documents the illiquidity during the *normal* time of post-crisis economic expansion, which transaction cost measures fail to capture, due to the longer trading delays.

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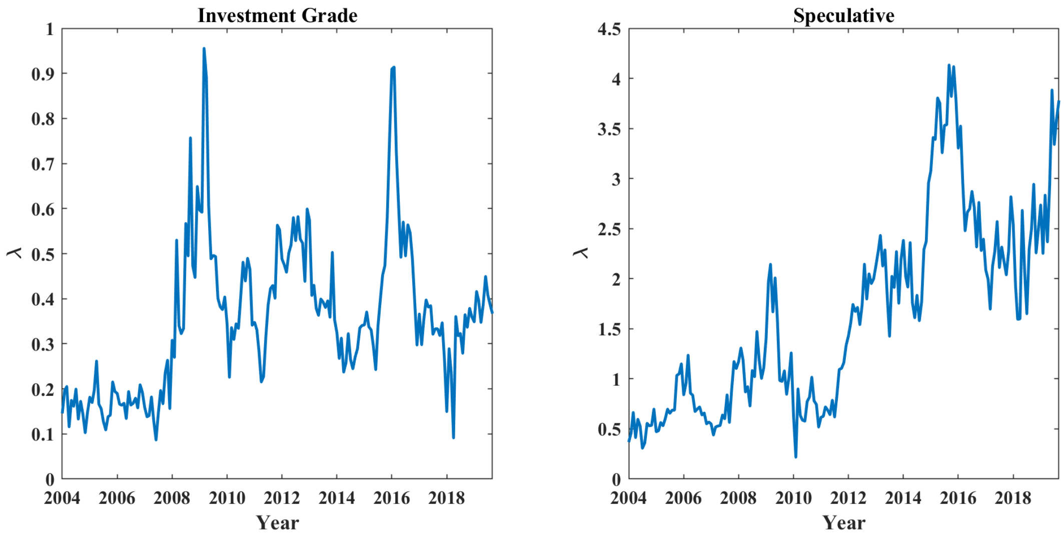
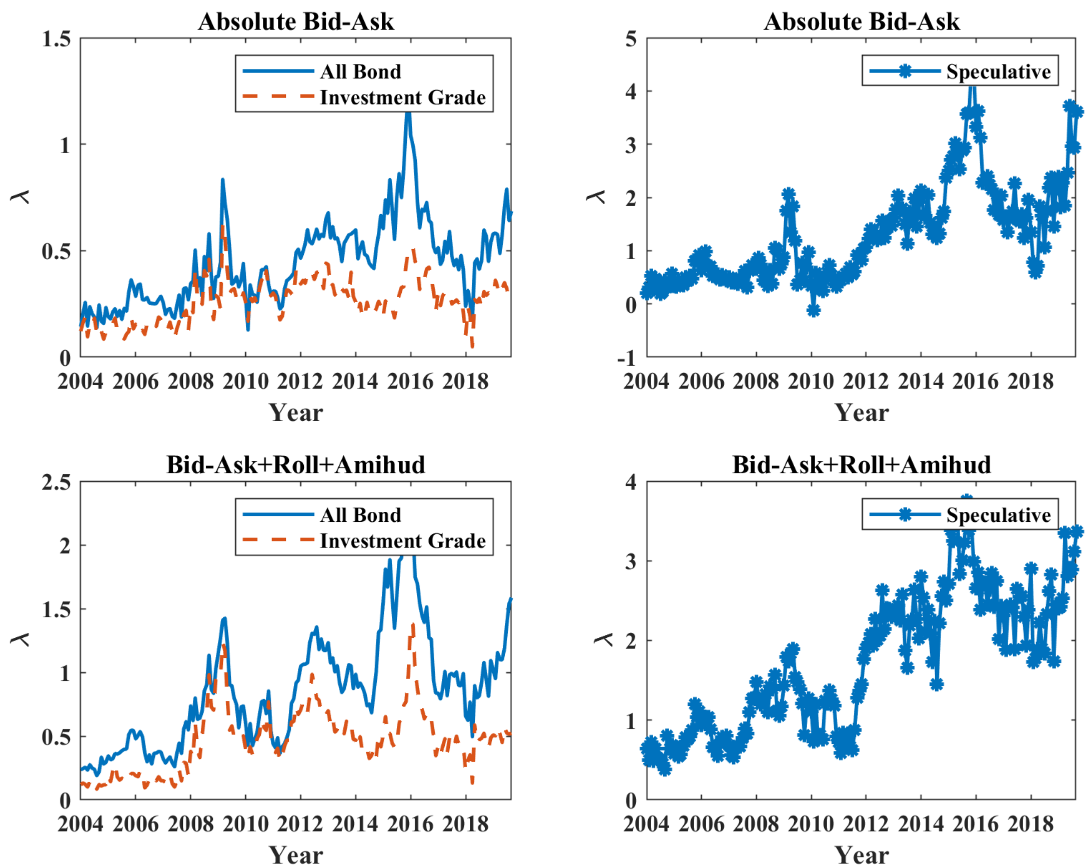
Figures

Figure 3: Cross-Sectional Transaction Cost Coefficient (λ_t) of Investment Grade and Speculative Bonds



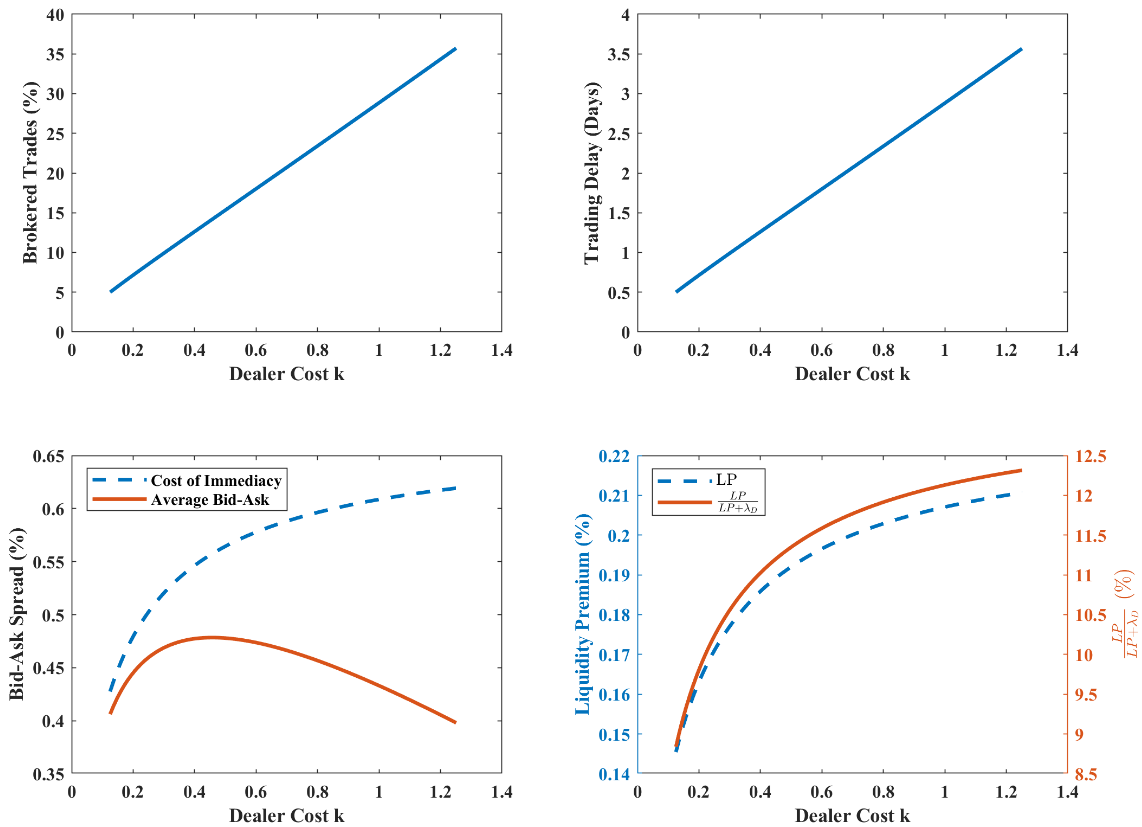
Notes: This figure presents the cross-sectional transaction cost coefficient (λ_t) of investment grade and speculative bonds, obtained by running the cross-sectional regression (1) on both samples. The left panel shows the λ_t of investment grade bonds. The right panel shows the λ_t of speculative bonds.

Figure 4: Cross-Sectional Coefficient of Alternative Transaction Cost Measures



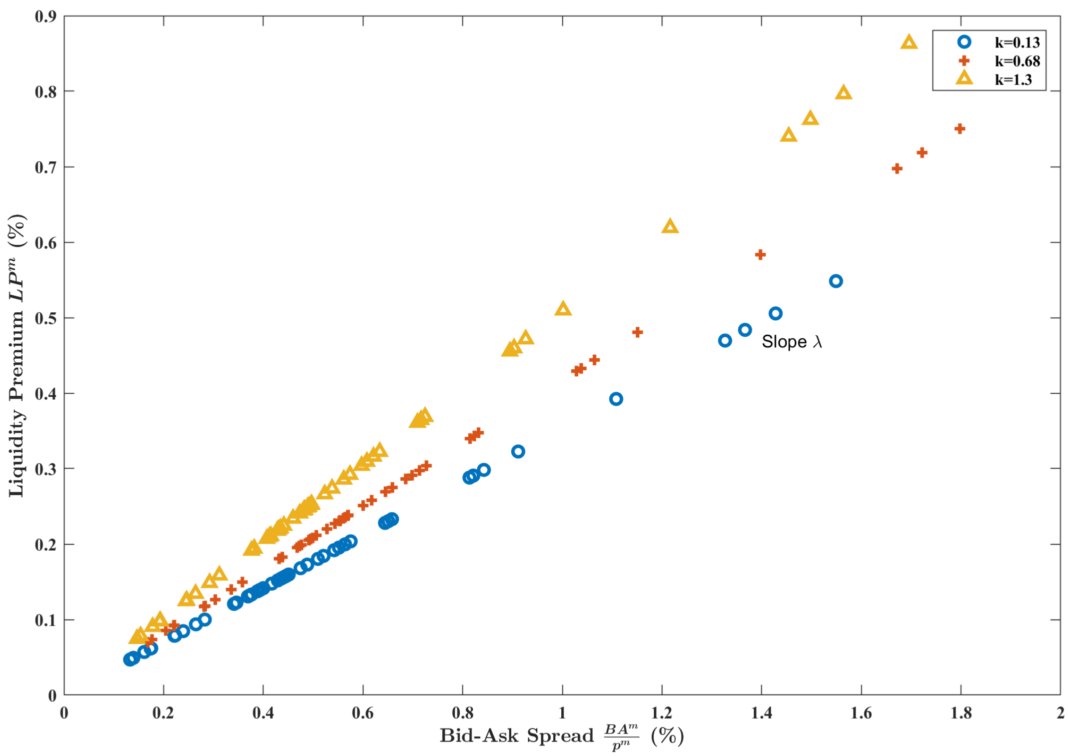
Notes: This figure presents the cross-sectional transaction cost coefficient (λ_t) obtained from the cross-sectional regression (1) with alternative measures of corporate bond transaction cost. The left panel shows the λ_t of the entire bond sample (solid blue line) and of the investment grade bond sample (dashed red line). The right panel shows the λ_t of the speculative bond sample. In the top panel, the bid-ask spread from the cross-sectional regression (1) is replaced by the absolute bid-ask difference. In the bottom panel, the bid-ask spread is replaced by the equally-weighted average of the standardized bid-ask spread, Roll, and Amihud measures.

Figure 5: Model Generated Statistics (Time Series)



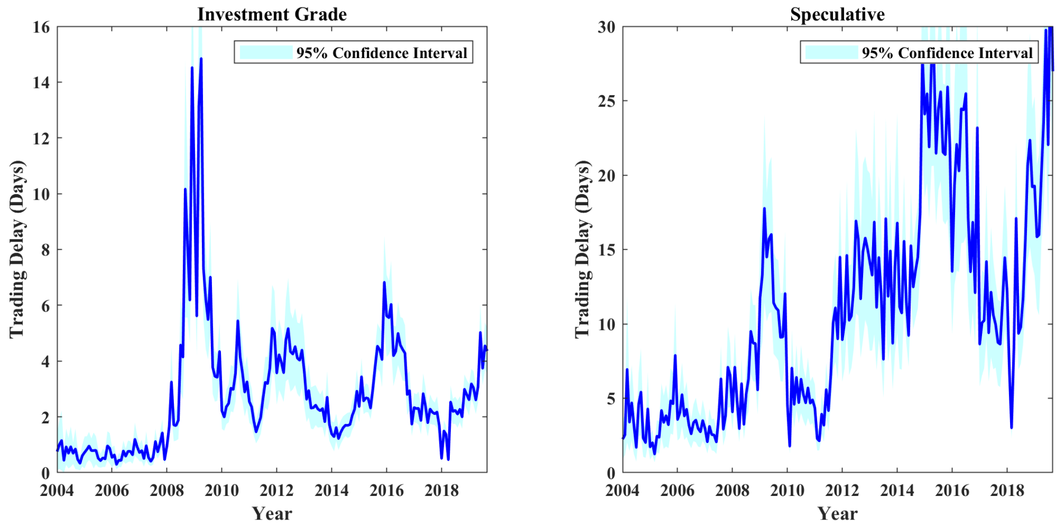
Notes: This figure presents the model generated statistics when the dealer's cost k increases from 0.13 to 1.3. Calibration is based on Feldhütter (2012) and the average BBB-rated bond: $r = 0.05$, $\lambda_T = 0.2$, $\lambda_D = 0.015$, $\epsilon_H = 5 + 100\lambda_T$, $\epsilon_L = 0$, $\delta = 3.58$, $\pi_L = 0.33/3.58$, $\eta = 0.97$, A=1, $\beta = 36$, and $\alpha(v) = \alpha \cdot v$, where $\alpha = 685$.

