Increasing Corporate Bond Liquidity Premium and Post-Crisis Regulations *

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Abstract

I employ corporate bond liquidity premium to understand the important changes in corporate bond market liquidity in the recent periods. I show that while the commonly-used transaction cost measures such as bid-ask spread have been declining, corporate bond liquidity premium has actually increased since the financial crisis. For speculative bonds, over 30% of their yield spread is now compensation for illiquidity. To demonstrate that this increasing liquidity premium is due to dealers being less willing to buy and hold inventory from investors, I show that the liquidity premium is more driven by dealers' inventory costs than search costs, and establish a causal relationship between the major post-crisis regulations and the variations in the corporate bond liquidity premium. I show that Basel II.5 contributed the most to the increasing liquidity premium out of all regulatory changes over the sample period. Finally, I develop an estimation of the latent execution delays implied by the size of the liquidity premium, and show that bonds that took less than one day to sell before the financial crisis now take weeks to trade. This is consistent with practitioners' description of the post-crisis market situation and further corroborates the relevance of using liquidity premium in understanding corporate bond market liquidity.

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

JEL classification: G10, G12, G18, G20

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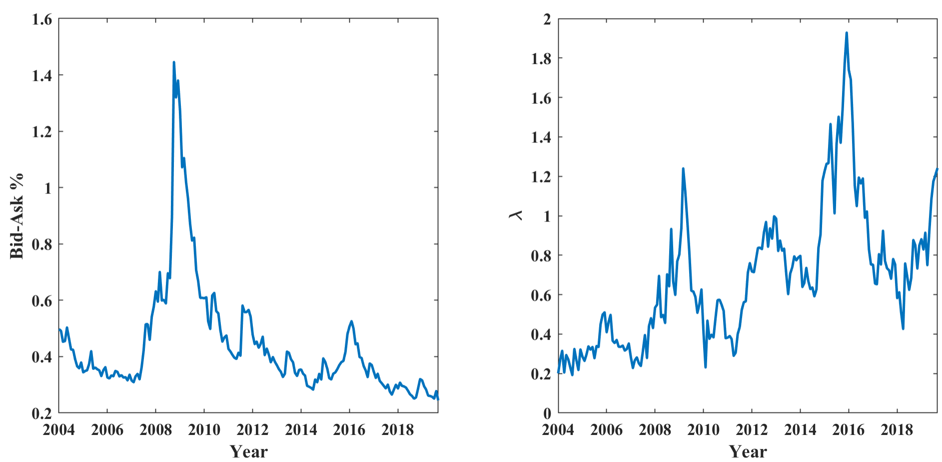
1 Introduction

The implementation of new regulations has shifted and disrupted liquidity provisions in the corporate bond market. Despite the low average transaction costs, industry participants have complained about the lack of liquidity in the market. According to 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]. When transaction costs are no longer representative of market liquidity, investors are looking for new variables to more accurately assess corporate bond market liquidity[2]. This paper reconciles these two seemingly contradictory pictures of low transaction costs yet lack of liquidity claimed by practitioners, and provides a feasible alternative liquidity indicator that better reflects corporate bond market liquidity by looking at how liquidity is priced in prices and yield spreads. I document that while the average corporate bond bid-ask spread is roughly the same as the pre-crisis level, cross-sectional variation in the corporate bond yield spread has become more and more sensitive to cross-sectional variation in the corporate bond transaction costs (Figure 1). The level of liquidity premium has also generally increased[3]. The average liquidity component of the yield spread is currently higher

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



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

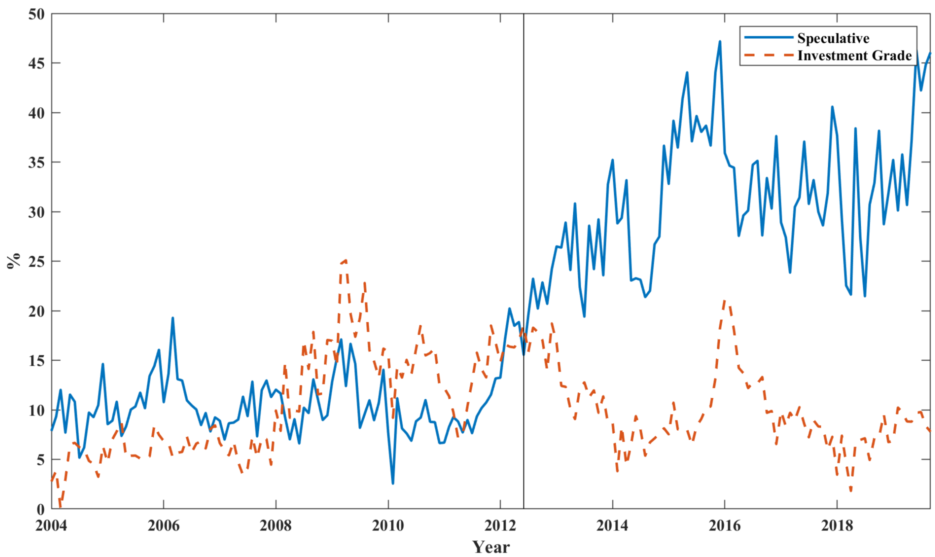
[1] Source: https://www.goldmansachs.com/insights/pages/macroeconomic-insights-folder/liquidy-top-of-mind/pdf.pdf .

[2] Source: https://www.markit.com/Company/Files/DownloadDocument?CMSID=3e73ade9d7c1461091776bd5afefa65d

[3] I use the word liquidity premium/liquidity component of the yield spread/illiquidity discount interchangeably.

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 is now compensation for illiquidity (Figure 2, page 3). Therefore, even though the actual transaction cost may have dropped since the crisis, the implied post-crisis cost of borrowing that is due to illiquidity has actually increased.

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



Notes: This figure presents corporate bond liquidity premium as a fraction of the yield spread. The vertical line is June 2012 when Basel II.5 was implemented.

To demonstrate that this liquidity premium is due to dealers being less willing to buy and hold inventory from the investors, I decompose the corporate bond bid-ask spread into the spreads that compensate for the inventory cost and the search cost. The spread that compensates for the inventory cost is the spread measure introduced in 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 inventory costs explain more cross-sectional variation in yield spreads than search costs. This result is consistent with the idea 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 liquidity to investors.

To uncover the potential cause of the dealers's unwillingness to provide liquidity to investors, I then 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 has increased since Basel II.5 started, while the liquidity premium of investment grade bonds has decreased during the Basel III period. The Volcker Rule has mainly increased the liquidity premium of the speculative bonds. To establish a causal relationship between the post-crisis regulations and the variations in the liquidity premium, I employ a difference-in-difference framework. I find that Basel II.5, by introducing the stressed value-at-risk (SVaR) and incremental risk capital charge (IRC), has 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, on the other hand, includes investment grade corporate bonds issued by non-financial firms as high quality liquid assets (HQLA), and has decreased the average liquidity premium of these bonds by 2 percentage points compared with 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 of the speculative bonds whose lead underwriters are more likely to be the Volcker-affected dealers has increased by 3 percentage points compared with the liquidity premium of the speculative bonds whose lead underwriters are less likely to be regulated by the Volcker Rule.

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) have suggested 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 market makers to avoid incurring inventory costs. The bid-ask spread charged by dealers as brokers, however, is low. Hence, a higher inventory cost 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.

This intrinsic link between the trading delay and liquidity prmeium allows me to employ a novel approach and estimate the latent trading delays implied by the size of the liquidity premium using a simple model in Longstaff (1995). The estimates suggest that the implied trading delay after the financial crisis has increased more than sixfold relative to the pre-crisis level. While it took less than one day to sell an average BBB-rated bond before the crisis, now takes roughly a week. For speculative bonds, the implied post-crisis trading delay is nearly 3 weeks.

This paper contributes to the following areas of the literature. First, it confirms and extends the early studies on the liquidity component of the yield spread during the financial crisis period. Dick-Nielsen, Feldhütter, and Lando (2012) find that the liquidity premium increased dramatically during the crisis period and the increase was persistent for investment grade corporate bonds[4]. 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 paper confirms their findings for the crisis period and extends the analysis by looking at the post-crisis period. Further, I show that during the crisis period it is mainly systematic liquidity risk that drives the liquidity premium (Pastor and Stambaugh 2003, Acharya and Pedersen 2005), while after the financial crisis 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 and to offer liquidity provision service to investors in need.

Second, a number of papers has been developed to decompose the corporate bond bid-ask spreads into components that compensate for different frictions. Ederington, Guan, and Yadav (2014) decompose corporate bond bid-ask spreads into components that compensate for dealers' dual roles as brokers and market makers. Choi and Huh (2019) measure the spread that compensates dealers for their role as liquidity providers. Few papers have looked at the extent to which each of these spread component explains cross-sectional variation in the corporate bond yield spreads. I show that the spread component that is compensation for liquidity provisions and

[4] Longstaff, Mithal, and Neis 2005 use the CDS spread to determine the liquidity component. Bai and Collin-Dufresne (2018) document that the CDS-bond basis has become more negative since the financial crisis.

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 (Longstaff, Mithal, and Neis 2005, Chen, A.Lesmond, and Wei 2007, Lin, Wang, and Wu 2011, Bongaerts, de Jong, and Driessen 2017 and many others). Friewald and Nagler (2019) and He, Khorrami, and Song (2019) use time-series analysis to show that aggregate OTC friction and market-wide intermediary balance sheet distress proxies can explain the large unexplained common factor in the yield spread changes documented in Collin-Dufresne, Goldstein, and Martin (2001). While these papers establish that liquidity (risk) is priced in the corporate bond yields and returns, I take a further step and show how the liquidity (risk) premium has varied across different times and is potentially affected by the regulatory changes in the corporate bond market.