Figure 6: Model Generated Statistics (Cross Section)



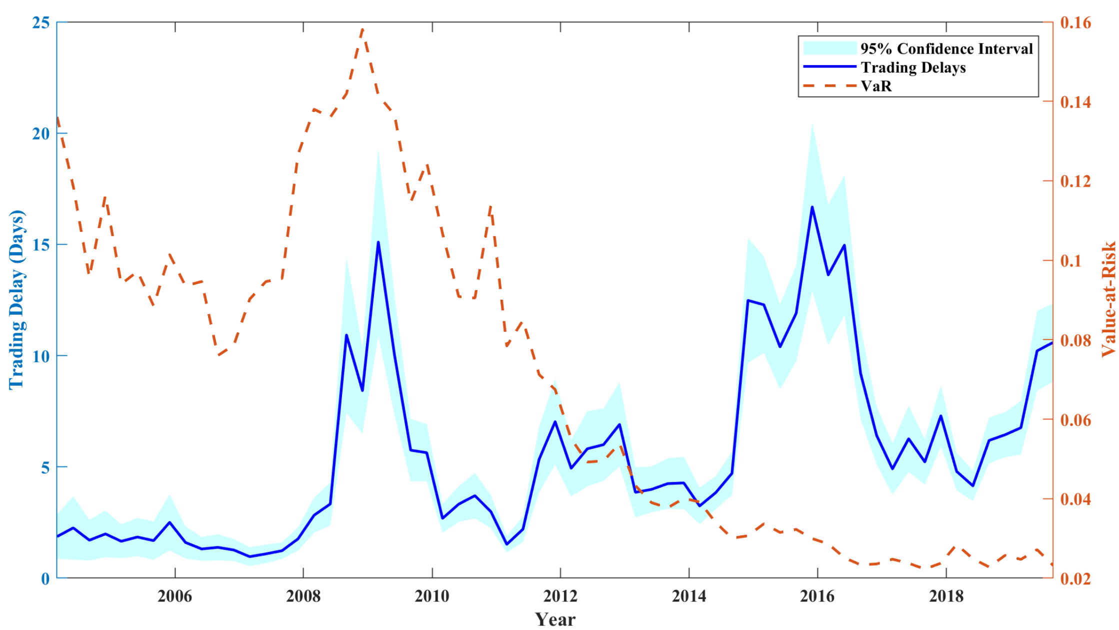
Notes: This figure presents the cross-sectional relationship between the model generated liquidity premium (LP^m) and the bid-ask spread ($\frac{BA^m}{p^m}$), when the dealer's cost k increases from 0.13 to 1.3. Calibration is based on Feldhütter (2012) and the average BBB-rated bond: $\log(r^m) \sim \text{Normal}(-3.00, 0.81^2)$, $\log(\lambda_T^m) \sim \text{Normal}(-1.60, 0.95^2)$, $\log(\lambda_D^m) \sim \text{Normal}(-4.20, 0.64^2)$, $\log(\epsilon_H^m) \sim \text{Normal}(3.22, 0.68^2)$, $\epsilon_L = 0$, $\delta = 3.58$, $\pi_L = 0.33/3.58$, $\eta = 0.97$, A=1, $\beta = 36$, and $\alpha(v) = \alpha \cdot v$, where $\alpha = 685$. 50 observations are randomly drawn in each cross section.

Figure 7: Trading Delays



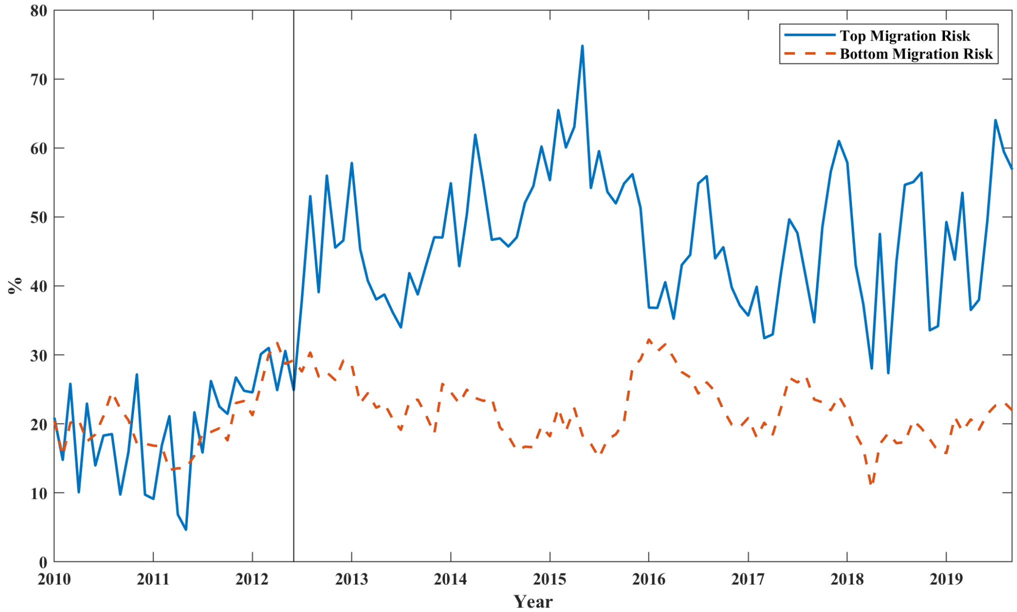
Notes: This figure presents the trading delays of executing investment grade and speculative bond trades, implied by the magnitude of the liquidity premium. The solid blue line is the trading delay estimated from the structural model in Section 4. The shaded area is the 95% confidence interval of the estimated trading delays based on the asymptotic normality and the delta method.

Figure 8: Dealer Value-at-Risk (VaR)



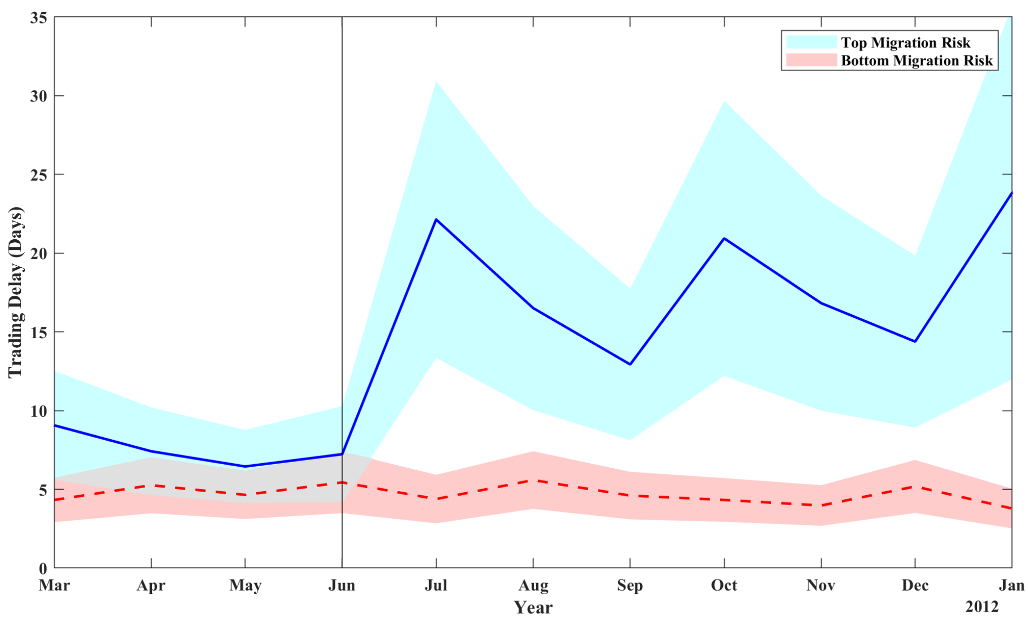
Notes: This figure presents the aggregate dealer VaR (dashed red line) and the estimated trading delays (solid blue line). The aggregate dealer VaR is calculated as the sum of the VaRs' of the top five dealer banks, scaled by their equity. The shaded area is the 95% confidence interval of the estimated trading delays based on the asymptotic normality and the delta method.

Figure 9: Basel II.5 and Liquidity Premium



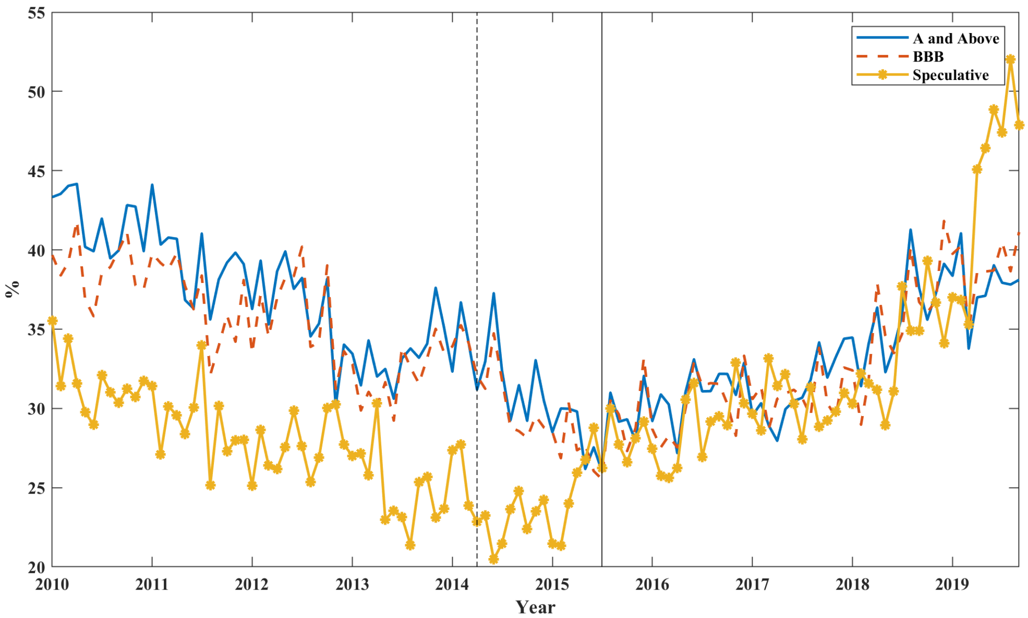
Notes: This figure presents the Liquidity premium (as a fraction of the yield spread) of the bonds at the top 10% (solid blue) and bottom 90% (dashed red) of the Basel II.5 risk charges each month, proxied by the corporate bond yield change volatility. The vertical line is June 2012 when the final implementation of Basel II.5 was announced.

Figure 10: Basel II.5 and Trading Delays



Notes: This figure presents the estimated trading delays of the bonds at the top 10% (solid blue) and bottom 90 % (dashed red) of the Basel II.5 risk charges each month, proxied by the corporate bond yield change volatility. The shaded area is the 95% confidence interval of the estimated trading delays based on the asymptotic normality and the delta method. The vertical line is June 2012 when the final implementation of Basel II.5 was announced.

Figure 11: Fraction of Interdealer Dollar Trading Volume



Notes: This figure shows the interdealer dollar trading volume (as a fraction of the total dollar trading volume). The vertical dashed line is April 2014 when the Volcker Rule was finalized; the vertical solid line is July 2015 when the full compliance of the Volcker Rule was required.

Tables

Table 1: Summary Statistics

	Credit Rating	Amt. Outstanding (USD millions)	Bid-Ask (%)	Yield-to-Maturity (%)	Price (USD thousands)	Return (%)
Full Sample: Jan 2004 - Sep 2019						
12,923 Bonds	BBB	606	0.58	4.66	104.89	0.50
	(BBB+)	(450)	(0.39)	(4.32)	(103.57)	(0.35)
Pre-Crisis: Jan 2004 - Jun 2007						
4,838 (4,838) Bonds	BBB	446	0.58	5.89	104.02	0.42
	(BBB)	(300)	(0.36)	(5.64)	(102.91)	(0.41)
Crisis: Jul 2007 - Apr 2009						
5,050 (893) Bonds	BBB	515	1.08	7.87	94.98	0.24
	(BBB)	(350)	(0.74)	(6.65)	(98.78)	(0.44)
Post-Crisis: May 2009 - May 2012						
6,602 (2,348) Bonds	BBB	590	0.73	4.79	106.62	1.05
	(BBB)	(400)	(0.53)	(4.56)	(106.39)	(0.67)
Basel II.5: Jun 2012 - Jun 2013						
5,920 (1,054) Bonds	BBB	616	0.52	3.31	111.63	0.25
	(BBB)	(499)	(0.38)	(3.05)	(109.24)	(0.24)
Basel III: Jul 2013 - Mar 2014						
6,166 (706) Bonds	BBB	634	0.48	3.59	107.14	0.62
	(BBB)	(500)	(0.36)	(3.62)	(105.81)	(0.41)
Post-Volcker: Apr 2014 - Sep 2019						
8,931 (3,084) Bonds	BBB	687	0.45	3.81	105.25	0.40
	(BBB+)	(500)	(0.32)	(3.57)	(102.92)	(0.26)

Notes: This table shows the summary statistics of the cleaned WRDS Bond Returns sample. The sample period is from January 2004 to September 2019. All variables are winsorized at 0.5% on both tails. In each period, sample averages are reported in the first row and sample medians are reported in the second row in parentheses. In the first column, the number of bonds in each subperiod is reported. The number of newly issued bonds that first appear in each subperiod is also reported in parentheses.

Table 2: Variations in λ

Rating	A and above	BBB	Speculative
Pre-Crisis: Jan 2004 - Jun 2007			
$\lambda_{\text{Pre-Crisis}}$	0.110***	0.211***	0.645***
	(6.90)	(15.49)	(10.67)
Crisis: Jul 2007 - Apr 2009			
λ_{Crisis}	0.505***	0.370***	1.155***
	(4.96)	(4.32)	(8.85)
Post-Crisis: May 2009 - May 2012			
$\lambda_{\text{Post-Crisis}}$	0.402***	0.405***	0.981***
	(12.27)	(14.47)	(8.22)
Basel II.5: Jun 2012 - Jun 2013			
$\lambda_{\text{Basel II.5}}$	0.365***	0.553***	2.021***
	(8.61)	(17.77)	(22.47)
Basel III: Jul 2013 - Mar 2014			
$\lambda_{\text{Basel III}}$	0.206***	0.453***	1.989***
	(3.97)	(33.14)	(23.70)
Post-Volcker: Apr 2014 - Sep 2019			
$\lambda_{\text{Post-Volcker}}$	0.191***	0.472***	2.665***
	(8.44)	(11.35)	(15.85)
Coefficient-Difference			
$\lambda_{\text{Crisis}} - \lambda_{\text{Pre-Crisis}}$	0.395***	0.159*	0.511***
	(3.84)	(1.85)	(3.58)
$\lambda_{\text{Basel II.5}} - \lambda_{\text{Post-Crisis}}$	-0.038	0.149***	1.041***
	(-0.71)	(3.75)	(6.42)
$\lambda_{\text{Basel III}} - \lambda_{\text{Basel II.5}}$	-0.159**	-0.100***	-0.032
	(-2.18)	(-3.07)	(-0.25)
$\lambda_{\text{Post-Volcker}} - \lambda_{\text{Basel III}}$	-0.015	0.019	0.676***
	(-0.27)	(0.43)	(3.59)
$\lambda_{\text{Post-Volcker}} - \lambda_{\text{Pre-Crisis}}$	0.081***	0.261***	2.020***
	(2.93)	(5.97)	(11.31)
Observations	287,172	337,053	169,880
Average R-squared	0.387	0.329	0.569

Notes: This table presents the result of the time series regression:

$$\lambda_t = \lambda_{\text{Pre-Crisis}} \mathbb{1}_{\{t \in \text{Pre-Crisis}\}} + \lambda_{\text{Crisis}} \mathbb{1}_{\{t \in \text{Crisis}\}} + \lambda_{\text{Post-Crisis}} \mathbb{1}_{\{t \in \text{Post-Crisis}\}} + \lambda_{\text{Basel II.5}} \mathbb{1}_{\{t \in \text{Basel II.5}\}} + \lambda_{\text{Basel III}} \mathbb{1}_{\{t \in \text{Basel III}\}} + \lambda_{\text{Post-Volcker}} \mathbb{1}_{\{t \in \text{Post-Volcker}\}} + \epsilon_t.$$

λ_t is obtained from the cross-sectional regression (1) run on each rating group. The R-squared is the average R-squared from the cross-sectional regression. T-statistics based on Newey and West (1987) with four lags are presented in parentheses. *** (**) [*] denotes statistical significance at 1% (5%) [10%] level.

Table 3: Liquidity Premium as a Fraction of Yield Spread

Rating	A and above	BBB	Speculative
Pre-Crisis: Jan 2004 - Jun 2007			
Fraction %	8.247***	9.654***	16.046***
	(8.78)	(10.36)	(14.50)
Crisis: Jul 2007 - Apr 2009			
Fraction %	22.920***	11.466***	15.573***
	(5.52)	(4.86)	(19.11)
Post-Crisis: May 2009 - May 2012			
Fraction %	23.229***	14.891***	14.226***
	(12.41)	(19.33)	(9.10)
Basel II.5: Jun 2012 - Jun 2013			
Fraction %	17.885***	17.495***	28.990***
	(6.80)	(16.26)	(19.15)
Basel III: Jul 2013 - Mar 2014			
Fraction %	9.675***	14.647***	32.709***
	(4.80)	(39.12)	(16.31)
Post-Volcker: Apr 2014 - Sep 2019			
Fraction %	8.275***	13.700***	37.679***
	(8.69)	(11.66)	(23.60)
Fraction-Difference			
Crisis − Pre-Crisis	14.673***	1.813	-0.473
	(3.48)	(0.72)	(-0.35)
Basel II.5 − Post-Crisis	-5.344	2.604**	14.763***
	(-1.64)	(2.08)	(6.06)
Basel III − Basel II.5	-8.210**	-2.848***	3.719
	(-2.20)	(-2.63)	(1.37)
Post-Volcker − Basel III	-1.401	-0.947	4.970*
	(-0.64)	(-0.77)	(1.90)
Post-Volcker − Pre-Crisis	0.028	4.047***	21.633***
	(0.02)	(2.70)	(11.13)
Observations	287,172	337,053	169,880
R-squared	0.481	0.506	0.593

Notes: This table presents the pooled averages of the liquidity premium $\lambda_t \times \textit{Bid-Ask-Spread}_{it} / \textit{Yield-Spread}_{it}$ in each rating group and subperiod. λ_t is obtained from the cross-sectional regression (1) run on each rating group. T-statistics based on Driscoll and Kraay (1998) with five lags are presented in parentheses to account for heteroskedasticity as well as temporal autocorrelations. *** (**) [*] denotes statistical significance at 1% (5%) [10%] level.

Table 4: Absolute Liquidity and Default Premia

Rating	A and above	BBB	Speculative
Pre-Crisis: Jan 2004 - Jun 2007			
Liquidity Premium (%)	0.060	0.113	0.449
Crisis: Jul 2007 - Apr 2009			
Liquidity Premium (%)	0.642	0.498	1.185
Post-Crisis: May 2009 - May 2012			
Liquidity Premium (%)	0.274	0.319	0.788
Basel II.5: Jun 2012 - Jun 2013			
Liquidity Premium (%)	0.162	0.305	1.166
Basel III: Jul 2013 - Mar 2014			
Liquidity Premium (%)	0.084	0.234	1.069
Post-Volcker: Apr 2014 - Sep 2019			
Liquidity Premium (%)	0.074	0.229	1.436
Liquidity Premium Differences			
Post-Volcker – Pre-Crisis	0.014	0.116***	0.987***
	(0.92)	(2.88)	(7.01)

Rating	A and above	BBB	Speculative
Pre-Crisis: Jan 2003 - Jun 2007			
Default Premium (%)	0.649	1.079	2.831
Crisis: Jul 2007 - Apr 2009			
Default Premium (%)	2.048	3.662	7.409
Post-Crisis: May 2009 - May 2012			
Default Premium (%)	0.958	1.891	5.234
Basel II.5: Jun 2012 - Jun 2013			
Default Premium (%)	0.793	1.439	3.384
Basel III: Jul 2013 - Mar 2014			
Default Premium (%)	0.747	1.256	2.412
Post-Volcker: Apr 2014 - Sep 2019			
Default Premium (%)	0.800	1.312	2.858
Default Premium Differences			
Post-Volcker – Pre-Crisis	0.151***	0.233***	0.027
	(4.47)	(3.28)	(0.10)

Notes: This table presents the pooled averages of the absolute liquidity premium $\lambda_t \times \textit{Bid-Ask-Spread}_{it}$ and default premium $\textit{Yield-Spread}_{it} - \lambda_t \times \textit{Bid-Ask-Spread}_{it}$ in each rating group and subperiod. λ_t is obtained from the cross-sectional regression (1) run on each rating group. T-statistics based on Driscoll and Kraay (1998) with five lags are presented in parentheses to account for heteroskedasticity as well as temporal autocorrelations. *** (**) [*] denotes statistical significance at 1% (5%) [10%] level.

Table 5: Estimated Trading Delays

Rating	A and above	BBB	Speculative
Pre-Crisis: Jan 2004 - Jun 2007			
Trading Delay (Days)	0.459	0.857	3.408
Crisis: Jul 2007 - Apr 2009			
Trading Delay (Days)	5.985	4.287	7.266
Post-Crisis: May 2009 - May 2012			
Trading Delay (Days)	3.437	3.882	7.763
Basel II.5: Jun 2012 - Jun 2013			
Trading Delay (Days)	2.758	4.619	14.168
Basel III: Jul 2013 - Mar 2014			
Trading Delay (Days)	1.158	2.743	12.517
Post-Volcker: Apr 2014 - Sep 2019			
Trading Delay (Days)	1.393	4.347	17.472
Trading Delay Difference			
Post-Volcker − Pre-Crisis	0.934***	3.491***	14.064***
	(4.01)	(6.76)	(8.85)

Notes: This table presents the trading delays implied by the magnitude of the liquidity premium. The trading delays are estimated from the structural model in Section 4. T-statistics based on Newey and West (1987) with four lags are presented in parentheses. *** (**) [*] denotes statistical significance at 1% (5%) [10%] level.

Table 6: Decomposition of Liquidity Premium: Inventory vs. Search

	Vol + 1min	CH + 1 min	Vol + 15min	CH + 15min
Pre-Crisis: Jan 2004 - Jun 2007				
Inventory (%)	0.741***	0.531***	0.619***	0.442***
	(6.00)	(16.42)	(6.02)	(19.49)
Search (%)	0.089***	0.045***	0.115***	0.067***
	(5.70)	(4.03)	(5.98)	(4.06)
Crisis: Jul 2007 - Apr 2009				
Inventory (%)	3.041***	1.795***	2.693***	1.629***
	(6.24)	(5.80)	(5.41)	(5.20)
Search (%)	0.261***	0.239**	0.323***	0.215***
	(3.19)	(2.59)	(3.43)	(2.97)
Post-Crisis: May 2009 - May 2012				
Inventory (%)	1.501***	1.107***	1.264***	0.919***
	(6.34)	(8.75)	(5.92)	(7.92)
Search (%)	0.185***	0.110***	0.227***	0.129***
	(7.39)	(5.13)	(9.17)	(6.62)
Basel II.5: Jun 2012 - Jun 2013				
Inventory (%)	1.538***	1.196***	1.220***	0.994***
	(7.55)	(33.33)	(7.35)	(34.61)
Search (%)	0.231***	0.139***	0.291***	0.180***
	(11.97)	(10.90)	(14.47)	(11.74)
Basel III: Jul 2013 - Mar 2014				
Inventory (%)	1.253***	1.108***	1.031***	0.930***
	(9.25)	(17.01)	(10.39)	(26.29)
Search (%)	0.141***	0.075***	0.192***	0.089***
	(21.56)	(7.79)	(28.28)	(9.70)
Post-Volcker: Apr 2014 - Sep 2019				
Inventory (%)	1.262***	1.033***	1.144***	0.931***
	(6.05)	(7.32)	(5.85)	(6.85)
Search (%)	0.098***	0.063***	0.127***	0.070***
	(9.59)	(5.18)	(10.13)	(9.59)
Inventory Premium Differences				
Post-Volcker − Pre-Crisis	0.520**	0.502***	0.525**	0.488***
	(2.15)	(3.46)	(2.38)	(3.54)
Search Premium Differences				
Post-Volcker − Pre-Crisis	0.010	0.018	0.012	0.003
	(0.53)	(1.09)	(0.51)	(0.19)
Observations	887,960	887,960	887,960	887,960

Notes: This table presents the pooled averages of the absolute inventory premium ($\lambda_t^{\text{Inventory}} \times \textit{Inventory-Spread}_{it}$) and search premium ($\lambda_t^{\text{Search}} \times \textit{Search-Spread}_{it}$) in each subperiod. $\lambda_t^{\text{Inventory}}$ and $\lambda_t^{\text{Search}}$ are obtained from the cross-sectional regression (15). T-statistics based on Driscoll and Kraay (1998) with five lags are presented in parentheses to account for heteroskedasticity as well as temporal autocorrelations. *** (**) [*] denotes statistical significance at 1% (5%) [10%] level.

Table 7: Decomposition of Liquidity Premium: Illiquidity Level vs. Liquidity Risk

	Baseline	Fama-French	BBW
Pre-Crisis: Jan 2004 - Jun 2007			
λ^{Shock}	-0.070***	-0.085***	-0.087***
	(-5.07)	(-8.23)	(-4.42)
λ^{Level}	0.393***	0.376***	0.359***
	(19.77)	(20.77)	(17.25)
Crisis: Jul 2007 - Apr 2009			
λ^{Shock}	-0.678***	-0.651***	-0.674***
	(-5.15)	(-5.31)	(-9.76)
λ^{Level}	0.150***	0.150***	0.213***
	(4.93)	(5.18)	(4.40)
Post-Crisis: May 2009 - May 2012			
λ^{Shock}	-0.559***	-0.538***	-0.591***
	(-6.00)	(-6.44)	(-6.07)
λ^{Level}	0.624***	0.617***	0.649***
	(8.04)	(8.15)	(11.64)
Basel II.5: Jun 2012 - Jun 2013			
λ^{Shock}	-0.452***	-0.436***	-0.490***
	(-12.48)	(-13.67)	(-10.75)
λ^{Level}	1.237***	1.205***	1.146***
	(42.14)	(34.92)	(31.60)
Basel III: Jul 2013 - Mar 2014			
λ^{Shock}	-0.315***	-0.295***	-0.397***
	(-9.21)	(-8.94)	(-38.50)
λ^{Level}	1.035***	0.928***	0.904***
	(37.73)	(41.95)	(38.68)
Post-Volcker: Apr 2014 - Sep 2019			
λ^{Shock}	-0.135***	-0.147***	-0.118*
	(-3.55)	(-4.45)	(-1.85)
λ^{Level}	0.997***	0.936***	0.916***
	(31.00)	(23.59)	(35.04)
$\lambda^{\text{Shock}}_{\text{Post-Volcker}}$ - $\lambda^{\text{Shock}}_{\text{Pre-Crisis}}$	-0.066	-0.062*	-0.031
	(-1.62)	(-1.80)	(-0.46)
$\lambda^{\text{Level}}_{\text{Post-Volcker}}$ - $\lambda^{\text{Level}}_{\text{Pre-Crisis}}$	0.604***	0.560***	0.557***
	(15.99)	(12.84)	(16.66)
Observations	887,960	887,960	693,807
Average R-squared	0.131	0.141	0.148

Notes: The table presents the time series averages of λ^{Level} and λ^{Shock} estimated from the two-stage asset pricing model (16) and (17). The R-squared is the average R-squared from the cross-sectional regression (17). T-statistics based on Newey and West (1987) with four lags are presented in parentheses. *** (**) [*] denotes statistical significance at 1% (5%) [10%] level.