Most importantly, this paper demonstrates the potential usefulness of *asset-pricing-based* liquidity measures like the liquidity premium to understand important aspects of post-crisis corporate bond liquidity conditions, by 1) weighing in on the debate of the impact of post-crisis banking regulations on market liquidity; and 2) uncovering the latent execution delay statistic that is not observed in the trade level data yet practitioners and academicians remain curious about. Whether the post-crisis regulations have affected *transaction-cost-based* liquidity measures such as 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). Many of these studies have relied on natural experiments during the 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 Stultz 2017). My paper, on the other hand, finds that post-crisis regulations have had sizeable impacts on the liquidity component of the yield spread. Furthermore, while the existing literature has focused on the impact of the Volcker Rule on corporate bond liquidity (Bessembinder et al. 2018, Bao, O'Hara, and Zhou 2018), my paper conducts a comprehensive study of the major post-crisis regulations and examines 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 crisis and drives the huge difference in the average liquidity premium as a fraction of the yield spread between the investment grade and speculative corporate bonds in the post-crisis period. The results are consistent with an informal survey of market participants which showed that Basel II.5 was seen to have had the largest impact on regulatory charges and corporate bond liquidity out of all regulations (CGFS 2016).

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. What industry participants have been experiencing is a loss of immediacy and longer execution delays, which are difficult, if not impossible to observe or measure[5]. My study, on the other hand, requires only publicly available data. It is motivated by the simple fact that if the corporate bond liquidity conditions have deteriorated, then the liquidity premium should become higher. Moreover, I demonstrate that the latent execution delay statistic, the precise dimension of illiquidity that has been rising and practitioners have been raising concerns about[6], can actually be estimated from the liquidity premium measure. Using a simple model by Longstaff (1995), for the first time in the literature I am able to show that the execution delay has increased since the financial crisis and it now takes more than a week or two to fully execute corporate bond trades.

2 Data

I use the Bond Returns database readily available from Wharton Research Data Services (WRDS). It is a cleaned version of the TRACE database merged with the Mergent Fixed Income Securities Database (FISD) by WRDS. The data is easily accessible and complied monthly from July 2002 to September 2019. It also computes several useful statistics such as monthly returns and bid-ask spreads. I focus on senior US corporate debentures that have not defaulted with amount outstanding greater than 100 thousand USD and principal amount equal to 1000 USD. I require

[5]Often times researchers have to rely on regulatory data and detailed dealer-level information that can reflect the decline in liquidity after the financial crisis (Adrian, Boyarchenko, and Shachar 2017). In a related manner, Chernenko and Sunderam (2020) use mutual fund data and show that the liquidity perceived by the funds has declined, particularly for speculative bonds.

[6]In the lively example given by Dick-Nielsen and Rossi (2018): *"Discouraging air travel might well lower the actual realized cost of transportation [...] 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."* The better indicator of travel convenience is indeed the length of the trip instead of the actual ticket cost.

each bond to be present in the sample for at least 24 months to avoid infrequently traded bonds. Table A1 of Appendix C.1 provides 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. Finally to keep the results from being affected by outliers, all variables are winsorized at 0.5% [7].

2.1 Summary statistics

The sample period of this study starts from January 2004 and ends in September 2019[8]. 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)[9]. Table 1 provides the summary statistics of my data. In 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, potentially due to the increase in the risk free rate. Bond prices, on the other hand, have dropped substantially during the financial crisis before recovering after the crisis. Similarly, bond returns are cut by 50% on average in the financial crisis before making a 5-time rebound during the post-Crisis period.

[Table 1]

2.2 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. In the baseline model, I run the following

[7] All the thresholds here are arbitrary and standard in the literature. The results are robust to alternative thresholds.

[8] Not all bond trades were disseminated when TRACE was introduced in 2002.

[9] Appendix C.2 provides a summary of the post-crisis regulations.

cross-sectional regression for each month:

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

The dependent variable is the monthly average corporate bond yield spread to the treasury yield of equivalent maturity. Time to maturity, coupon, bond age and offering amount control for bond characteristics, and bond rating dummies control for credit risk. The same specification has been used extensively in Friewald, Jankowitsch, and Subrahmanyam (2012), Schwert (2017) and many others. Given the recent concerns about rating inflations for the lower-end investment grade corporate bonds[10], I also consider alternative cross-sectional regression specifications using the firm-level accounting variables to control for credit risk in Appendix C.4.

The cross-sectional regression coefficient of liquidity, λ_t, is my main variable of interest. It measures how much the yield spread will change given per unit change in corporate bond transaction costs. I use the bid-ask spread measure computed by the WRDS Bond Returns database (variable *t_spread*) as my main measure of corporate bond transaction costs. It is calculated as the following. 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 a concern. I also use alternative corporate bond transaction cost measures as robustness checks in Appendix C.5 and C.6.

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

3 Increasing Corporate Bond Liquidity Premium

Figure 1 (page 2) presents my major finding. On the left panel I plot the median bid-ask spread for each month. On the right panel, I plot the cross-sectional liquidity coefficient λ from the regression (1). We see that while the aggregate bid-ask spread has generally been declining over time 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 picture shows that the cross-sectional coefficient of liquidity has been increasing since the financial crisis and is now higher than the pre-crisis level. 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-). Figure 3 plots the cross-sectional liquidity coefficient λ for each subsample. For both investment grade and speculative bonds, the cross-sectional liquidity coefficient λ has increased and remained larger than the pre-crisis level. Excluding the spikes, for investment grade bonds, the post-2016 cross-sectional liquidity coefficient 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 and even reaching more than twice as large as the financial crisis level (3 versus 1.5).

[Figure 3]

3.1 Liquidity Regression

To study the liquidity effect on the yield spread more closely, I split the sample into 3 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 time-series 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 use Fama-MacBeth procedure and Newey and West (1987) standard errors with 4 lags to report the results. I also test the differences between the average λ of different subperiods to understand its variations in each regulatory regime.

[Table 2]

Table 2 shows that liquidity is priced in the cross-sectional yield spreads. The average λ is significantly positive at 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 huge for A- and above-rated bonds, as their average λ nearly quintuples from 0.110 to 0.505 during the Crisis period, while it has only doubled at best for BBB-rated and speculative bonds. After the financial crisis, different regulations regimes all have non-trivial impacts on the cross-sectional liquidity coefficient λ. The λ's of BBB-rated and speculative bonds have increased significantly during the Basel II.5 period. Compared with the previous post-Crisis level, the average λ of the Basel II.5 period has increased from 0.405 to 0.553 by over 25% for BBB-rated bonds and by more than 100% for speculative bonds from 0.981 to 2.021. On the other hand, the cross-sectional liquidity coefficient λ of the investment grade corporate bonds has actually decreased during the Basel III period compared with the previous Basel II.5 level. For A- and above-rated bonds, the average λ has decreased from 0.365 to 0.206 by over 40%. For BBB-rated bonds, it has decreased by nearly 20% from 0.553 to 0.453. Finally, the Volcker Rule appears to have mainly affected the cross-sectional liquidity coefficient of the speculative bonds. Compared with the previous Basel III level, the average λ during the post-Volcker period has increased 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 with 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 versus 2.665)[11]. Even compared with the financial crisis level, the average λ of the speculative bonds has more than doubled from 1.155 to 2.665 following the introductions of Basel II.5 and the Volcker Rule.

A few robustness checks are conducted to check the increasing cross-sectional liquidity coefficient λ and the differential impacts of the post-crisis regulations. To control for changes in the market

[11]Even if I exclude the 2015-2017 period, the difference between the average post-Volcker and pre-Crisis λ is still significant for BBB-rated and speculative bonds. The spikes at the end of 2015 might be attributed to the Federal Reserve hiking the interest rate, the US gas and oil industry defaults, or the Chinese stock market crash (Goldberg and Nozawa 2020). However, the spikes are temporary and do not affect our analysis of the average trends

conditions throughout the sample, following Bessembinder et al. (2018) I add controls of the market-wide stock (SP 500 index) and bond (Barclays Capital U.S. Corporate Bond Index) returns, and the changes in the stock market volatility index (VIX) and the three-month LIBOR in the time-series regression (2). Appendix Table A2 in Appendix C.3 presents the results. To address the concern of rating inflations in recent years, I follow Blume, Lim, and Mackinlay (1998) and Chen, A.Lesmond, and Wei (2007), 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 as a separate robustness check[12]. Appendix Tables A3 and A4 present the regression results. Finally, there are alternative measures of corporate bond transaction costs. Instead of using the bid-ask spread calculated 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 liquidity and trading activity variables in the literature (Dick-Nielsen, Feldhütter, and Lando 2012, Friewald, Jankowitsch, and Subrahmanyam 2012, Schwert 2017 and among others). Figure 4 clearly shows that the general trend of λ is not affected if I use alternative measures of corporate bond transaction cost. The regression results are shown in Appendix Tables A5 and A6.

[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 liquidity 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 specifications, post-crisis regulations have had non-trivial impacts on the cross-sectional liquidity coefficient λ. While the λ of BBB-rated and speculative bonds has increased during the Basel II.5 episode, the λ of investment grade bonds has declined following Basel III, and the Volcker Rule has mainly increased the cross-sectional liquidity coefficient of the speculative bonds.

[12] The results are similar using the Altman (1968) Z-score, or the Merton (1974) distance-to-default to control for credit risk. The absolute magnitude of λ might depend on credit risk controls. However, the increasing trend of λ is robust and worth more attention.

The increasing λ could mean increasing price of liquidity. Alternatively, the increasing λ loads up the unobserved increase in the corporate bond illiquidity which has not been captured by the transaction-cost-based liquidity measures. In Appendix C.6, in addition to the equally weighted average of the standardized bid-ask spread, Roll and Amihud measures ('PC1'), I 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 liquidity and trading activity variables (Dick-Nielsen, Feldhütter, and Lando 2012). These trading activity variables have been declining since the financial crisis, an indication of potentially difficult executions of large orders and a decline in corporate bond market liquidity in general (Adrian et al. 2017[13]). Table A8 of Appendix C.6 presents the regression results. Compared with the Appendix Table A6, there is no substantial decrease in the magnitude of the cross-sectional regression coefficient of the first principal component ('PC1'), even if the second principal component is added to the cross-sectional regression. The increase in the average R-squared of the cross-sectional regression is minimal too, at best 4%. Still, it is possible that the increase in the illiquidity of the market cannot be measured nor be observed in the TRACE data where only the realized transactions are recorded. Dealers may reject large orders and customers may have to wait longer for their transactions to be fully completed[14]. However, the big picture is certain: the liquidity premium (price of liquidity $\times$ illiquidity) has increased.

3.2 Size of Liquidity Premium

I define the liquidity premium of each bond as the fraction of yield spread due to its compensation for illiquidity: $\lambda_t$bid-ask$_{it}$/yield-spread$_{it}$. In Figure 2 (page 3), I plot the median liquidity premium (as a fraction of the yield spread) of the investment grade and speculative corporate bonds for each month. The picture is striking. 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[15]. During the financial crisis period, liquidity can explain nearly 25% of the investment

[13]Customers may be splitting up large trade quantities for dealers to take the order. However, Adrian et al. (2017) notice that the declining turnover comes with increasing debt issues. Therefore it is not clear whether the decline in turnover means a decline in liquidity.

[14]Section 6 looks at this unobserved execution delay implied by the size of liquidity premium.

[15]The increase in the speculative bond liquidity premium (as a fraction of the yield spread) at the end of 2005/beginning of 2006 may be attributed to the GM/Ford bonds downgraded to the junk bond status.

grade bond yield spread. Consistent with Dick-Nielsen, Feldhütter, and Lando (2012), the liquidity premium of the investment grade bonds has spiked and persisted until after the financial crisis in 2010. On the other hand, even if the average λ of the speculative bonds has increased by nearly 100% during the financial crisis, the overall liquidity premium as a fraction of the speculative bond yield spread has remained constant 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 period. After the crisis however, while the liquidity premium of the investment grade bonds is generally declining, the liquidity premium of the speculative bonds has been steadily increasing and has now made up about 30% of the total yield spread.

[Table 3]

To give a quantitative view of the liquidity premium as a fraction of the yield spread, I perform a pooled regression of $\lambda_t \text{bid-ask}_{it}/\text{spread}_{it}$ for each rating class and subperiod, and test their differences between different subperiods. I use Driscoll and Kraay (1998) type of standard errors with 5 lags to account for heteroskedasticity as well as temporal autocorrelations. Results in Table 3 are consistent with the picture. The liquidity premium (as a fraction of the yield spread) of A- and above-rated bonds has increased substantially by over 14 percentage points during the Crisis period, while the liquidity premium of the speculative bonds has remained as 15% of the yield spread before and during the financial crisis. After the financial crisis, we observe nontrivial variations in the liquidity premium in each regulatory regime as before. The average liquidity component of the yield spread of the BBB-rated and speculative bonds has increased following Basel II.5. The impact is huge for speculative bonds as their liquidity premium has doubled by over 14 percentage points compared with the post-Crisis level. The average liquidity component of the yield spread of the investment grade bonds has decreased following Basel III. For BBB-rated bonds, their liquidity premium has decreased by nearly 3 percentage points while for A- and above-rated bonds, the decrease is by more than 8 percentage points. Finally, the Volcker Rule has increased the average liquidity component of the speculative bond yield spread by almost 5 percentage points, at the marginally significant level. Compared with the pre-Crisis level, the liquidity premium has increased for all bonds rated below A. For speculative bonds, over 30% of their yield spread is now compensation for illiquidity.

[Table 4]

Finally, we take a look at the absolute liquidity premium $\lambda_t$bid-ask$_{it}$. Table 4 reports the pooled average of the absolute liquidity premium, as well as the default premium, defined as the rest of the yield spread: default-spread$_{it}$ = yield-spread$_{it}$ $-$ $\lambda_t$bid-ask$_{it}$. While it is hard to compare the absolute liquidity premium across different regulation regimes as the total yield spread has been declining since the financial crisis, it is still meaningful to compare the post-Volcker and the pre-Crisis levels to see how the liquidity and default premia have evolved over time. We see that the financial crisis has 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 has 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 increase in the speculative bond yield spread from 2004 to 2019 is entirely due to illiquidity! On the other hand, the default premium of investment grade bonds has increased by at least 15 basis points over the years. This evidence supports the recent claims that the ratings may have been inflated in recent years and so investment grade bonds, especially the BBB-rated ones, have become riskier than before[16].

These results suggest that corporate bond liquidity premium, both in terms of the fraction of the yield spread and the absolute size, is now significantly higher than the pre-crisis level for BBB-rated and speculative bonds. Investors now require a higher liquidity compensation for holding these bonds. While the actual transaction cost of 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[17].

[16] `https://fortune.com/2020/01/27/investors-near-junk-corporate-bonds-bbb/`

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

4 Decompositions of Corporate Bond Liquidity Premium

Why do investors increase their required compensation for investing in illiquid bonds? If investors experience difficulties trading with dealers in the secondary market, is it because dealers have become less willing to provide liquidity using inventory? Also, is the increasing liquidity premium a compensation for the illiquidity level/characteristic of individual bonds, or is it a compensation for the systematic liquidity shock/risk? In this section, I study which type of frictions contributes to the increasing liquidity premium and whether the liquidity premium is driven by illiquidity level or liquidity risk.

4.1 Inventory vs Search

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 immediacy to investors, and as broker agents who merely match the market participants without taking the bonds into their inventory. Furthermore, these papers find that the spread charged by dealers as brokers is lower than the spread charged by dealers who use their own inventory to provide immediacy. The spread that dealers charge as brokers compensate for the search costs because dealers 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 happen within 1 minute and with the same quantity as the brokered (*agency*) trades. Randall (2015) shows that effects of dealers' inventory costs are much less significant on these matched agency trades. I take the (relative) price difference of these immediately matched brokered trades as the spread that compensates for dealers' effort to search for counterparties. 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 [18].

[18] 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 agency trades. Since I do observe the buy-sell directions, my search spreads are more similar to the "immediate match" spread in Green, Hollifield, and Schürhoff (2007), the original inspiration of the imputed round-trip costs.

To measure the spreads that compensate for dealers' role as market makers who use inventory to provide liquidity to investors, in the similar spirit of Ederington, Guan, and Yadav (2014), Randall (2015) and Choi and Huh (2019), I use the following spread measure introduced in Choi and Huh (2019)[19]:

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

where $Q = 1(-1)$ refers to the customer buy (sell) direction and reference price is the volume weighted average of the interdealer price of the day. To get the monthly spread that compensates for inventory costs, I again 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 solely should be proportional to the volatility of the asset fundamentals.

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

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

where the variable *Inventory-Spread*$_{it}$ is either the spread in Choi and Huh (2019) (CH) or the bond return volatility (Vol), and the variable *Search-Spread*$_{it}$ is the spread of the immediate matched trades that happen within 1 minute or 15 minutes. As before, I use Fama-MacBeth procedure and compute the time-series average of $\lambda_t^{\text{Inventory}}$ and $\lambda_t^{\text{Search}}$ in each subperiods [20]

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

[20]Since the spread of the immediate matched trades and the spread from Choi and Huh (2019) are both measures of transaction costs, their regression coefficients are comparable. However, volatility is not on the same scale as the bid-ask spread. To make the comparisons reasonable, I follow Feldhütter and Poulsen (2018) and project the bond return volatility on the bid-ask spread: $\text{bid-ask}_{it} = \beta_t \text{vol}_{it} + \epsilon_{it}$. I use the predicted spread as compensation for inventory friction: $\widehat{\text{inventory}}_{it} = \hat{\beta}_t \text{vol}_{it}$.

[Table 5]

Table 5 presents time series regression results of the cross-sectional coefficients of inventory and search spreads. As we see, both types of costs are significantly priced. However in all specifications, the average $\lambda^{\text{Inventory}}$ is always larger than the average λ^{Search} of each subperiod. Results using the Choi and Huh (2019) spread (CH) and 15-min "immediate match" spread (15min) suggest that the average $\lambda^{\text{inventory}}$ is almost twice as large as the average λ^{search} in each subperiod, and the results using volatility (Vol) shows the magnitudes are even larger. In terms of variations, we see that the financial crisis significantly increases the average $\lambda^{\text{Inventory}}$ while the increase in λ^{Search} is marginally significant at best. This echoes the findings in Randall (2015) that dealers' inventory costs increased dramatically during the financial crisis period. Since the regulations have come into effect, the average post-Volcker $\lambda^{\text{Inventory}}$ and λ^{Search} are both higher than their pre-Crisis levels and the differences are statistically significant. In the specification with Choi and Huh (2019) measure (CH) as the inventory spread and 15-min spread (15min) as the search spread, the average $\lambda^{\text{Inventory}}$ has increased by 0.928 from the pre-Crisis level, and the average λ^{search} has increased by 0.558. Even compared with the financial crisis period, the cross-sectional coefficients of both spreads are larger. For the entire sample, we see that the increase in $\lambda^{\text{Inventory}}$ and λ^{Search} is mainly following Basel II.5. Take into account that the inventory spread is always larger than the search spread as liquidity provisions are more costly, and that the average $\lambda^{\text{Inventory}}$ is often twice as large as the average λ^{Search}. These results suggest that inventory costs can explain more cross-sectional variation in yield spreads than search costs.

Theory suggests that dealers' inventory affects liquidity mainly through two channels: the risk aversion of the dealers (Stoll 1978 and Ho and Stoll 1981), and limited inventory positions (Amihud and Mendelson 1980). It is possible that Basel II.5 by introducing incremental risk charges that account for credit migration and default risks, increases dealers' risk aversion towards those bonds that are more likely to default or whose ratings are more likely to change. On the other hand, liquidity coverage ratio qualifies certain investment grade corporate bonds as high quality liquid assets. This can potentially free up some of dealers' balance sheet space for those investment grade bonds. Finally, the Volcker Rule prohibits proprietary trading, which can impose greater limits of dealers' ability to finance large positions. Section 5 studies these regulations and variations in the liquidity premium in detail.