Table 8: Dealer VaR and Liquidity Premium

	λ		Liquidity Premium		Trading Delay	
	$\Delta\lambda_t$	ΔVaR_t	ΔLP_t	ΔVaR_t	$\Delta Delay_t$	ΔVaR_t
ΔVaR_{t-1}	-4.790***	-0.398*	-111.844***	-0.415	-59.108***	-0.409*
	(-4.10)	(-1.71)	(-3.38)	(-1.55)	(-2.89)	(-1.72)
ΔVaR_{t-2}	-3.929**	-0.039	-103.267**	0.008	-23.738	-0.053
	(-2.49)	(-0.19)	(-2.62)	(0.04)	(-0.68)	(-0.23)
$\Delta\lambda_{t-1}$	-0.193	0.009				
	(-1.15)	(1.20)				
$\Delta\lambda_{t-2}$	0.017	0.001				
	(0.17)	(0.10)				
ΔLP_{t-1}			-0.491***	0.001		
			(-3.90)	(1.42)		
ΔLP_{t-2}			-0.076	0.000		
			(-0.77)	(0.21)		
$\Delta Delay_{t-1}$					-0.019	0.001
					(-0.20)	(1.24)
$\Delta Delay_{t-2}$					0.041	0.000
					(0.28)	(0.29)
Constant	-0.008	-0.004*	-0.420	-0.004*	-0.068	-0.004*
	(-0.30)	(-1.86)	(-0.86)	(-1.80)	(-0.17)	(-1.86)
Observations	39	39	39	39	39	39
R-squared	0.096	0.178	0.311	0.216	0.040	0.170

Notes: This table presents the results of the following time series regressions:

$$\Delta VaR_t = c_1 + a_1 \Delta VaR_{t-1} + a_2 \Delta VaR_{t-2} + b_1 \Delta Y_{t-1} + b_2 \Delta Y_{t-2} + \epsilon_t$$

$$\Delta Y_t = \tilde{c}_1 + \tilde{a}_1 \Delta VaR_{t-1} + \tilde{a}_2 \Delta VaR_{t-2} + \tilde{b}_1 \Delta Y_{t-1} + \tilde{b_2} \Delta Y_{t-2} + \tilde{\epsilon}_t$$

where Y is either the cross-sectional transaction cost coefficient (λ), the liquidity premium as a fraction of the total yield spread (LP), or the estimated trading delays ($Delay$). The data is quarterly. The sample period is between 2010 Q1 and 2019 Q3. T-statistics based on Newey and West (1987) with four lags are presented in parentheses. *** (**) [*] denotes statistical significance at 1% (5%) [10%] level.

Table 9: Impact of Basel II.5

Bond Yield Volatility	Baseline		Accounting		Alternative Transaction Cost	
	(1)	(2)	(3)	(4)	(5)	(6)
$Post_t \times Treat_{it}$	14.930***	14.969***	16.007***	16.086***	12.670***	12.721***
	(4.33)	(4.22)	(5.22)	(5.10)	(3.58)	(3.55)
Controls	NO	YES	NO	YES	NO	YES
Observations	47,247	47,247	47,247	47,247	47,247	47,247
R-squared	0.283	0.286	0.286	0.289	0.289	0.292

Probability of Downgrade	Baseline		Accounting		Alternative Transaction Cost	
	(1)	(2)	(3)	(4)	(5)	(6)
$Post_t \times Treat_{it}$	14.457***	14.173***	15.557***	15.274***	14.117***	14.148***
	(5.92)	(5.71)	(4.35)	(4.15)	(6.85)	(6.73)
Controls	NO	YES	NO	YES	NO	YES
Observations	47,247	47,247	47,247	47,247	47,247	47,247
R-squared	0.273	0.277	0.276	0.281	0.283	0.286

Notes: This table presents the results of the following regression:

$$\textit{Liquidity-Premium}_{it} = \eta^{\text{Basel II.5}} Post_t^{\text{Basel II.5}} \times Treat_{it}^{\text{Basel II.5}} + \alpha_i + \alpha_t + X'_{it}\gamma + u_{it}.$$

$Post_t^{\text{Basel II.5}}$ is a dummy variable that equals 1 if the observation occurs after June 2012. $Treat_{it}^{\text{Basel II.5}}$ is a dummy variable that equals 1 if bond i is in the top 10% of the Basel II.5 risk charges at time t, proxied by the daily yield change volatility or a credit transition matrix. X_{it} controls for equity volatility, rating dummies and bond time-to-maturity. Bond fixed effect and (monthly) time fixed effect are included in the specification. The dependent variable is the liquidity premium as a fraction of the total yield spread: $\lambda_t \times \textit{Bid-Ask-Spread}_{it} / \textit{Yield-Spread}_{it}$. In the *Baseline* model, the cross-sectional transaction cost coefficient λ_t is obtained from the cross-sectional regression (1). In the *Accounting* model, λ_t is obtained from the cross-sectional regression (23) where the firm-level accounting variables replace rating dummies. In the *Alternative Transaction Cost* model, the bid-ask spread from the cross-sectional regression (1) is replaced by the absolute bid-ask difference. The sample period is from December 2011 to November 2012. T-statistics based on standard errors clustered at the issuer-month level are presented in parentheses. *** (**) [*] denotes statistical significance at 1% (5%) [10%] level.

Table 10: Impact of Liquidity Coverage Ratio

Investment Grade	Baseline		Accounting		Alternative Transaction Cost	
	(1)	(2)	(3)	(4)	(5)	(6)
$Post_t \times Treat_i$	-2.518***	-2.589***	-2.545***	-2.610***	-2.254***	-2.298***
	(-4.48)	(-4.55)	(-4.56)	(-4.62)	(-4.69)	(-4.72)
Controls	NO	YES	NO	YES	NO	YES
Observations	41,351	41,351	41,351	41,351	41,351	41,351
R-squared	0.368	0.370	0.359	0.361	0.368	0.369

Speculative	Baseline		Accounting		Alternative Transaction Cost	
	(1)	(2)	(3)	(4)	(5)	(6)
$Post_t \times Treat_i$	1.042	1.094	1.287	1.363	1.042	1.102
	(0.54)	(0.57)	(0.56)	(0.61)	(0.69)	(0.74)
Controls	NO	YES	NO	YES	NO	YES
Observations	9,889	9,889	9,889	9,889	9,889	9,889
R-squared	0.468	0.469	0.467	0.469	0.478	0.479

Notes: This table presents the results of the following regression:

$$\textit{Liquidity-Premium}_{it} = \eta^{\text{LCR}} \textit{Post}_t^{\text{LCR}} \times \textit{Treat}_i^{\text{LCR}} + \alpha_i + \alpha_t + X_{it}'\gamma + u_{it}.$$

$Post_t^{\text{LCR}}$ is a dummy variable that equals 1 if the observation occurs after July 2013. $Treat_i^{\text{LCR}}$ is a dummy variable that equals 1 if bond i is issued by a non-financial firm. X_{it} controls for equity volatility, rating dummies and bond time-to-maturity. Bond fixed effect and (monthly) time fixed effect are included in the specification. The dependent variable is the liquidity premium as a fraction of the total yield spread: $\lambda_t \times \textit{Bid-Ask-Spread}_{it}/\textit{Yield-Spread}_{it}$. In the *Baseline* model, the cross-sectional transaction cost coefficient λ_t is obtained from the cross-sectional regression (1). In the *Accounting* model, λ_t is obtained from the cross-sectional regression (23) where the firm-level accounting variables replace rating dummies. In the *Alternative Transaction Cost* model, the bid-ask spread from the cross-sectional regression (1) is replaced by the absolute bid-ask difference. The sample period is from July 2012 to June 2013. T-statistics based on standard errors clustered at the issuer-month level are presented in parentheses. *** (**) [*] denotes statistical significance at 1% (5%) [10%] level.

Table 11: Impact of the Volcker Rule

	Baseline		Accounting		Alternative Transaction Cost	
Jan 2014 - Dec 2015	(1)	(2)	(3)	(4)	(5)	(6)
$Post_t \times Treat_i$	4.035***	3.987***	3.346**	3.319**	3.612***	3.502***
	(3.03)	(3.06)	(2.62)	(2.65)	(3.05)	(3.06)
Controls	NO	YES	NO	YES	NO	YES
Observations	22,559	22,559	22,559	22,559	22,559	22,559
R-squared	0.503	0.506	0.491	0.493	0.510	0.518
Placebo Test	Baseline		Accounting		Alternative Transaction Cost	
Jan 2012 - Dec 2013	(1)	(2)	(3)	(4)	(5)	(6)
$Post_t \times Treat_i$	-0.058	-0.129	-0.086	-0.162	-0.137	-0.189
	(-0.06)	(-0.13)	(-0.08)	(-0.14)	(-0.16)	(-0.22)
Controls	NO	YES	NO	YES	NO	YES
Observations	19,432	19,432	19,432	19,432	19,432	19,432
R-squared	0.412	0.414	0.414	0.415	0.422	0.425

Notes: This table presents the results of the following regression:

$$\textit{Liquidity-Premium}_{it}^{HY} = \eta^{\text{Volcker}} \textit{Post}_t^{\text{Volcker}} \times \textit{Treat}_i^{\text{Volcker}} + \alpha_i + \alpha_t + X_{it}'\gamma + u_{it}.$$

$Post_t^{\text{Volcker}}$ is a dummy variable that equals 1 if the observation occurs after April 2014. $Treat_i^{\text{Volcker}}$ is a dummy variable that equals 1 if all of bond i's lead underwriters are the Volcker-affected dealers identified in Wyman and SIFMA (2011). X_{it} controls for equity volatility, rating dummies and bond time-to-maturity. Bond fixed effect and (monthly) time fixed effect are included in the specification. The dependent variable is the liquidity premium as a fraction of the total yield spread: $\lambda_t \times \textit{Bid-Ask-Spread}_{it} / \textit{Yield-Spread}_{it}$. In the *Baseline* model, the cross-sectional transaction cost coefficient λ_t is obtained from the cross-sectional regression (1). In the *Accounting* model, λ_t is obtained from the cross-sectional regression (23) where the firm-level accounting variables replace rating dummies. In the *Alternative Transaction Cost* model, the bid-ask spread from the cross-sectional regression (1) is replaced by the absolute bid-ask difference. The sample period is from January 2014 to December 2015. The bottom panel presents the results of a placebo test of the same regression from January 2012 to December 2013, where the treatment is assigned in April 2012. T-statistics based on standard errors clustered at the issuer-month level are presented in parentheses. *** (**) [*] denotes statistical significance at 1% (5%) [10%] level.

APPENDIX

A Appendix

A.1 Bond Sample Cleaning and Construction

Table A1: Sample Constructions

Cleaning Procedures	Number of Observations (CUSIP-Month)
WRDS Bond Returns Data	1,734,248
Drop primary market transactions	1,585,791
Drop privately-placed, convertible, puttable and defaulted bonds	1,556,470
Keep senior security level and US corporate debentures (bond type="CDEB")	1,073,908
Keep amount-outstanding larger than 100 thousand USD and principal-amount equal to 1000 USD	1,061,262
Drop zero yields, no ratings, and time-to-maturity less than 1 month or longer than 30 years	1,000,583
Restrict sample size from Jan 2004 to Sept 2019	931,172
Keep bonds with at least 24 observations	887,960

Notes: Cleaning procedures of the WRDS Bond Returns data. The results are robust to alternative cleaning thresholds or procedures or no cleaning at all.

A.2 Post-crisis Banking Regulations

The 2007-2009 financial crisis has profoundly changed the regulatory framework of dealer banks as these institutions experienced severe liquidity problems during the crisis. The post-crisis Basel regulatory framework and the Dodd-Frank Act are thought to have heavily impacted the U.S. corporate bond market. The final rule of implementing the revisions to the Basel II market risk framework ("Basel II.5") was announced on June 7, 2012. The framework introduces an incremental risk capital charge (IRC) that accounts for default risk and migration risk for credit products. It also introduces a stressed value-at-risk (VaR) requirement based on a one-year loss horizon. Basel II.5 therefore increases the balance sheet costs for trading credit products, especially for corporate bonds.

The final rules of implementing Basel III were announced on July 9, 2013. Basel III raised the regulatory capital base to constrain the excess leverage in the banking system. For instance, Basel III requires that the common tier 1 equity has to be at least 4.5% of the risk weighted assets at all times.[54] In addition to the capital regulations, Basel III also introduced liquidity regulations. Specifically, the liquidity coverage ratio (LCR) requires that banks should hold enough high-quality liquid assets (HQLA) that can be liquidated to cover 30 days of expected net cash outflows during a stress event. HQLA are classified into three categories based on their liquidity. Level 1 assets are the most liquid category and are not subject to a haircut. These include Federal Reserve bank balances, foreign resources that can be withdrawn quickly, securities issued or guaranteed by specific sovereign entities, and U.S. government-issued or guaranteed securities. Level 2A assets are subject to 15% haircuts and include securities issued or guaranteed by specific multilateral development banks or sovereign entities, and securities issued by U.S. government-sponsored enterprises. Finally and related to the corporate bond market, level 2B assets are subject to 50% haircuts and include publicly-traded common stock and investment-grade corporate debt securities issued by non-financial sector corporations.[55]

The implementation of the Volcker Rule, as part of the Dodd-Frank Act, was finalized in April 2014, and large banks were required to be fully compliant by July 2015. The Volcker Rule prohibits banks with access to Federal Deposit Insurance Corp. (FDIC) or the Federal Reserve's discount window from engaging in proprietary trading of risky securities. While market making activities are exempt, various trading activity measures (e.g., inventory turnover, standard deviation of daily trading profits, etc.) need to be reported, potentially disincentivizing dealer banks from active market making for fear of violations of the Volcker Rule.

A.3 Variations in λ: Market Condition Controls

To allow for changes in market conditions as well as changes in the investor demand over the sample period, following Bessembinder et al. (2018) I add to the time-series regression (2) changes in the S&P500 stock return (*SP500*), Barclays Capital U.S. Corporate Bond Index returns (*Barclays*), the stock market volatility index (*VIX*), the three-month *LIBOR*, the aggregate outstanding amount (*Amt-Outstanding*), and the aggregate corporate bond mutual fund flows (*Flow*) standardized by

[54] The capital requirement of Basel III has not been fully implemented as of 2020 June, because it takes time for banks to build capital. Moreover, as argued by Adrian, Boyarchenko, and Shachar (2017), the leverage ratio is more costly to low-risk assets such as Treasuries or reverse repos.