4.2 Illiquidity Level vs Liquidity Risk

To see whether the increasing liquidity premium is a compensation for individual corporate bond illiquidity level (Amihud and Mendelson 1986) or systematic liquidity risk (Pastor and Stambaugh 2003, Acharya and Pedersen 2005), I examine corporate bond returns to separately study the pricing of these two liquidity effects. 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 time-series rolling regression (24 months of observations are required) on the individual bond excess return:

$$r_{i,t}^e = \beta_i^0 + \beta_i^M EMK_t + \beta_i^{\text{Shock}} \text{SHOCK}_t + \epsilon_{it} \tag{4}$$

where EMK_t is the equity market excess return, and SHOCK_t is the corporate bond liquidity shock, measured as the standardized 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:

$$\mathbb{E}_t r_{i,t+1}^e = \lambda_{0t} + \lambda_t^M \beta_i^M + \lambda_t^{\text{Shock}} \beta_i^{\text{Shock}} + \lambda_t^{\text{Level}} \text{bid-ask}_{it} + \alpha_{it} \tag{5}$$

where bid-ask is the corporate bond liquidity level measured by its bid-ask spread. I use the forward measure of the corporate bond expected excess return suggested in Campello, Chen, and Zhang (2008), Bongaerts, de Jong, and Driessen (2017) and many others:

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

where y_{it} is the yield-to-maturity of the bond i, L is the loss given default assumed to be 60%, T_{it} is the duration, y_{gt} is the corresponding government bond yield with the same duration, and finally π_{it} is the cumulative default probability. 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 the monthly default probability up to 5 years. Assuming a flat curve beyond 5 years allows me to calculate the cumulative default probability over the bond's entire duration. If there is no matching at the firm level, I use the Merton (1974) distance-to-default model to calculate the default probability.

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 Fama-French 3 factors as well as the 4 risk factors from Bai, Bali, and Wen (2019) (BBW) [21] in addition to the liquidity risk and level variables. I use Fama-MacBeth procedure to report the results and calculate the time-series average of λ_t^{Level} and λ_t^{Shock} in each subperiod.

[Table 6]

Table 6 presents the results. The signs are all as expected. We see that during the Crisis period, liquidity risk is more strongly priced as the average absolute value of λ^{Shock} has increased more than 9 times from 0.070 to 0.678 in the baseline model, while the average λ^{Level} actually drops by 50% from 0.393 to 0.150 [22]. However, once regulations have come into effect, investors have required a higher compensation for bearing illiquidity level rather than liquidity risk, as the magnitude of λ^{Shock} has been declining since the financial crisis. 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} has 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 bond's exposure to the systematic liquidity shock. The increase in the post-crisis liquidity premium documented in this paper, on the other hand, is about investors' increasing required compensation for holding bonds whose secondary market liquidity has been jeopardized by the increasing balance

[21] There are fewer observations if I use the BBW factors because these factors provided in Bai, Bali, and Wen (2019) end in December 2016.

[22] The liquidity premium and λ_t during the financial crisis period are potentially underestimated in the yield spread analysis because a large premium is due to liquidity risk. The results presented in Table A6 where I combine bid-ask spread, Roll and Amihud measures as a single transaction cost measure could potentially alleviate the problem because that measure can better capture the liquidity commonality and liquidity risk. However, the problem does not weaken my analysis of the post-crisis liquidity premium because the increasing premium is about compensation for illiquidity level rather than liquidity risk.

sheet charges that have made dealers averse to holding inventory [23]. Year 2019 is not systematically more illiquid than year 2004.

5 Regulations and Corporate Bond Liquidity Premium

The yield spread analysis suggests that the liquidity premium (as a fraction of the yield spread) has non-trivial variations in each regulatory regime. The liquidity premium of BBB-rated and speculative bonds has increased during the Basel II.5 period, while the liquidity premium of the investment grade bonds has actually decreased following Basel III. The Volcker-Rule has mainly increased the liquidity premium of the speculative bonds. In this section, I establish a causal relation between post-crisis regulations and variations in the corporate bond liquidity premium.

5.1 Impact of Basel II.5

The final rules for implementing Basel II.5 were announced on June 7, 2012. Compared with previous regulations, the incremental risk capital charge (IRC) and a stressed value-at-risk (SVaR) were introduced to supplement the value-at-risk (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 [24]. 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. Figure 5 plots the average liquidity premium (as a fraction of total yield spread) of the bonds at the top 10% and bottom 90% of the yield change volatility in each month. As we see, the liquidity premium of the two groups only start to diverge in June 2012, the exact month that the final implementation of Basel II.5 was announced. While the bonds at the bottom 90% of the yield volatility have roughly

[23] The increasing liquidity premium is not driven by funding liquidity shocks (TED spread) either. Nor is it driven by the margin requirement (Gârleanu and Pedersen 2011) because ratings are controlled for.

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

20-25% 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 has increased to over 40% since Basel II.5 came into effect. The striking pattern that we see in Figure 2 of the diverging investment grade and speculative bond liquidity premia after the financial crisis is indeed due to Basel II.5.

[Figure 5]

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

$$\text{Liquidity-Premium}_{it} = \eta^{\text{Basel II.5}} \text{Post}_t^{\text{Basel II.5}} \times \text{Treat}_{it}^{\text{Basel II.5}} + \alpha_i + \alpha_t + X_{it}'\gamma + u_{it}. \tag{6}$$

$Post_t^{\text{Basel II.5}}$ is a dummy variable that equals 1 if the observation occurs after June 2012, the month that the final rule of Basel II.5 was announced; $Treat_{it}^{\text{Basel II.5}}$ is a dummy variable that equals 1 if bond i is the at the top 10% of the risk changes proxied by yield change volatility at time t; α_i is the bond fixed effect and α_t is 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 $\lambda_t \times \text{bid-ask}_{it}/\text{yield-spread}_{it}$. The sample period is the one-year span between December 2011 and November 2012 to focus on Basel II.5 (June 2012). I separately run the regression with λ_t obtained with different credit risk controls and corporate bond transaction cost measures as robustness checks. Finally, the standard errors are clustered at the issuer-month level.

[Table 7]

Table 7 presents the result. As we see, compared with bonds at the bottom 90% of the calculated risk charges, since Basel II.5 came into effect, the liquidity premium (as a fraction of 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 whether controls are added or not. The impact is huge and suggests that the liquidity premium of the speculative bonds has increased dramatically after the financial crisis because these bonds have been associated with higher balance sheet costs under Basel II.5.

5.2 Impact of Liquidity Coverage Ratio

The liquidity coverage ratio (LCR) was finalized in January 2013 by the Basel Committee[25]. 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 [26]. Therefore, the balance sheet costs of the bonds qualified as HQLA are likely to have decreased due to the liquidity coverage ratio and so the liquidity premium of these bonds should decline. To quantify this impact of Liquidity Coverage Ratio, I employ the following difference-in-difference model:

$$\text{Liquidity-Premium}_{it} = \eta^{\text{LCR}}\text{Post}_t^{\text{LCR}} \times \text{Treat}_i^{\text{LCR}} + \alpha_i + \alpha_t + X_{it}'\gamma + u_{it}. \tag{7}$$

$Post_t^{\text{LCR}}$ 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; $Treat_i^{\text{LCR}}$ is a dummy variable that equals 1 if bond i is issued by a non-financial firm; α_i is the bond fixed effect and α_t is 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 the one-year span between July 2012 and 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. 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 [27].

[Table 8]

Table 8 presents the results. As expected, within the investment grade corporate bond, once

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

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

[27] 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. `https://www.govinfo.gov/content/pkg/CFR-2019-title12-vol1/xml/CFR-2019-title12-vol1-part1.xml`.

the liquidity coverage ratio has come into effect, the liquidity premium (as a fraction of the yield spread) of those bonds issued by non-financial firms has declined on average by 2 percentage points compared with the liquidity premium of the 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. Figure 6 checks the pre-trend using the following regression framework within the investment grade corporate bond sample at the yearly level:

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

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 6 suggests 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 percentage points lower than the liquidity premium of investment grade corporate bonds issued by financial firms.

[Figure 6]

5.3 Impact of the Volcker Rule

The Volcker Rule came into effect in April 2014, and the full compliance of the Rule is 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 activties (Duffie 2012), the Volcker Rule is thought to have discouraged dealers from effectively providing liquidity when customers request immediacy. Tables 2 and 3 shows that at least in terms of the liquidity premium, the Volcker Rule has mainly affected the 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 7 plots the monthly interdealer dollar trading volume (as a fraction of the total dollar trading volume) of the A- and above-rated, BBB-rated, and the speculative bonds separately. After the full compliance of the Volcker Rule is required in July 2015, the fraction of interdealer trades reverts the downward trend and starts to increase for all bonds, suggesting that dealers have been heavily relying on the interdealer market to manage their inventory positions. The effect appears to be more striking for speculative bonds, as 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 have converged to the level of investment grade bonds.

[Figure 7]

To establish a causal link, I compare the liquidity premium of bonds whose dealers are likely to be affected by the Volcker Rule and 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-difference model for the speculative high yield bonds:

$$\text{Liquidity-Premium}_{it}^{HY} = \eta^{\text{Volcker}}\text{Post}_t^{\text{Volcker}} \times \text{Treat}_i^{\text{Volcker}} + \alpha_i + \alpha_t + X_{it}'\gamma + u_{it}. \quad (8)$$

$Post_t^{\text{Volcker}}$ is a dummy variable that equals 1 if the observation occurs after April 2014, the month that the Volcker Rule came into effect; $Treat_i^{\text{Volcker}}$ is a dummy variable that equals 1 if the all of bond i's lead underwriter are the dealers affected by the Volcker Rule identified in Wyman and SIFMA (2011), a proxy for bonds whose dealers are affected by the Volcker Rule; α_i is the bond fixed effect and α_t is 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 the two-year span between January 2014 and December 2015 that 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.

[Table 9]

Table 9 presents the results. Within the speculative high yield bond sample, since the Volcker Rule came into effect, 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 has increased by around 3 percentage points compared with 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. Finally to check the pre-trend, I use the following regression framework:

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

The analysis is conducted at the yearly level because the Volcker Rule has been proposed yet postponed long before its implementation date. 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 8 presents the results. 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 is required[28].

[Figure 8]

5.4 Future Policy Implications

The Federal Deposit Insurance Corp.(FDIC) approved in August 2019 a weakened version of the Volcker Rule that granted more exemptions for market making activities from the proprietary trading ban[29]. Although the regulation ease is mainly for small sized banks, market watchers

[28] 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. The significance of my results suggests that the actual impact of the Volcker Rule is likely to be even larger.