[55] Source: https://www.federalregister.gov/documents/2014/10/10/2014-22520/liquidity-coverage-ratio-liquidity-risk-measurement-standards

the amount outstanding in the prior month.[56] Appendix Table A2 presents the results.

$$\begin{aligned}\lambda_t = {} & \lambda_{\text{Pre-Crisis}} \mathbb{1}_{\{t \in \text{Pre-Crisis}\}} + \lambda_{\text{Crisis}} \mathbb{1}_{\{t \in \text{Crisis}\}} + \lambda_{\text{Post-Crisis}} \mathbb{1}_{\{t \in \text{Post-Crisis}\}} \\ & + \lambda_{\text{Basel II.5}} \mathbb{1}_{\{t \in \text{Basel II.5}\}} + \lambda_{\text{Basel III}} \mathbb{1}_{\{t \in \text{Basel III}\}} + \lambda_{\text{Post-Volcker}} \mathbb{1}_{\{t \in \text{Post-Volcker}\}} \\ & + \beta_1 \Delta \log(\mathit{SP500})_{t-1} + \beta_2 \Delta \log(\mathit{Barclays})_{t-1} + \beta_3 \Delta \mathit{VIX}_{t-1} + \beta_4 \Delta \mathit{LIBOR}_{t-1} \\ & + \beta_5 \Delta \log(\mathit{Amt\text{-}Outstanding})_{t-1} + \beta_6 |\mathit{Flow}_{t-1}| / \mathit{Amt\text{-}Outstanding}_{t-2} + \epsilon_t. \end{aligned} \tag{22}$$

A.4 Variations in λ: Firm-Level Variables

To address the concern of rating inflations, instead of using rating dummies, I follow Blume, Lim, and Mackinlay (1998) and use firm-level accounting variables (3-month equity volatility, operating income, leverage, long-term debt, and pretax interest coverage) to control for credit risk in the cross-sectional regression. The following cross-sectional regression is run instead of equation (1) in the baseline regression. Table A3 presents the time series regression results for the resulting λ_t.

$$\begin{aligned}\mathit{Yield\text{-}Spread}_{it} = {} & \beta_{0t} + \lambda_t \mathit{Bid\text{-}Ask\text{-}Spread}_{it} + \beta_{1t} \mathit{Bond\text{-}Age}_{it} + \beta_{2t} \log(\mathit{Amount\text{-}Issued}_{it}) \\ & + \beta_{3t} \mathit{Coupon}_{it} + \beta_{4t} \mathit{Time\text{-}to\text{-}Maturity}_{it} \\ & + \beta_{5t} \mathit{Equity\text{-}Volatility}_{it} + \beta_{6t} \mathit{Leverage}_{it} + \beta_{7t} \mathit{Long\text{-}Term\text{-}Debt}_{it} \\ & + \beta_{8t} \mathit{Operating\text{-}Income}_{it} + \beta_{9t} \mathit{Pretax\text{-}Interest\text{-}Coverage}_{it} + \epsilon_{it}. \end{aligned} \tag{23}$$

Alternatively instead of using rating dummies, I use the 5-year probability of default of the issuer to control for credit risk in the cross-sectional regression:

$$\begin{aligned}\mathit{Yield\text{-}Spread}_{it} = {} & \beta_{0t} + \lambda_t \mathit{Bid\text{-}Ask\text{-}Spread}_{it} + \beta_{1t} \mathit{Bond\text{-}Age}_{it} + \beta_{2t} \log(\mathit{Amount\text{-}Issued}_{it}) \\ & + \beta_{3t} \mathit{Coupon}_{it} + \beta_{4t} \mathit{Time\text{-}to\text{-}Maturity}_{it} + \beta_{5t} \mathit{Default\text{-}Probability}_{it} + \epsilon_{it}. \end{aligned} \tag{24}$$

The firm-level default probability data are from the Risk Management Institute of the University of Singapore. If there is no matching at the firm level, I use Merton (1974) distance-to-default model to calculate the default probability. Table A4 presents the time series regression results for λ_t.

[56] The aggregate corporate bond mutual fund flow data were kindly provided by the Investment Company Institute.

A.5 Variations in λ: Alternative Measures of Corporate Bond Transaction Cost

Instead of the bid-ask spread (variable *t_spread*) calculated in the WRDS Bond Return database, Table A5 presents the time series regression results if I use the absolute bid-ask difference. I also use the equally-weighted average of the standardized bid-ask spread, the Amihud (2002) price impact measure, and the Roll (1984) autocorrelation measure in the cross-sectional regression (1) as an alternative transaction cost measure. Specifically, the daily Amihud measure of each bond is computed as:

$$Amihud_t = \frac{1}{N_t} \sum_{j=1}^{N_t} \frac{|\frac{P_j - P_{j-1}}{P_{j-1}}|}{Q_j},$$

where N_t is the number of returns on day t, P_j is trade price of transaction j and Q_j is the dollar volume of trade j. At least two transactions are required on a given day to calculate this daily measure. The monthly Amihud measure is defined as the average of the daily Amihud measures within each month. The monthly Roll measure is defined as the square root of minus the covariance between consecutive returns:

$$Roll_m = \sqrt{-\text{Cov}(\Delta \log P_j, \Delta \log P_{j-1})},$$

where the covariance estimation is based on the data points of each month. Finally, positive covariance is replaced with 0.

Moreover, in addition to the transaction cost-based liquidity measures (bid-ask spread, Amihud, and Roll), I also consider trading activity variables, such as monthly turnover and trade size. Turnover is the ratio of the monthly trading volume to the bond's amount outstanding. Trade size is the ratio of the monthly trading volume to the number of trades executed in that month. Table A6 summarizes both trading activity measures. Table A7 conducts a principal component analysis (PCA) of the transaction cost-based liquidity measures (bid-ask spread, Amihud, and Roll) and trading activity variables (turnover and trade size). Indeed, the first PC is approximately the equally-weighted average of the transaction cost-based liquidity measures. The second PC resembles the equally-weighted average of turnover and trade size.

Following Schwert (2017), I run the following cross-sectional regression with trading activity variables:

$$\begin{aligned} \textit{Yield-Spread}_{it} &= \beta_{0t} + \lambda_t \textit{PC1}_{it} + \lambda'_t \textit{PC2}_{it} + \beta_{1t}\textit{Bond-Age}_{it} + \beta_{2t}\log(\textit{Amount-Issued}_{it}) \\ &\quad + \beta_{3t}\textit{Coupon}_{it} + \beta_{4t}\textit{Time-To-Maturity}_{it} + \beta_{5t}\textit{Rating-Dummy}_{it} + \epsilon_{it}, \end{aligned} \tag{25}$$

where PC1 is the equally-weighted average of the standardized bid-ask spread, Amihud, and Roll measures, and PC2 is the equally-weighted average of the standardized turnover and trade size. Table A8 presents the time series regression result for the cross-sectional regression coefficient of PC1 (λ_t).

A.6 Model Solution

Here I solve a general version of the model in Section 4 where customer i with asset holding a has the flow utility function $c_i u(a)$ with $c_L < c_H$. I shall consider the case of $u(a) = \frac{a^{1-\gamma}}{1-\gamma}$ when $\gamma \to 0$. As in Section 4, the value function of customer $i \in \{H, L\}$ with asset holding a satisfies the following Hamilton-Jacobi-Bellman (HJB) equation:

$$\begin{aligned} rV_i(a) = c_i u(a) + \delta\pi_j\big(V_j(a) - V_i(a)\big) + \lambda_T\big(V_i(0) + F_i a - V_i(a)\big) + \lambda_D\big(V_i(0) - V_i(a)\big) \\ + \alpha(v)\big(V_i(a_i) - V_i(a) - p(a_i - a) - \phi_i(a)\big) + \beta\big(V_i(a_i) - V_i(a) - p(a_i - a)\big), \end{aligned} \tag{26}$$

where $u(a) = \frac{a^{1-\gamma}}{1-\gamma}$ and $j \neq i$. Trades with dealers are determined by Nash bargaining: $(a_i, \phi_i) = \text{argmax}\big[V_i(a_i) - V_i(a) - p(a_i - a) - \phi_i\big]^{(1-\eta)}\phi_i^{\eta}$, where η is the dealer's bargaining power.

Following similar calculations in Lagos and Rocheteau (2009), I define:

$$U_i(a) = \bar{c}_i u(a) + \lambda_T \bar{F}_i a,$$

where $\bar{c}_i = \frac{(r+\lambda_T+\lambda_D+\sigma(v))c_i+\delta\bar{c}}{r+\lambda_T+\lambda_D+\sigma(v)+\delta}$, $\bar{F}_i = \frac{(r+\lambda_T+\lambda_D+\sigma(v))F_i+\delta\bar{F}}{r+\lambda_T+\lambda_D+\sigma(v)+\delta}$, $\bar{c} = \pi_L c_L + \pi_H c_H$, $\bar{F} = \pi_L F_L + \pi_H F_H$, and $\sigma(v) = \alpha(v)(1-\eta) + \beta$. The value function (26) therefore can be written as:

$$V_i(a) = \frac{1}{r + \lambda_T + \lambda_D + \sigma(v)}\Big\{U_i(a) + \sigma p a + \Omega_i\Big\},$$

where $\Omega_i = \frac{(r+\lambda_T+\lambda_D+\sigma(v))\Delta_i+\delta\sum_j \pi_j\Delta_j}{r+\lambda_T+\lambda_D+\sigma(v)+\delta}$ and $\Delta_i = \sigma \max_{a_i}\big[V_i(a_i) - p a_i\big] + (\lambda_T+\lambda_D)V_i(0)$. Therefore, given the price p, the optimal asset holding is $a_i = U_i'^{-1}\big((r + \lambda_T + \lambda_D)p\big)$. Finally, trading fees satisfy: $\phi_i(a) = \frac{\eta}{r+\lambda_T+\lambda_D+\sigma(v)}\Big\{\bar{c}_i\big(u(a_i) - u(a)\big) + \lambda_T\bar{F}_i(a_i - a) - (r + \lambda_T + \lambda_D)p(a_i - a)\Big\}$.

To solve for optimal asset holdings and the price, let n_{ij} denote the distribution of customers with asset holding a_i and preference type j. The distributions sum up to 1 and evolve according to the following:

$$\dot{n}_{0H} = (\lambda_T + \lambda_D)(n_{HH} + n_{LH}) - \delta\pi_L n_{0H} + \delta\pi_H n_{0L} - (\alpha + \beta)n_{0H}$$

$$\dot{n}_{0L} = (\lambda_T + \lambda_D)(n_{HL} + n_{LL}) - \delta\pi_H n_{0L} + \delta\pi_L n_{0H} - (\alpha + \beta)n_{0L}$$

$$\dot{n}_{HL} = \delta\pi_L n_{HH} - \delta\pi_H n_{HL} - (\alpha + \beta)n_{HL} - (\lambda_T + \lambda_D)n_{HL}$$

$$\dot{n}_{LH} = \delta\pi_H n_{LL} - \delta\pi_L n_{LH} - (\alpha + \beta)n_{LH} - (\lambda_T + \lambda_D)n_{LH}$$

$$\dot{n}_{LL} = \delta\pi_L n_{LH} - \delta\pi_H n_{LL} + (\alpha + \beta)(n_{HL} + n_{0L}) - (\lambda_T + \lambda_D)n_{LL}$$

$$\dot{n}_{HH} = \delta\pi_H n_{HL} - \delta\pi_L n_{HH} + (\alpha + \beta)(n_{LH} + n_{0H}) - (\lambda_T + \lambda_D)n_{HH},$$

where $\alpha = \alpha(v)$. The evolution of n_{0H} says that customers of H type, regardless of asset holdings, will enter the $0H$ state if the bond matures or default at rate $\lambda_T + \lambda_D$. Their preference switches from H to L at the rate $\delta\pi_L$ while customers in the $0L$ state enter the $0H$ state at the rate $\delta\pi_H$. Finally, customers in the $0H$ state trade to buy assets at the rate $\alpha(v) + \beta$ to enter the state HH. One can solve for these distributions as the following:

$$\begin{aligned}
n_{0H} &= \frac{\lambda_T + \lambda_D}{\alpha + \beta + \lambda_T + \lambda_D}\pi_H \\
n_{0L} &= \frac{\lambda_T + \lambda_D}{\alpha + \beta + \lambda_T + \lambda_D}\pi_L \\
n_{HL} = n_{LH} &= \frac{\alpha + \beta}{\alpha + \beta + \lambda_T + \lambda_D}\frac{\delta\pi_H\pi_L}{\alpha + \beta + \delta + \lambda_T + \lambda_D} \\
n_{LL} &= \frac{\alpha + \beta}{\alpha + \beta + \lambda_T + \lambda_D}\frac{\delta\pi_L^2 + (\alpha + \beta + \lambda_T + \lambda_D)\pi_L}{\alpha + \beta + \delta + \lambda_T + \lambda_D} \\
n_{HH} &= \frac{\alpha + \beta}{\alpha + \beta + \lambda_T + \lambda_D}\frac{\delta\pi_H^2 + (\alpha + \beta + \lambda_T + \lambda_D)\pi_H}{\alpha + \beta + \delta + \lambda_T + \lambda_D}.
\end{aligned} \tag{27}$$

Using the market clearing: $(n_{HH} + n_{HL})a_H + (n_{LL} + n_{LH})a_L + (n_{0H} + n_{0L})0 = A$, I solve for the optimal asset holdings and price: $\pi_H \frac{\bar{c}_H^{\frac{1}{\gamma}}}{\left((r+\lambda_T+\lambda_D)p-\bar{F}_H\lambda_T\right)^{\frac{1}{\gamma}}} + \pi_L \frac{\bar{c}_L^{\frac{1}{\gamma}}}{\left((r+\lambda_T+\lambda_D)p-\bar{F}_L\lambda_T\right)^{\frac{1}{\gamma}}} = (1 + \frac{\lambda_T+\lambda_D}{\alpha+\beta})A$, and $a_i = \frac{\bar{c}_i^{\frac{1}{\gamma}}}{\left((r+\lambda_T+\lambda_D)p-\bar{F}_i\lambda_T\right)^{\frac{1}{\gamma}}}$. When preference is linear ($\gamma = 0$), $a_H = (1 + \frac{\lambda_T+\lambda_D}{\alpha+\beta})\frac{A}{\pi_H}$, $a_L = 0$, and price becomes:

$$p = \frac{1}{r + \lambda_T + \lambda_D}\left\{\frac{\big(r + \lambda_T + \lambda_D + \sigma(v)\big)\epsilon_H + \delta\bar{\epsilon}}{r + \lambda_T + \lambda_D + \sigma(v) + \delta}\right\}, \tag{28}$$

where $\epsilon_i = c_i + \lambda_T F_i$, $\bar{\epsilon} = \pi_L\epsilon_L + \pi_H\epsilon_H$ and $\sigma(v) = \alpha(v)(1 - \eta) + \beta$.