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

expect further steps towards easing the rule for large banks. However, in terms of the liquidity conditions of the corporate bond market, Table 2 and 3 suggest that at least the liquidity premium will still be higher than the pre-crisis level for BBB-rated and speculative bonds. For speculative bonds, liquidity premium has already made up 30% of the total yield spread before the Volcker Rule came into effect following Basel II.5. Finally, the COVID-19 pandemic has unexpectedly disrupted the global economy. A brief examination of the corporate bond liquidity during the initial pandemic through the lens of the liquidity premium is presented in Appendix C.7 [30].

6 Low Bid-ask Spread vs High Liquidity Premium: Implied Trading Delay

The declining bid-ask spread does not contradict that the liquidity premium has increased after the financial crisis. In Appendix C.8, I present a stylized model of the over-the-counter market using 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 that 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. Figure 9 shows the model generated statistics as a function of the dealer cost.

[Figure 9]

As we see, as dealer cost increases, dealership will become more costly and dealers will execute less trades. The cost of immediacy/bid-ask spread charged by dealers (dashed blue) will increase too. However, this happens less frequently because more trades are being brokered than being processed by dealers. This is why the existing literature has to rely on natural experiments to measure the cost of immediacy. On the other hand, the empirically observed average bid-ask spread (solid red) can decrease as more trades are just being brokered with zero bid-ask spreads. However, low average bid-ask spread does not mean that the liquidity premium is low. On the contrary, the declining

[30] Notice the COVID pandemic is a *CRISIS* and so traditional transaction costs should reflect well the increase in illiquidity as most investors request immediacy. This paper, however, documents the illiquidity during the *NORMAL* time of the post-crisis economic expansions, which traditional transaction cost measures fail to capture, due to the longer execution delays.

immediacy provision by dealers means that the illiquidity discount/liquidity premium can actually be huge because customers now have to wait longer for trades to be executed.

The upper panel of Table 10 summarizes the fraction of the total dealer-customer trade volumes that are immediately matched within 1 minute and 15 minutes (in parentheses) respectively, a proxy of the brokered trades used widely in the literature. Bonds with lower quality generally are associated with a higher fraction of the brokered trades. Moreover as theory suggests, after the financial crisis, more fractions of the trades are now being immediately matched, compared with the pre-Crisis level [31].

[Table 10]

If the investors increase the required illiquidity compensation because they now need to wait longer to execute trades (as dealers become reluctant to use inventory to provide immediacy), then the liquidity premium measure may contain useful information about the execution delays. The existing literature has conjectured a rising trading delay, which is however not observable in the transaction-level TRACE data. As a final demonstration of the usefulness of liquidity premium to understand the illiquidity of the corporate bond market, I estimate the trading delays implied by the size of the liquidity premium of the yield spread, using a simple model by Longstaff (1995). In his model, security prices follow a Geometric Brownian Motion:

$$dP = \mu P dt + \sigma P dW \tag{9}$$

Suppose the investor is restricted from selling the security prior to some fixed time τ. The value of security to the investor is just the present value of P_τ to be received by the investor. If instead the investor can sell the security at the perfect market timing and reinvest the proceeds at the riskless rate r, the time τ payoff will be $M_\tau = \max_{0 \le s \le \tau} e^{r(\tau - s)} P_s$. The present value of the price-discount

[31] Regulatory data with dealer-level information allows one to keep track of the prearranged matched trades that are not in the same quantity, and therefore can potentially show even a higher fraction of the brokered trades

due to the restricted trading period τ, can be calculated in closed-form:

$$\begin{aligned}\Delta P(P,\tau) &= e^{-r\tau}\mathbb{E}[M_\tau] - e^{-r\tau}\mathbb{E}[P_\tau] \\ &= P\big(2+\frac{\sigma^2\tau}{2}\big)\text{Normal}\big(\frac{\sqrt{\sigma^2\tau}}{2}\big) + P\sqrt{\frac{\sigma^2\tau}{2\pi}}\exp\big(-\frac{\sigma^2\tau}{8}\big) - P\end{aligned} \tag{10}$$

where Normal($\cdot$) is the cumulative normal distribution. What Longstaff had in mind is the trading delay of the stock markets during market crashes or for certain Rule 144 restricted stocks. However, τ has a more natural interpretation in the corporate bond market as it is over-the-counter and investors and dealers have to search for each other in order to execute the trades. I naturally interpret τ as the average trading delay or investor waiting times [32].

Equation (10) gives a theoretical price-discount due to the trading delay τ. Empirically, I have measured the liquidity component of the yield spread using the regression model (1) as $\lambda\times$Bid-Ask. The modified duration formula connects the theoretical price discount to the empirical liquidity premium (increase in the yield space):

$$\big(2+\frac{\sigma^2\tau}{2}\big)\text{Normal}\big(\frac{\sqrt{\sigma^2\tau}}{2}\big) + \sqrt{\frac{\sigma^2\tau}{2\pi}}\exp\big(-\frac{\sigma^2\tau}{8}\big) - 1 = \text{Modified-Duration}\times\big(\lambda\times\text{Bid-Ask}\big) \tag{11}$$

The absolute liquidity premium (in the yield space), together with bond duration and price volatility calculated from the data, allows the trading delay τ to be easily estimated from Equation (11)[33]. The lower panel of Table 10 summarizes the estimated trading delays. As one can see, the trading delays implied by the liquidity premium have increased by more than 6 times compared with 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 around one week to be able to execute the trades. For speculative bonds, the implied trading delay is nearly 3 weeks. One average, it seems that the implied trading delays increased the most during the Basel II.5 episode. The magnitude of the implied 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*

[32] In the language of the search model, τ could be seen as the inverse of the search intensity of the investors.

[33] I here add accounting variables in the baseline regression (1).

two to execute"[34].

7 Conclusion

Traditional transaction-cost-based liquidity measures such as the bid-ask spread tend to give a misleading picture of the liquidity condition of the post-crisis corporate bond market, as many other aspects of illiquidity (e.g., the cost of immediacy, execution delays etc.) are not easily observable nor measured. This paper is based on the idea that if the liquidity condition has generally deteriorated, liquidly should be more strongly priced and so the liquidity premium should be higher. It employs the asset-pricing-based measure of liquidity to assess corporate bond liquidity conditions and provides important findings on the impact of different post-crisis regulations on the market liquidity.

In this paper I have shown that the post-crisis regulations have made 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. These findings have important implications for the real economy. As of November 2019, there are 10 trillion outstanding US corporate debts, out of which over 50% are BBB-rated and are likely to be downgraded to speculative ratings. As the Federal Reserve Chairman has pointed out, if the financial conditions were to deteriorate, overly indebted firms could face severe strains[35]. Parts of the strains also come from the illiquidity of the market as we see in the recent pandemic. 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.

[34]Source: https://www.goldmansachs.com/insights/pages/macroeconomic-insights-folder/liquidy-top-of-mind/pdf.pdf Also An and Zheng (2019) suggests a lower bound of 2-3 weeks. Of course, one should not expect that it takes an average investor 1-2 weeks to be able to telephone a dealer. Rather and more realistically, the results suggests that it now takes 1-2 weeks to fully execute the trades, for instance, by splitting large trades into smaller pieces over time. Notice that the gradual electronification of corporate bond trading may help traders to better execute trades over time using some high frequency algorithms, suggesting better liquidity management. However, the regulatory constraint of dealers forces traders to prolong trading horizons in the magnitude of weeks. The net effect is certainly a worse liquidity condition.

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

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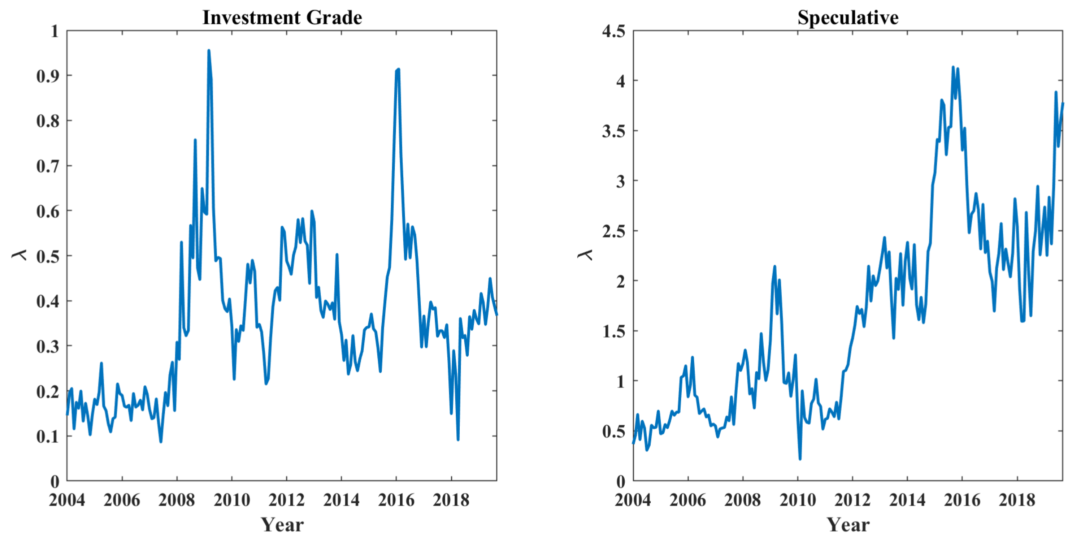
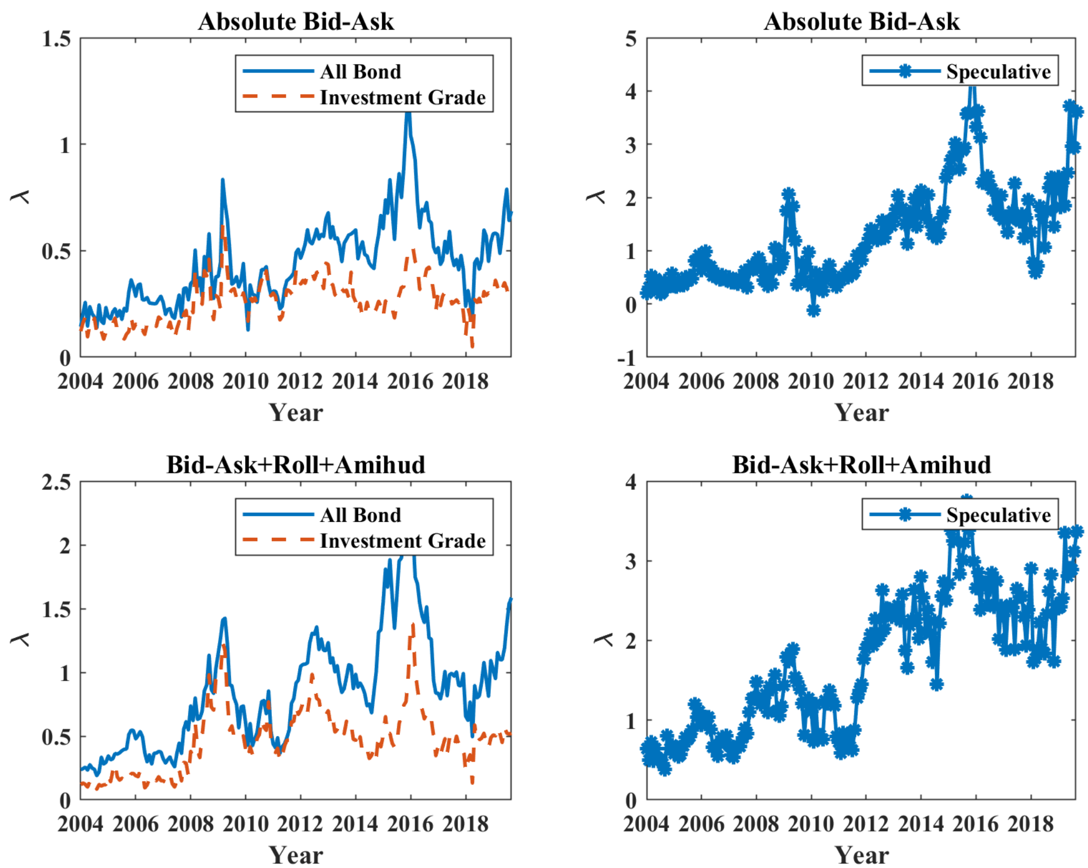
A Figures