A.7 Proof of $\frac{\partial LP}{\partial \beta} < 0$ when β affects dealer's zero-profit condition

For simplicity and brevity, consider $\alpha(v) = \alpha \cdot v$ and $\lambda_T = \lambda_D = 0$. The free-entry of dealers suggests that dealers' profit must be zero: $\frac{\alpha v}{v} \times \Big\{\phi_L(a_H)n_{HL} + \phi_H(a_L)n_{LH}\Big\} - k = 0$, which can be simplified to:

$$\alpha\frac{\eta A\delta\pi_L(\epsilon_H - \epsilon_L)}{(r+\delta+\alpha v(1-\eta)+\beta)(\alpha v+\beta+\delta)} = k. \tag{29}$$

Take the derivative with respect to β on both sides and simplify:

$$\Big(\alpha(1-\eta)\frac{\partial v}{\partial \beta}+1\Big)\Big(\alpha v+\beta+\delta\Big) + \Big(r+\delta+\alpha v(1-\eta)+\beta\Big)\Big(\alpha\frac{\partial v}{\partial \beta}+1\Big) = 0.$$

I can therefore solve $\frac{\partial v}{\partial \beta}$ as the following:

$$\begin{aligned}\frac{\partial v}{\partial \beta} &= -\frac{\alpha v(2-\eta)+2\beta+2\delta+r}{2\alpha^2(1-\eta)v+\alpha\beta(2-\eta)+\alpha\delta(2-\eta)+\alpha r}\\ &\leq -\frac{\alpha v(2-\eta)+(2-\eta)\beta+(2-\eta)\delta+r}{\alpha^2(2-\eta)v+\alpha\beta(2-\eta)+\alpha\delta(2-\eta)+\alpha r}\\ &\leq -\frac{1}{\alpha} < 0.\end{aligned}$$

Finally define the liquidity premium (illiquidity discount) in the price space as $LP = \frac{\epsilon_H}{r} - p = \frac{1}{r}\frac{\delta\pi_L(\epsilon_H-\epsilon_L)}{r+\delta+\alpha v(1-\eta)+\beta}$. So by equation (29), I have:

$$LP\frac{1}{\alpha v+\beta+\delta} = \frac{k}{r\alpha\eta A}.$$

Take the derivative with respect to β on both sides, I get:

$$\frac{\partial LP}{\partial \beta} - LP\frac{1}{\alpha v+\beta+\delta}\Big(\alpha\frac{\partial v}{\partial \beta}+1\Big) = 0$$

$$\begin{aligned}\frac{\partial LP}{\partial \beta} &= LP\frac{1}{\alpha v+\beta+\delta}\Big(\alpha\frac{\partial v}{\partial \beta}+1\Big)\\ &\leq LP\frac{1}{\alpha v+\beta+\delta}\Big(\alpha\big(-\frac{1}{\alpha}\big)+1\Big) = 0.\end{aligned}$$

So rising β reduces the liquidity premium. □

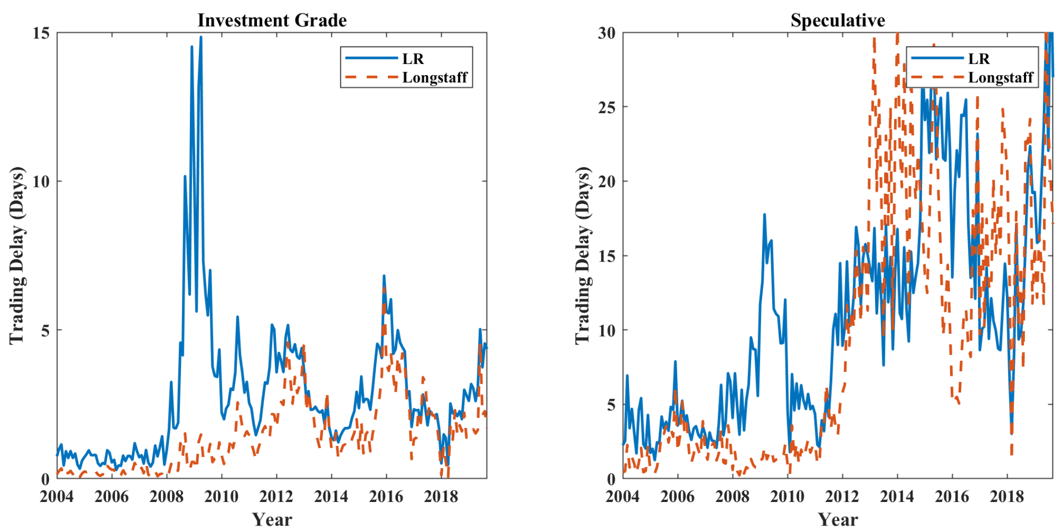
A.8 Trading Delays Estimated from the Longstaff (1995) Model

Longstaff (1995) shows that if security prices follow a geometric brownian motion: $dP = \mu P dt + \sigma P dW$, and investors are restricted from selling the security prior to some fixed time τ, then the present value of the price discount due to the trading delay τ can be calculated in closed-form:

$$\Delta P(P,\tau) = P\big(2 + \frac{\sigma^2\tau}{2}\big)\text{Normal}\big(\frac{\sqrt{\sigma^2\tau}}{2}\big) + P\sqrt{\frac{\sigma^2\tau}{2\pi}}\exp\big(-\frac{\sigma^2\tau}{8}\big) - P,$$

where Normal$(\cdot)$ is the cumulative normal distribution. To estimate the trading delay τ, I connect the theoretical illiquidity discount (in terms of price) to the empirical liquidity premium (in terms of the yield) using a modified duration formula: $\frac{\Delta P(P,\tau)}{P} = \text{Modified-Duration} \times \big(\lambda \times \text{Bid-Ask}\big)$.

Figure A1: Trading Delays



Notes: This figure presents the trading delays of executing investment grade and speculative bond trades, implied by the magnitude of the liquidity premium. The solid blue line (LR) is the trading delay estimated from my structural model in Section 4. The dashed red line (Longstaff) is the trading delay τ, estimated from the Longstaff (1995) model, where the cross-sectional liquidity premium and return volatility are used in the estimation.

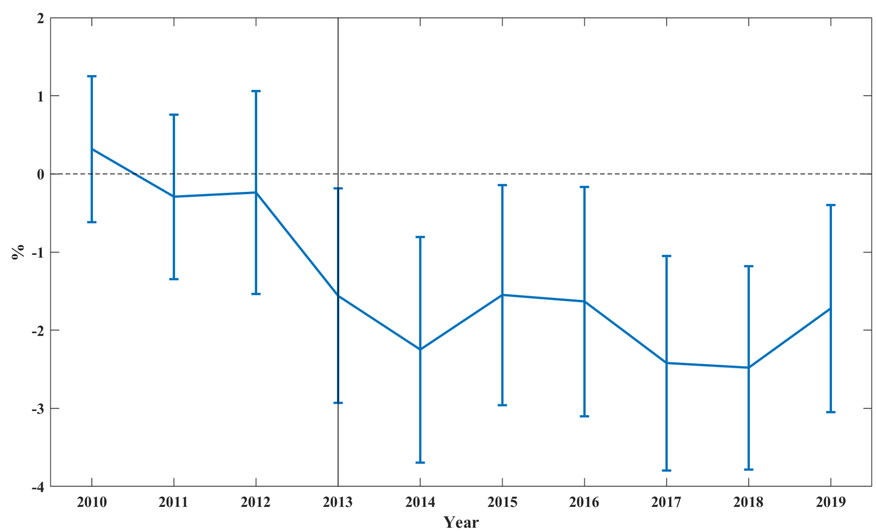
A.9 Pre-Trend of the LCR

I check the pre-trend using the following regression framework within the investment grade corporate bond sample at the yearly level:

$$\textit{Liquidity-Premium}_{it}^{IG} = \sum_{t=2010}^{2019} \eta_t (Y_t \times \textit{Treat}_i^{\text{LCR}}) + \alpha_i + \alpha_t + X_{it}'\gamma + u_{it}.$$

Y_t is the yearly dummy variable, and the second half of 2009 serves as the reference year. Bond fixed effect and yearly time fixed effect are used, and the standard errors are clustered at the issuer's level. Figure A2 shows that there is no pre-trend before 2013. Since 2013, the liquidity premium (as fraction of the total yield spread) of the investment grade corporate bonds issued by non-financial firms is on average 2-3 percentage points lower than the liquidity premium of the investment grade bonds issued by financial firms.

Figure A2: Pre-Trend of the Liquidity Coverage Ratio within Investment Grade Bonds



Notes: This figure presents the coefficient η_t of the following model:

$\textit{Liquidity-Premium}_{it}^{IG} = \sum_{t=2010}^{2019} \eta_t (Y_t \times \textit{Treat}_i^{\text{LCR}}) + \alpha_i + \alpha_t + X_{it}'\gamma + u_{it}.$

The analysis is conducted at the yearly level within the investment grade bond sample. The dependent variable is $\lambda_t \times \textit{Bid-Ask-Spread}_{it} / \textit{Yield-Spread}_{it}$. Y_t is the year dummy. $\textit{Treat}_i^{\text{LCR}}$ is a dummy variable equal to 1 if bond i is issued by a non-financial firm. X_{it} controls for equity volatility, rating dummies, and time-to-maturity. Bond fixed effect and (yearly) time fixed effect are included. Standard errors are clustered at issuer's level and the error bars represent the 95% confidence interval. The second half of 2009 serves as the reference year.

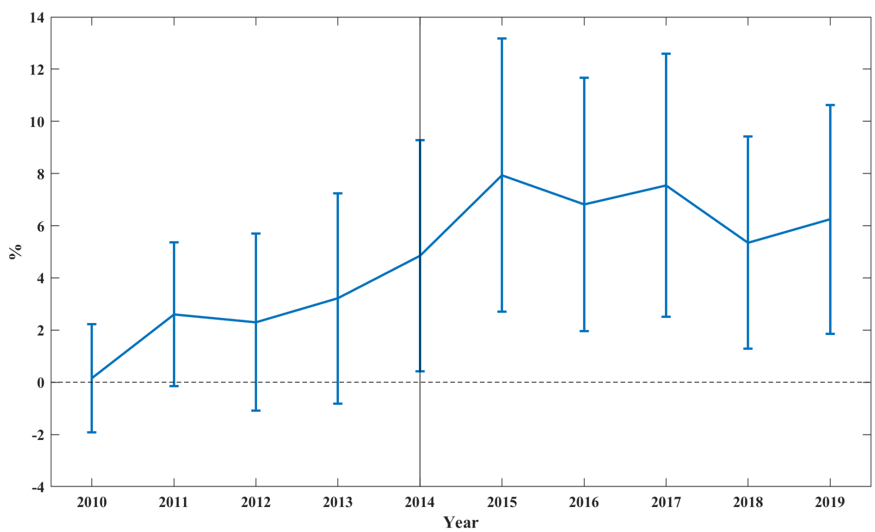
A.10 Pre-Trend of the Volcker Rule

I use the following regression framework:

$$\text{Liquidity-Premium}_{it}^{HY} = \sum_{t=2010}^{2019} \eta_t (Y_t \times \text{Treat}_i^{\text{Volcker}}) + \alpha_i + \alpha_t + X_{it}'\gamma + u_{it}.$$

Y_t is the yearly dummy variable, and the second half of 2009 serves as the reference year. Bond fixed effect and yearly time fixed effect are used, and the standard errors are clustered at the issuer's level. Figure A3 shows that the pre-trend is not significant before 2014. Since 2014 the liquidity premium (as a fraction of the total yield spread) of the speculative high yield bonds whose lead underwriters are more likely to be affected by the Volcker Rule is on average 3-4 percentage points significantly higher than the liquidity premium of the speculative bonds whose lead underwriters are less likely to be affected by the Volcker Rule. The impact appears to be the largest in year 2015 when the full compliance of the Volcker Rule was required.

Figure A3: Pre-Trend of the Volcker Rule within Speculative Bonds



Notes: This figure presents the coefficient η_t of the following model:

$\textit{Liquidity-Premium}_{it}^{HY} = \sum_{t=2010}^{2019} \eta_t (Y_t \times \textit{Treat}_i^{\text{Volcker}}) + \alpha_i + \alpha_t + X_{it}'\gamma + u_{it}$.

The analysis is conducted at yearly level within the speculative bond sample. The dependent variable is $\lambda_t \times$ *Bid-Ask-Spread*$_{it}$/ *Yield-Spread*$_{it}$. Y_t is the yearly dummy variable. $Treat_i^{\text{Volcker}}$ is a dummy variable equal to 1 if all of bond i's lead underwriters are the Volcker-affected dealers identified in Wyman and SIFMA (2011). X_{it} controls for equity volatility, ratings and time-to-maturity. Bond fixed effect and (yearly) time fixed effect are included. Standard errors are clustered at issuer's level and the error bars represent the 95% confidence interval. The second half of 2009 serves as the reference year.

A.11 A Brief Look at COVID-19

On March 23 2020, the Federal Reserve directly intervened in the corporate bond market by announcing the Primary and Secondary Market Corporate Credit Facilities (PMCCF and SMCCF). Specifically, the SMCCF allows the Fed to purchase corporate bonds in the secondary market that, as of March 22, have an investment grade rating and a remaining maturity of five years or less.[57]

Nozawa and Qiu (2020), Faria-e-Castro, Kozlowski, and Ebsim (2020), and Kargar et al. (2020) study the corporate bond yield spread and bid-ask spread during the COVID-19 pandemic. They find that both the yield spread and the bid-ask spread dropped after the announcement of SMCCF. The liquidity premium offers another interesting angle to look at the corporate bond liquidity condition during the pandemic. In Figure A4, I plot the evolutions of the liquidity and default premia[58] of the investment grade bonds with time-to-maturity of less than five years, and compare them to the liquidity and default premia of the investment grade bonds with time-to-maturity longer than five years and the speculative bonds.[59] Clearly, the default component of the yield spread has dropped since the Fed intervention, consistent with Nozawa and Qiu (2020). Interestingly, the liquidity premium only dropped for the bonds eligible for the Fed's purchases: investment grade bonds with time-to-maturity of less than five years. Their liquidity premium dropped from 1% to 0.5%. On the other hand, for investment grade bonds with time-to-maturity of more than five years, their liquidity premium stays at 0.5% before and after the announcement of SMCCF, and for speculative bonds, their liquidity premium remains at 3%. The liquidity premium therefore offers more direct evidence of the impact of SMCCF on corporate bond liquidity. The result is consistent with the evidence found in Kargar et al. (2020) that the Fed intervention has had a larger impact on the transaction cost measure (bid-ask spread) of the investment grade bonds than that of the

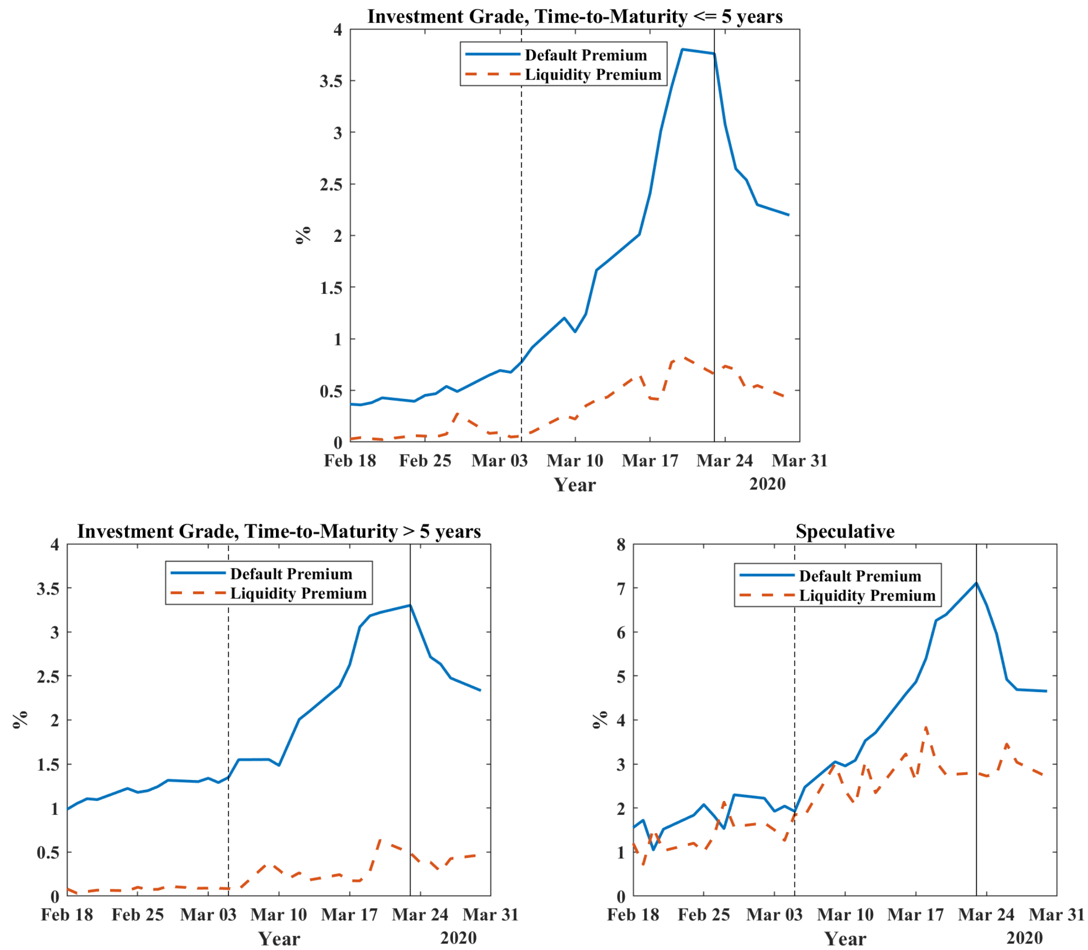
[57] Source: `https://www.federalreserve.gov/newsevents/pressreleases/files/monetary20200409a2.pdf`.

[58] The liquidity premium is computed as $\lambda_t(\text{liq}_{it} - \text{liq}_{1t})$ where liq_{it} is the equally-weighted average of the standardized bid-ask spread, Roll and Amihud measures, and liq_{1t} is the 1% quantile. I use this combined measure of corporate bond transaction cost because at the daily frequency, individual measures of transaction cost may suffer from missing values and liquidity risk may rise too during this period. Because liq_{it} is standardized, it could be negative and I subtract a very liquid portion liq_{1t} to compute the premium, as in Dick-Nielsen, Feldhütter, and Lando (2012) and Schwert (2017). In any case, the liquidity premium at the daily frequency is likely to be underestimated because there may not be enough data points to compute the daily transaction cost measures due to the infrequent trading in the market.

[59] The rating data are from Mergent FISD, and most recently updated in August 2019. Therefore, the rating information is not up-to-date.

speculative bonds.

Figure A4: Liquidity and Default Premia during COVID-19



Notes: This figure presents the liquidity and default premia during the COVID-19 pandemic. The liquidity premium is $\lambda_t(\text{liq}_{it} - \text{liq}_{1t})$ where liq_{it} is the equally weighted average of the standardized bid-ask spread, Roll and Amihud measures, and liq_{1t} is the 1% quantile. The default premia is $\text{yield-spread}_{it} - \text{liquidity premium}_{it}$. Each day the median liquidity and default premia are plotted here. The dashed line is March 5, 2020 when the stock market crashed; the solid line is March 23, 2020 when the Fed announced SMCCF.

Table A2: Variations in λ: Market Condition Controls

Rating	A and above	BBB	Speculative
Pre-Crisis: Jan 2004 - Jun 2007			
$\lambda_{\text{Pre-Crisis}}$	0.115***	0.218***	0.663***
	(4.79)	(9.90)	(7.48)
Crisis: Jul 2007 - Apr 2009			
λ_{Crisis}	0.427***	0.319***	1.022***
	(3.71)	(6.38)	(7.83)
Post-Crisis: May 2009 - May 2012			
$\lambda_{\text{Post-Crisis}}$	0.396***	0.416***	0.973***
	(9.36)	(9.77)	(6.02)
Basel II.5: Jun 2012 - Jun 2013			
$\lambda_{\text{Basel II.5}}$	0.366***	0.569***	2.026***
	(9.21)	(19.60)	(14.82)
Basel III: Jul 2013 - Mar 2014			
$\lambda_{\text{Basel III}}$	0.196***	0.475***	2.009***
	(4.05)	(14.17)	(17.70)
Post-Volcker: Apr 2014 - Sep 2019			
$\lambda_{\text{Post-Volcker}}$	0.188***	0.480***	2.669***
	(6.38)	(8.97)	(13.68)
Coefficient-Difference			
$\lambda_{\text{Crisis}} - \lambda_{\text{Pre-Crisis}}$	0.312***	0.101*	0.360**
	(2.59)	(1.78)	(2.19)
$\lambda_{\text{Basel II.5}} - \lambda_{\text{Post-Crisis}}$	-0.031	0.154***	1.053***
	(-0.64)	(4.57)	(5.84)
$\lambda_{\text{Basel III}} - \lambda_{\text{Basel II.5}}$	-0.170***	-0.095***	-0.016
	(-3.06)	(-3.67)	(-0.12)
$\lambda_{\text{Post-Volcker}} - \lambda_{\text{Basel III}}$	-0.007	0.006	0.659***
	(-0.17)	(0.15)	(3.72)
$\lambda_{\text{Post-Volcker}} - \lambda_{\text{Pre-Crisis}}$	0.073**	0.262***	2.006***
	(2.53)	(5.78)	(11.20)
Observations	287,172	337,053	169,880
Average R-squared	0.387	0.329	0.569

Notes: This table presents the result of the time series regression:

$$\lambda_t = \lambda_{\text{Pre-Crisis}}\mathbb{1}_{\{t\in\text{Pre-Crisis}\}} + \lambda_{\text{Crisis}}\mathbb{1}_{\{t\in\text{Crisis}\}} + \lambda_{\text{Post-Crisis}}\mathbb{1}_{\{t\in\text{Post-Crisis}\}} + \lambda_{\text{Basel II.5}}\mathbb{1}_{\{t\in\text{Basel II.5}\}} + \lambda_{\text{Basel III}}\mathbb{1}_{\{t\in\text{Basel III}\}} + \lambda_{\text{Post-Volcker}}\mathbb{1}_{\{t\in\text{Post-Volcker}\}} + \beta_1\Delta\log(\mathit{SP500})_{t-1} + \beta_2\Delta\log(\mathit{Barclays})_{t-1} + \beta_3\Delta \mathit{VIX}_{t-1} + \beta_4\Delta \mathit{LIBOR}_{t-1} + \beta_5\Delta\log(\mathit{Amt\text{-}Outstanding})_{t-1} + \beta_6|\mathit{Flow}_{t-1}|/\mathit{Amt\text{-}Outstanding}_{t-2} + \epsilon_t.$$

λ_t is obtained from the cross-sectional regression (1). The R-squared is the average R-squared from the cross-sectional regression. T-statistics based on Newey and West (1987) with four lags are presented in parentheses. *** (**) [*] denotes statistical significance at 1% (5%) [10%] level.

Table A3: Variations in λ: Firm-Level Variables

Rating	A and above	BBB	Speculative
Pre-Crisis: Jan 2004 - Jun 2007			
$\lambda_{\text{Pre-Crisis}}$	0.090***	0.187***	0.765***
	(5.06)	(14.20)	(11.48)
Crisis: Jul 2007 - Apr 2009			
λ_{Crisis}	0.232***	0.216***	1.099***
	(6.01)	(4.03)	(6.76)
Post-Crisis: May 2009 - May 2012			
$\lambda_{\text{Post-Crisis}}$	0.314***	0.359***	1.333***
	(14.92)	(11.93)	(9.98)
Basel II.5: Jun 2012 - Jun 2013			
$\lambda_{\text{Basel II.5}}$	0.338***	0.554***	2.192***
	(13.67)	(16.41)	(47.07)
Basel III: Jul 2013 - Mar 2014			
$\lambda_{\text{Basel III}}$	0.173***	0.454***	2.107***
	(3.19)	(35.21)	(26.20)
Post-Volcker: Apr 2014 - Sep 2019			
$\lambda_{\text{Post-Volcker}}$	0.169***	0.470***	2.755***
	(8.70)	(17.24)	(17.67)
Coefficient-Difference			
$\lambda_{\text{Crisis}} - \lambda_{\text{Pre-Crisis}}$	0.142***	0.029	0.334*
	(3.35)	(0.53)	(1.91)
$\lambda_{\text{Basel II.5}} - \lambda_{\text{Post-Crisis}}$	0.024	0.195***	0.859***
	(0.75)	(4.71)	(6.17)
$\lambda_{\text{Basel III}} - \lambda_{\text{Basel II.5}}$	-0.164**	-0.100***	-0.085
	(-2.61)	(-2.93)	(-0.94)
$\lambda_{\text{Post-Volcker}} - \lambda_{\text{Basel III}}$	-0.004	0.015	0.648***
	(-0.08)	(0.51)	(3.90)
$\lambda_{\text{Post-Volcker}} - \lambda_{\text{Pre-Crisis}}$	0.079***	0.283***	1.991***
	(3.01)	(9.36)	(11.74)
Observations	287,172	337,053	169,880
Average R-squared	0.454	0.379	0.423

Notes: This table presents the result of the time series regression:

$$\lambda_t = \lambda_{\text{Pre-Crisis}} \mathbb{1}_{\{t \in \text{Pre-Crisis}\}} + \lambda_{\text{Crisis}} \mathbb{1}_{\{t \in \text{Crisis}\}} + \lambda_{\text{Post-Crisis}} \mathbb{1}_{\{t \in \text{Post-Crisis}\}} + \lambda_{\text{Basel II.5}} \mathbb{1}_{\{t \in \text{Basel II.5}\}} + \lambda_{\text{Basel III}} \mathbb{1}_{\{t \in \text{Basel III}\}} + \lambda_{\text{Post-Volcker}} \mathbb{1}_{\{t \in \text{Post-Volcker}\}} + \epsilon_t.$$

λ_t is obtained from the cross-sectional regression (23) where the rating dummies are replaced by the firm-level accounting variables. The R-squared is the average R-squared from the cross-sectional regression. T-statistics based on Newey and West (1987) with four lags are presented in parentheses. *** (**) [*] denotes statistical significance at 1% (5%) [10%] level.