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



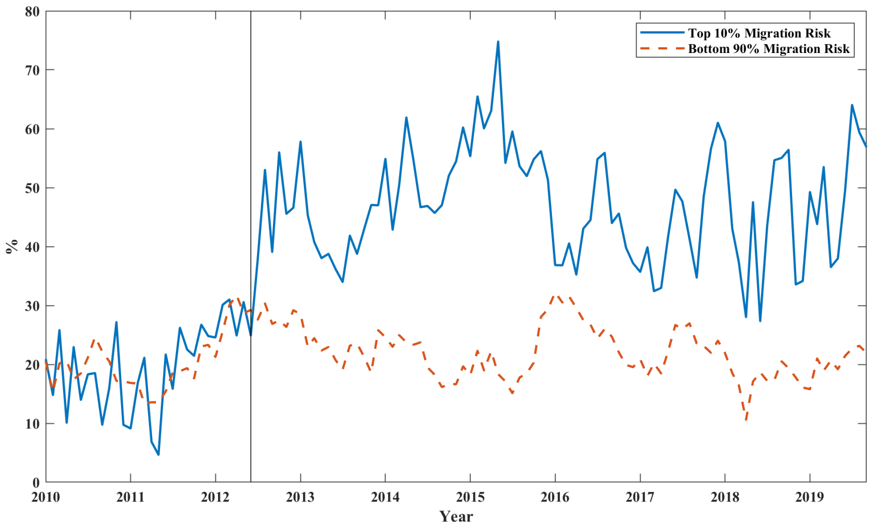
Notes: This figure presents the cross-sectional liquidity coefficient (λ_t) of investment grade and speculative bonds, obtained by running the cross-sectional regression (1) on both samples. Left panel shows λ_t of investment grade bonds. Right panel shows λ_t of speculative bonds.

Figure 4: Cross-Sectional Coefficient of Different Bond Transaction Cost Measures



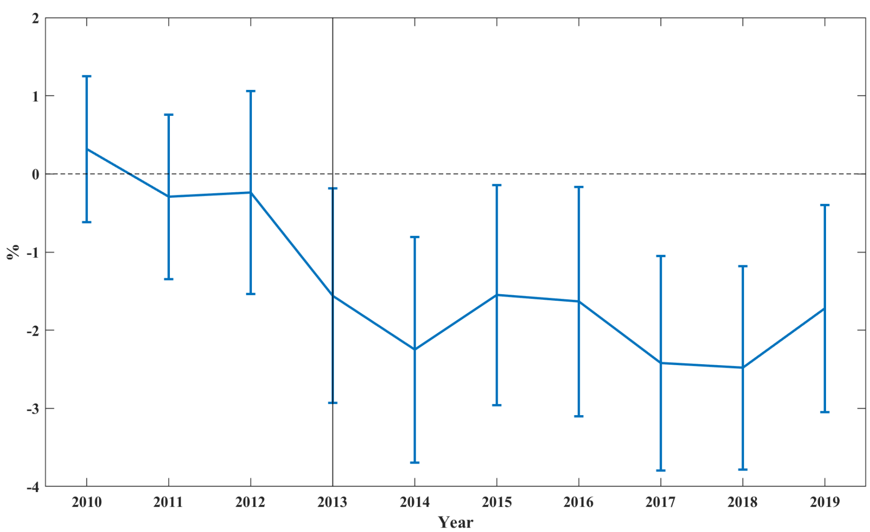
Notes: This figure presents the cross-sectional liquidity coefficient (λ_t) obtained from the cross-sectional regression (1) with alternative measures of corporate bond transaction cost. Left panel shows λ_t of all the bond sample (solid blue) and of the investment grade bond sample (dashed red). Right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

Figure 5: Basel II.5 and Liquidity Premium



Notes: This figures plots the Liquidity premium (as a fraction of the yield spread) of the bonds at the top 10% and bottom 90 % of the Basel II.5 risk charge 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 6: Pre-Trend of the Liquidity Coverage Ratio within Investment Grade Bonds

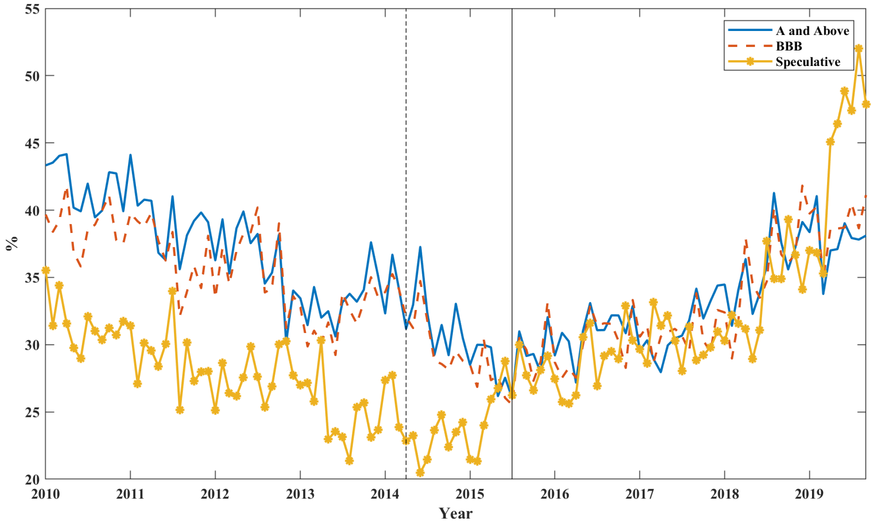


Notes:This figure plots the coefficient η_t of the following model:

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

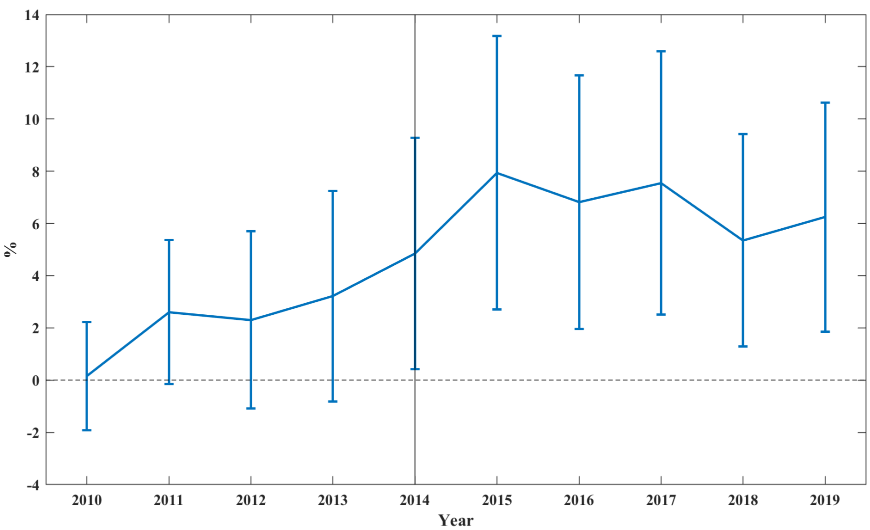
The analysis is conducted at yearly level within the investment grade bond sample. The dependent variable is $\lambda_t \times \text{bid-ask}_{it}/\text{yield-spread}_{it}$. Y_t is the year dummy. $Treat_i^{\text{LCR}}$ is a dummy variable equal to 1 if bond i is issued by a non-financial firm. X_{it} 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.

Figure 7: Fraction of Interdealer Dollar Trading Volume



Notes: The interdealer dollar trading volumes (as a fraction of the total dollar trading volume) is plotted here. 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 is required.