Table A4: Variations in λ: Default Probability

Rating	A and above	BBB	Speculative
Pre-Crisis: Jan 2004 - Jun 2007			
$\lambda_{\text{Pre-Crisis}}$	0.107***	0.206***	0.719***
	(6.71)	(13.22)	(13.21)
Crisis: Jul 2007 - Apr 2009			
λ_{Crisis}	0.383***	0.285***	1.256***
	(4.08)	(4.79)	(5.60)
Post-Crisis: May 2009 - May 2012			
$\lambda_{\text{Post-Crisis}}$	0.419***	0.424***	1.436***
	(11.23)	(13.71)	(8.41)
Basel II.5: Jun 2012 - Jun 2013			
$\lambda_{\text{Basel II.5}}$	0.369***	0.564***	2.148***
	(10.16)	(23.18)	(22.18)
Basel III: Jul 2013 - Mar 2014			
$\lambda_{\text{Basel III}}$	0.194***	0.472***	2.062***
	(3.58)	(24.81)	(14.32)
Post-Volcker: Apr 2014 - Sep 2019			
$\lambda_{\text{Post-Volcker}}$	0.189***	0.532***	2.916***
	(7.86)	(13.21)	(18.81)
Coefficient-Difference			
$\lambda_{\text{Crisis}} - \lambda_{\text{Pre-Crisis}}$	0.276***	0.079	0.537***
	(2.9)	(1.29)	(2.34)
$\lambda_{\text{Basel II.5}} - \lambda_{\text{Post-Crisis}}$	-0.05	0.139***	0.712***
	(-0.98)	(3.91)	(3.69)
$\lambda_{\text{Basel III}} - \lambda_{\text{Basel II.5}}$	-0.174**	-0.091***	-0.085
	(-2.48)	(-2.87)	(-0.58)
$\lambda_{\text{Post-Volcker}} - \lambda_{\text{Basel III}}$	-0.005	0.06	0.854***
	(-0.09)	(1.37)	(3.97)
$\lambda_{\text{Post-Volcker}} - \lambda_{\text{Pre-Crisis}}$	0.082***	0.326***	2.197***
	(2.83)	(7.55)	(13.37)
Observations	287,172	337,053	169,880
Average R-squared	0.373	0.325	0.406

Notes: This table presents the result of the time series regression:

$$\lambda_t = \lambda_{\text{Pre-Crisis}}\mathbb{1}_{\{t\in\text{Pre-Crisis}\}} + \lambda_{\text{Crisis}}\mathbb{1}_{\{t\in\text{Crisis}\}} + \lambda_{\text{Post-Crisis}}\mathbb{1}_{\{t\in\text{Post-Crisis}\}} + \lambda_{\text{Basel II.5}}\mathbb{1}_{\{t\in\text{Basel II.5}\}} + \lambda_{\text{Basel III}}\mathbb{1}_{\{t\in\text{Basel III}\}} + \lambda_{\text{Post-Volcker}}\mathbb{1}_{\{t\in\text{Post-Volcker}\}} + \epsilon_t.$$

λ_t is obtained from the cross-sectional regression (24) where the rating dummies are replaced by the five-year probability of default. The R-squared is the average R-squared from the cross-sectional regression. T-statistics based on Newey and West (1987) with four lags are presented in parentheses. *** (**) [*] denotes statistical significance at 1% (5%) [10%] level.

Table A5: Variations in λ: Absolute Bid-Ask Difference

Rating	A and above	BBB	Speculative
Pre-Crisis: Jan 2004 - Jun 2007			
$\lambda_{\text{Pre-Crisis}}$	0.099***	0.173***	0.490***
	(6.64)	(16.28)	(9.58)
Crisis: Jul 2007 - Apr 2009			
λ_{Crisis}	0.359***	0.208***	0.800***
	(5.91)	(6.47)	(5.68)
Post-Crisis: May 2009 - May 2012			
$\lambda_{\text{Post-Crisis}}$	0.307***	0.300***	0.700***
	(16.60)	(15.97)	(6.66)
Basel II.5: Jun 2012 - Jun 2013			
$\lambda_{\text{Basel II.5}}$	0.282***	0.411***	1.549***
	(11.02)	(27.57)	(14.64)
Basel III: Jul 2013 - Mar 2014			
$\lambda_{\text{Basel III}}$	0.172***	0.365***	1.703***
	(3.95)	(33.69)	(19.71)
Post-Volcker: Apr 2014 - Sep 2019			
$\lambda_{\text{Post-Volcker}}$	0.156***	0.357***	2.176***
	(8.81)	(15.55)	(10.65)
Coefficient-Difference			
$\lambda_{\text{Crisis}} - \lambda_{\text{Pre-Crisis}}$	0.259***	0.036	0.309**
	(4.16)	(1.05)	(2.07)
$\lambda_{\text{Basel II.5}} - \lambda_{\text{Post-Crisis}}$	-0.025	0.110***	0.850***
	(-0.79)	(4.84)	(5.35)
$\lambda_{\text{Basel III}} - \lambda_{\text{Basel II.5}}$	-0.110**	-0.045***	0.153
	(-2.01)	(-2.62)	(1.04)
$\lambda_{\text{Post-Volcker}} - \lambda_{\text{Basel III}}$	-0.016	-0.009	0.473**
	(-0.35)	(-0.34)	(2.13)
$\lambda_{\text{Post-Volcker}} - \lambda_{\text{pre-Crisis}}$	0.057**	0.184***	1.685***
	(2.47)	(7.29)	(8.00)
Observations	287,172	337,053	169,880
Average R-squared	0.378	0.315	0.537

Notes: This table presents the result of the time series regression:

$$\lambda_t = \lambda_{\text{Pre-Crisis}} \mathbb{1}_{\{t \in \text{Pre-Crisis}\}} + \lambda_{\text{Crisis}} \mathbb{1}_{\{t \in \text{Crisis}\}} + \lambda_{\text{Post-Crisis}} \mathbb{1}_{\{t \in \text{Post-Crisis}\}} + \lambda_{\text{Basel II.5}} \mathbb{1}_{\{t \in \text{Basel II.5}\}} + \lambda_{\text{Basel III}} \mathbb{1}_{\{t \in \text{Basel III}\}} + \lambda_{\text{Post-Volcker}} \mathbb{1}_{\{t \in \text{Post-Volcker}\}} + \epsilon_t.$$

λ_t is obtained from the cross-sectional regression (1) where the bid-ask spread is replaced by the absolute bid-ask difference. The R-squared is the average R-squared from the cross-sectional regression. T-statistics based on Newey and West (1987) with four lags are presented in parentheses. *** (**) [*] denotes statistical significance at 1% (5%) [10%] level.

Table A6: Turnover and Trade Size (Standardized)

	Turnover (Standardized)	Trade Size (Standardized)
Pre-Crisis: Jan 2003 - Jun 2007		
	0.179	0.386
Crisis: Jul 2007 - Apr 2009		
	-0.026	0.209
Post-Crisis: May 2009 - May 2012		
	0.054	-0.006
Basel II.5: Jun 2012 - Jun 2013		
	0.014	-0.032
Basel III: Jul 2013 - Mar 2014		
	-0.014	-0.028
Post-Volcker: Apr 2014 - Sep 2019		
	-0.085	-0.181
Differences		
Post-Volcker − Pre-Crisis	-0.264***	-0.567***
	(-6.99)	(13.93)

Notes: This table reports the pooled averages of the standardized turnover and trade size. Turnover is the ratio of the monthly trading volume to the bond's amount outstanding. Trade size is the ratio of the monthly trading volume to the number of trades executed in that month. Both are standardized by subtracting the sample mean and dividing over the sample standard deviation. T-statistics based on Driscoll and Kraay (1998) with five lags are presented in parentheses. *** (**) [*] denotes statistical significance at 1% (5%) [10%] level.

Table A7: Principal Component Analysis

	PC1	PC2	PC3	PC4	PC4
Bid-Ask Spread	56.17	9.76	60.76	37.03	41.06
Amihud	54.52	17.70	-20.30	-76.71	-20.43
Roll	53.18	27.61	-44.21	42.06	-51.83
Turnover	-18.71	67.88	50.39	-22.82	-44.53
Trade Size	-26.35	64.97	-37.45	21.31	56.81
Cumulative (%) Explained	44.12 %	75.21%	84.59%	93.52%	100%

Notes: This table reports the results of a principal component analysis of various corporate bond transaction cost and trading activity measures. The values are standardized scoring coefficients scaled up by a factor of 100.

Table A8: Variations in λ: PC1 (Bid-Ask+Roll+Amihud)

Rating	A and above	BBB	Speculative
Pre-Crisis: Jan 2004 - Jun 2007			
$\lambda_{\text{Pre-Crisis}}$	0.118***	0.225***	0.791***
	(9.08)	(13.78)	(12.61)
Crisis: Jul 2007 - Apr 2009			
λ_{Crisis}	0.677***	0.592***	1.417***
	(4.69)	(3.84)	(17.84)
Post-Crisis: May 2009 - May 2012			
$\lambda_{\text{Post-Crisis}}$	0.513***	0.512***	1.207***
	(15.50)	(13.15)	(8.68)
Basel II.5: Jun 2012 - Jun 2013			
$\lambda_{\text{Basel II.5}}$	0.503***	0.667***	2.251***
	(8.55)	(15.06)	(40.13)
Basel III: Jul 2013 - Mar 2014			
$\lambda_{\text{Basel III}}$	0.244***	0.525***	2.242***
	(3.72)	(40.63)	(20.43)
Post-Volcker: Apr 2014 - Sep 2019			
$\lambda_{\text{Post-Volcker}}$	0.233***	0.579***	2.623***
	(9.16)	(8.39)	(22.87)
Coefficient-Difference			
$\lambda_{\text{Crisis}} - \lambda_{\text{Pre-Crisis}}$	0.559***	0.367**	0.626***
	(3.86)	(2.37)	(6.18)
$\lambda_{\text{Basel II.5}} - \lambda_{\text{Post-Crisis}}$	0.010	0.155***	1.044***
	(-0.15)	(2.79)	(6.54)
$\lambda_{\text{Basel III}} - \lambda_{\text{Basel II.5}}$	-0.259***	-0.141***	-0.009
	(-2.72)	(-2.95)	(-0.07)
$\lambda_{\text{Post-Volcker}} - \lambda_{\text{Basel III}}$	-0.011	0.054	0.380**
	(-0.16)	(0.78)	(2.39)
$\lambda_{\text{Post-Volcker}} - \lambda_{\text{pre-Crisis}}$	0.114***	0.354***	1.832***
	(4.01)	(4.99)	(14.01)
Observations	287,172	337,053	169,880
Average R-squared	0.475	0.399	0.609

Notes: This table presents the result of the time series regression:

$$\lambda_t = \lambda_{\text{Pre-Crisis}}\mathbb{1}_{\{t\in\text{Pre-Crisis}\}} + \lambda_{\text{Crisis}}\mathbb{1}_{\{t\in\text{Crisis}\}} + \lambda_{\text{Post-Crisis}}\mathbb{1}_{\{t\in\text{Post-Crisis}\}} + \lambda_{\text{Basel II.5}}\mathbb{1}_{\{t\in\text{Basel II.5}\}} + \lambda_{\text{Basel III}}\mathbb{1}_{\{t\in\text{Basel III}\}} + \lambda_{\text{Post-Volcker}}\mathbb{1}_{\{t\in\text{Post-Volcker}\}} + \epsilon_t.$$

λ_t is obtained from the cross-sectional regression (25). It is the cross-sectional regression coefficient of the equally weighted average of the standardized bid-ask spread, Roll and Amihud measures. The R-squared is the average R-squared from the cross-sectional regression. T-statistics based on Newey and West (1987) with four lags are presented in parentheses. *** (**) [*] denotes statistical significance at 1% (5%) [10%] level.

Table A9: Fraction of Brokered Trades

Rating	A and above	BBB	Speculative
Pre-Crisis: Jan 2004 - Jun 2007			
Brokered Trade (%)	11.522	9.984	13.713
Crisis: Jul 2007 - Apr 2009			
Brokered Trade (%)	17.755	19.604	19.470
Post-Crisis: May 2009 - May 2012			
Brokered Trade (%)	16.284	18.671	19.531
Basel II.5: Jun 2012 - Jun 2013			
Brokered Trade (%)	13.373	15.705	17.423
Basel III: Jul 2013 - Mar 2014			
Brokered Trade (%)	13.667	14.467	15.773
Post-Volcker: Apr 2014 - Sep 2019			
Brokered Trade (%)	20.790	22.573	23.511

Notes: This table provides a summary the fraction of the total customer-dealer dollar trading volume that is immediately matched within one minute and with the same quantity.

Table A10: Estimated Trading Delays: Matching λ

Rating	A and above	BBB	Speculative
Pre-Crisis: Jan 2004 - Jun 2007			
Trading Delay (Days)	0.145	1.106	5.161
Crisis: Jul 2007 - Apr 2009			
Trading Delay (Days)	13.149	6.799	8.708
Post-Crisis: May 2009 - May 2012			
Trading Delay (Days)	6.957	7.072	9.477
Basel II.5: Jun 2012 - Jun 2013			
Trading Delay (Days)	8.340	15.123	22.419
Basel III: Jul 2013 - Mar 2014			
Trading Delay (Days)	1.968	8.158	22.631
Post-Volcker: Apr 2014 - Sep 2019			
Trading Delay (Days)	1.120	9.857	17.938
Trading Delay Difference			
Post-Volcker − Pre-Crisis	0.974***	8.751***	12.777***
	(2.98)	(5.30)	(8.09)

Notes: This table presents the trading delays implied by the magnitude of the liquidity premium. The trading delays are estimated from the structural model in Section 4. Parameter restrictions using the cross-sectional transaction cost coefficient λ are employed to separately identify $\alpha(\cdot)$ and β. T-statistics based on Newey and West (1987) with four lags are presented in parentheses. *** (**) [*] denotes statistical significance at 1% (5%) [10%] level.

Table A11: Implied Trading Delays and Preference Shocks

	Trading Delay $\frac{1}{\alpha(\cdot)+\beta}$	Preference Shocks δ
Pre-Crisis: Jan 2003 - Jun 2007		
	1.786 (days)	3.139
Crisis: Jul 2007 - Apr 2009		
	16.396 (days)	3.334
Post-Crisis: May 2009 - May 2012		
	5.240 (days)	3.998
Basel II.5: Jun 2012 - Jun 2013		
	10.763 (days)	4.227
Basel III: Jul 2013 - Mar 2014		
	8.367 (days)	3.806
Post-Volcker: Apr 2014 - Sep 2019		
	11.547 (days)	3.344
Differences		
Post-Volcker − Pre-Crisis	9.761***	0.205
	(7.24)	(0.57)

Notes: This table presents the implied trading delay $\frac{1}{\alpha(\cdot)+\beta}$ and the preference shock intensity δ estimated from the structural model by targeting the moments of liquidity premium and turnover, with parameter restrictions using the cross-sectional transaction cost coefficient λ. T-statistics based on Newey and West (1987) with four lags are presented in parentheses. *** (**) [*] denotes statistical significance at 1% (5%) [10%] level.