Figure 8: Pre-Trend of the Volcker Rule within Speculative Bonds

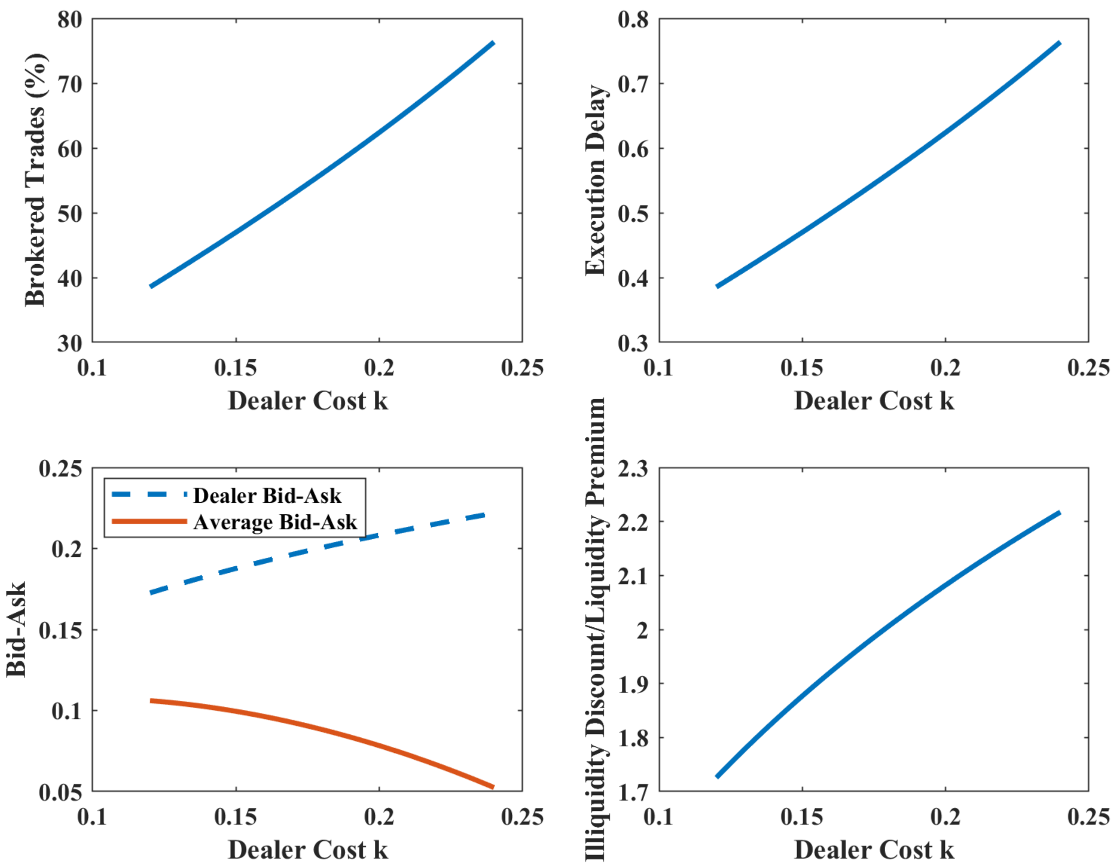


Notes: This figure plots the coefficient η_t of the following model:

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

The analysis is conducted at yearly level within the speculative bond sample. The dependent variable is $\lambda_t \times$ bid-ask$_{it}$/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.

Figure 9: Model Generated Statistics



Notes: This figure presents the model generated statistics when the dealer cost k increases from 0.12 to 0.24. The following values are used: $r = 0.1$, $\epsilon_H = 1$, $\epsilon_L = 0$, $\delta = 1$, $\pi_L = \pi_H = 0.5$, $\alpha = 5$, $\beta = 1$, and $\eta = 1$ and A=1.

B 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 used in this paper. 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: Liquidity Regression

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)
$\lambda_{\text{post-Crisis}} - \lambda_{\text{Crisis}}$	-0.102	0.034	-0.175
	(0.98)	(0.39)	(-1.08)
$\lambda_{\text{Basel II.5}} - \lambda_{\text{post-Crisis}}$	-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 4 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)
Post-Crisis − Crisis	0.309	3.425	-1.347
	(0.07)	(1.42)	(-0.79)
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
Average R-squared	0.481	0.506	0.593

Notes: This table presents the pooled averages of the liquidity premium $\lambda_t \times \text{bid-ask}_{it}/\text{spread}_{it}$ 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 5 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			
Crisis − Pre-Crisis	0.582***	0.385**	0.737***
	(3.04)	(6.48)	(2.84)
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			
Crisis − Pre-Crisis	1.399***	2.583***	4.578***
	(4.12)	(3.34)	(3.22)
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 $\lambda_t \times \text{bid-ask}_{it}$ and default premium $\text{yield-spread}_{it} - \lambda_t \times \text{bid-ask}_{it}$ 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 5 lags are presented in parentheses to account for heteroskedasticity as well as temporal autocorrelations. *** (**) [*] denotes statistical significance at 1% (5%) [10%] level.

Table 5: Decomposition of Liquidity Premium: Inventory vs Search

	Vol + 1min	CH + 1 min	Vol + 15min	CH + 15min
Pre-Crisis: Jan 2004 - Jun 2007				
$\lambda^{\text{Inventory}}$	1.452***	0.608***	1.215***	0.490***
	(5.65)	(9.86)	(5.66)	(11.63)
λ^{Search}	0.365***	0.195***	0.408***	0.263***
	(4.74)	(3.85)	(5.51)	(4.03)
Crisis: Jul 2007 - Apr 2009				
$\lambda^{\text{Inventory}}$	3.387***	1.103***	2.958***	0.996***
	(23.42)	(12.48)	(17.13)	(11.29)
λ^{Search}	0.821***	0.790**	0.717***	0.566***
	(3.39)	(2.51)	(3.88)	(3.03)
Post-Crisis: May 2009 - May 2012				
$\lambda^{\text{Inventory}}$	2.414***	1.036***	2.010***	0.847***
	(7.65)	(10.51)	(8.03)	(9.70)
λ^{Search}	0.862***	0.614***	0.787***	0.554***
	(6.51)	(5.49)	(7.34)	(7.17)
Basel II.5: Jun 2012 - Jun 2013				
$\lambda^{\text{Inventory}}$	3.735***	1.662***	2.951***	1.440***
	(12.03)	(28.46)	(11.27)	(44.16)
λ^{Search}	1.543***	1.037***	1.461***	0.997***
	(18.95)	(12.98)	(24.45)	(14.69)
Basel III: Jul 2013 - Mar 2014				
$\lambda^{\text{Inventory}}$	3.183***	1.731***	2.618***	1.452***
	(8.51)	(13.98)	(9.22)	(16.30)
λ^{Search}	1.251***	0.704***	1.127***	0.545***
	(18.70)	(11.55)	(33.27)	(9.49)
Post-Volcker: Apr 2014 - Sep 2019				
$\lambda^{\text{Inventory}}$	3.404***	1.574***	3.082***	1.418***
	(9.36)	(12.39)	(8.86)	(11.48)
λ^{Search}	1.150***	1.062***	1.020***	0.822***
	(11.10)	(7.52)	(13.80)	(11.35)
$\lambda^{\text{Inventory}}_{\text{Crisis}} - \lambda^{\text{Inventory}}_{\text{pre-Crisis}}$	1.935***	0.494***	1.743***	0.506***
	(6.28)	(4.77)	(6.18)	(5.27)
$\lambda^{\text{Inventory}}_{\text{post-Volcker}} - \lambda^{\text{Inventory}}_{\text{pre-Crisis}}$	1.952***	0.966***	1.867***	0.928***
	(4.38)	(6.84)	(4.57)	(7.11)
$\lambda^{\text{Search}}_{\text{Crisis}} - \lambda^{\text{Search}}_{\text{pre-Crisis}}$	0.456*	0.596*	0.309	0.303
	(1.82)	(1.87)	(1.58)	(1.55)
$\lambda^{\text{Search}}_{\text{post-Volcker}} - \lambda^{\text{Search}}_{\text{pre-Crisis}}$	0.785***	0.867***	0.612***	0.558***
	(6.08)	(5.78)	(5.85)	(5.73)
Observations	887,960	887,960	887,960	887,960
Average R-squared	0.725	0.723	0.725	0.722

Notes: This table presents the results of the time-series regression:

$$\lambda_t^i = \lambda^i_{\text{pre-Crisis}} \mathbb{1}_{\{t \in \text{pre-Crisis}\}} + \lambda^i_{\text{Crisis}} \mathbb{1}_{\{t \in \text{Crisis}\}} + \lambda^i_{\text{post-Crisis}} \mathbb{1}_{\{t \in \text{post-Crisis}\}} + \lambda^i_{\text{Basel II.5}} \mathbb{1}_{\{t \in \text{Basel II.5}\}} + \lambda^i_{\text{Basel III}} \mathbb{1}_{\{t \in \text{Basel III}\}} + \lambda^i_{\text{post-Volcker}} \mathbb{1}_{\{t \in \text{post-Volcker}\}} + \epsilon_t.$$

$\lambda_t^{\text{Inventory}}$ and $\lambda_t^{\text{Search}}$ are obtained from the cross-sectional regression (3). T-statistics based on Newey and West (1987) with 4 lags are presented in parentheses. *** (**) [*] denotes statistical significance at 1% (5%) [10%] level.

Table 6: Pricing of Corporate Bond Returns: Liquidity 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 (4) and (5). The R-squared is the average R-squared from the cross-sectional regression (5). T-statistics based on Newey and West (1987) with 4 lags are presented in parentheses. *** (**) [*] denotes statistical significance at 1% (5%) [10%] level.

Table 7: Impact of Basel II.5

	Baseline		Accounting Model		Alternative Transaction Cost	
	(1)	(2)	(3)	(4)	(5)	(6)
$Post_t \times Treat_{it}$	14.197***	14.969***	15.160***	16.086***	12.009***	12.721***
	(4.19)	(4.22)	(4.99)	(5.10)	(3.44)	(3.55)
Controls	NO	YES	NO	YES	NO	YES
Observations	51,863	47,247	51,863	47,247	51,863	47,247
R-squared	0.285	0.286	0.287	0.289	0.291	0.292

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

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

$Post_t^{\text{Basel II.5}}$ 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 the at the top 10% of the Basel II.5 risk charges at time t, proxied by the daily yield change volatility. X_{it} controls for equity volatility 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: $\lambda_t \times \text{bid-ask}_{it}/\text{yield-spread}_{it}$. In the *Baseline* model, the cross-sectional liquidity coefficient λ_t is obtained from the cross-sectional regression (1). In the *Accounting Model*, λ_t is obtained from the cross-sectional regression (13) 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 between December 2011 and 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 8: Impact of Basel III: Liquidity Coverage Ratio

Investment Grade	Baseline		Accounting Model		Alternative Transaction Cost	
	(1)	(2)	(3)	(4)	(5)	(6)
$Post_t \times Treat_i$	-2.338***	-2.589***	-2.368***	-2.610***	-2.084***	-2.298***
	(-4.43)	(-4.55)	(-4.55)	(-4.62)	(-4.58)	(-4.72)
Controls	NO	YES	NO	YES	NO	YES
Observations	43,591	41,351	43,591	41,351	43,591	41,351
R-squared	0.367	0.370	0.358	0.361	0.366	0.369

Speculative	Baseline		Accounting Model		Alternative Transaction Cost	
	(1)	(2)	(3)	(4)	(5)	(6)
$Post_t \times Treat_i$	1.423	1.094	1.539	1.363	1.286	1.102
	(0.93)	(0.57)	(0.86)	(0.61)	(1.04)	(0.74)
Controls	NO	YES	NO	YES	NO	YES
Observations	11,625	9,889	11,625	9,889	11,625	9,889
R-squared	0.482	0.469	0.481	0.469	0.492	0.479

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

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

$Post_t^{\text{LCR}}$ 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: $\lambda_t \times \text{bid-ask}_{it}/\text{yield-spread}_{it}$. In the *Baseline* model, the cross-sectional liquidity coefficient λ_t is obtained from the cross-sectional regression (1). In the *Accounting Model*, λ_t is obtained from the cross-sectional regression (13) 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 between July 2012 and 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 9: Impact of the Volcker Rule

Speculative	Baseline		Accounting Model		Alternative Transaction Cost	
	(1)	(2)	(3)	(4)	(5)	(6)
$Post_t \times Treat_i$	2.773**	3.680**	2.275*	3.203**	2.614**	3.268**
	(2.37)	(2.66)	(1.94)	(2.26)	(2.47)	(2.68)
Controls	NO	YES	NO	YES	NO	YES
Observations	26,022	22,559	26,022	22,559	26,022	22,559
R-squared	0.502	0.505	0.482	0.486	0.511	0.518

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

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

$Post_t^{\text{Volcker}}$ 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: $\lambda_t \times \text{bid-ask}_{it}/\text{yield-spread}_{it}$. In the *Baseline* model, the cross-sectional liquidity coefficient λ_t is obtained from the cross-sectional regression (1). In the *Accounting Model*, λ_t is obtained from the cross-sectional regression (13) 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 between January 2014 and December 2015. 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: Fraction of Brokered Trades and Trading Delays

Rating	A and above	BBB	Speculative
Pre-Crisis: Jan 2004 - Jun 2007			
Brokered Trade (%)	11.522 (19.346)	9.984 (17.291)	13.713 (21.417)
Crisis: Jul 2007 - Apr 2009			
Brokered Trade (%)	17.755 (27.269)	19.604 (29.278)	19.470 (28.331)
Post-Crisis: May 2009 - May 2012			
Brokered Trade (%)	16.284 (24.016)	18.671 (27.086)	19.531 (27.928)
Basel II.5: Jun 2012 - Jun 2013			
Brokered Trade (%)	13.373 (20.306)	15.705 (22.954)	17.423 (25.420)
Basel III: Jul 2013 - Mar 2014			
Brokered Trade (%)	13.667 (20.241)	14.467 (21.483)	15.773 (23.639)
Post-Volcker: Apr 2014 - Sep 2019			
Brokered Trade (%)	20.790 (26.240)	22.573 (28.318)	23.511 (30.803)

Rating	A and above	BBB	Speculative
Pre-Crisis: Jan 2003 - Jun 2007			
Implied Trading Delay (Days)	0.207	0.879	2.947
Crisis: Jul 2007 - Apr 2009			
Implied Trading Delay (Days)	1.777	1.314	3.716
Post-Crisis: May 2009 - May 2012			
Implied Trading Delay (Days)	2.241	2.433	4.436
Basel II.5: Jun 2012 - Jun 2013			
Implied Trading Delay (Days)	5.602	8.000	18.461
Basel III: Jul 2013 - Mar 2014			
Implied Trading Delay (Days)	1.563	4.309	20.493
Post-Volcker: Apr 2014 - Sep 2019			
Implied Trading Delay (Days)	1.397	5.053	16.465

Notes: The top panel summarizes the fraction of the total customer-dealer dollar trading volume that is immediately matched within 1 minute (15 minutes in parentheses). The lower panel presents the implied trading delay τ calculated from: $\big(2+\frac{\sigma^2\tau}{2}\big)\text{Normal}\big(\frac{\sqrt{\sigma^2\tau}}{2}\big)+\sqrt{\frac{\sigma^2\tau}{2\pi}}\exp\big(-\frac{\sigma^2\tau}{8}\big)-1=\text{Modified-Duration}\times\big(\lambda\times\text{Bid-Ask}\big)$.

APPENDIX

C Appendix

C.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.

C.2 Post-crisis Banking Regulations

The 2007-2009 financial crisis has dramatically 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 US 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) which 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 [36]. In addition to the capital regulations, Basel III has 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. Levels 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 [37].

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.

C.3 Liquidity Regression with Market Condition Controls

To allow for changes in market conditions, following Bessembinder et al. (2018) I add changes in the SP500 stock return (SP500) and Barclays Capital U.S. Corporate Bond Index returns (Barclays), the stock market volatility index (VIX), the three-month LIBOR to the time-series regression (2). Appendix Table A2 presents the results.

[36] The capital requirement of Basel III has not been fully implemented yet 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 risky assets such as Treasuries or reverse repos.

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

$$
\begin{aligned}
\lambda_t = {} & \lambda_{\text{pre-Crisis}} \mathbb{1}_{\{t \in \text{pre-Crisis}\}} + \lambda_{\text{Crisis}} \mathbb{1}_{\{t \in \text{Crisis}\}} + \lambda_{\text{post-Crisis}} \mathbb{1}_{\{t \in \text{post-Crisis}\}} \\
& + \lambda_{\text{Basel II.5}} \mathbb{1}_{\{t \in \text{Basel II.5}\}} + \lambda_{\text{Basel III}} \mathbb{1}_{\{t \in \text{Basel III}\}} + \lambda_{\text{post-Volcker}} \mathbb{1}_{\{t \in \text{post-Volcker}\}} \\
& + \Delta \log(\text{SP500}_{t-1}) + \Delta \log(\text{Barclays}_{t-1}) + \Delta \text{VIX}_{t-1} + \Delta \text{LIBOR}_{t-1} + \epsilon_t
\end{aligned}
\tag{12}
$$

C.4 Liquidity Regression with 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 result for the resulting λ_t.

$$
\begin{aligned}
\text{Yield-Spread}_{it} = {} & \beta_{0t} + \lambda_t \text{Bid-Ask-Spread}_{it} + \beta_{1t} \text{Bond-Age}_{it} + \beta_{2t} \log(\text{Amount-Issued}_{it}) \\
& + \beta_{3t} \text{Coupon}_{it} + \beta_{4t} \text{Time-To-Maturity}_{it} \\
& + \beta_{5t} \text{Equity Volatility}_{it} + \beta_{6t} \text{Leverage}_{it} + \beta_{7t} \text{Long-Term Debt}_{it} \\
& + \beta_{8t} \text{Operating Income}_{it} + \beta_{9t} \text{Pretax Interest Coverage}_{it} + \epsilon_{it}.
\end{aligned}
\tag{13}
$$

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:

$$
\begin{aligned}
\text{Yield-Spread}_{it} = {} & \beta_{0t} + \lambda_t \text{Bid-Ask-Spread}_{it} + \beta_{1t} \text{Bond-Age}_{it} + \beta_{2t} \log(\text{Amount-Issued}_{it}) \\
& + \beta_{3t} \text{Coupon}_{it} + \beta_{4t} \text{Time-To-Maturity}_{it} + \beta_{5t} \text{Default-Probability}_{it} + \epsilon_{it}.
\end{aligned}
\tag{14}
$$

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

C.5 Liquidity Regression with Alternative Measures of Corporate Bond Liquidity

Instead of the bid-ask spread (variable *t_spread*) calculated in the WRDS Bond Return database, I use the absolute bid-ask difference, and the equally weighted average of the standardized bid-ask spread, the Roll (1984) measure and the Amihud (2002) measure in the cross-sectional regression (1) to get the cross-sectional liquidity coefficient λ_t. Specifically, the daily Amihud measure of each bond is computed as:

$$\text{Amihud}_t = \frac{1}{N_t} \sum_{j=1}^{N_t} \frac{\left|\frac{P_j - P_{j-1}}{P_{j-1}}\right|}{Q_j}$$

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:

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

where the covariance estimation is based on the data points of each month. Finally, positive covariance is replaced with 0. Tables A5 and A6 present the time-series regression result.

C.6 Liquidity Regression with Additional Trading Activity Variables

In addition to the transaction-cost-based liquidity measures (bid-ask spread, Amihud, Roll), I add 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. Both have been declining since the financial crisis, potentially suggesting a decline in market liquidity. Table A7 conducts a principal component analysis (PCA) of the transaction-cost-based liquidity measures (bid-ask spread, Amihud, 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:

$$\begin{aligned}\text{Yield-Spread}_{it} = \beta_{0t} + \lambda_t \text{PC1}_{it} + \lambda_t' \text{PC2}_{it} + \beta_{1t}\text{Bond-Age}_{it} + \beta_{2t}\log(\text{Amount-Issued}_{it}) \\ + \beta_{3t}\text{Coupon}_{it} + \beta_{4t}\text{Time-To-Maturity}_{it} + \beta_{5t}\text{Default-Probability}_{it} + \epsilon_{it}.\end{aligned} \tag{15}$$

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).

C.7 A Brief Look At COVID-19

On March 23, 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 in the secondary market corporate bonds that, as of March 22, have an investment grade rating and a remaining maturity of 5 years or less [38].

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 yield spread and bid-ask spread have dropped after the announcement of SMCCF. The liquidity premium offers another interesting angle to look at the corporate bond liquidity condition during the pandemic. Figure A1 plots the evolutions of the liquidity and default premia [39] of the investment grade bonds with time-to-maturity less than 5 years, and compare them with the liquidity and default premia of the investment grade bonds with time-to-maturity longer than 5

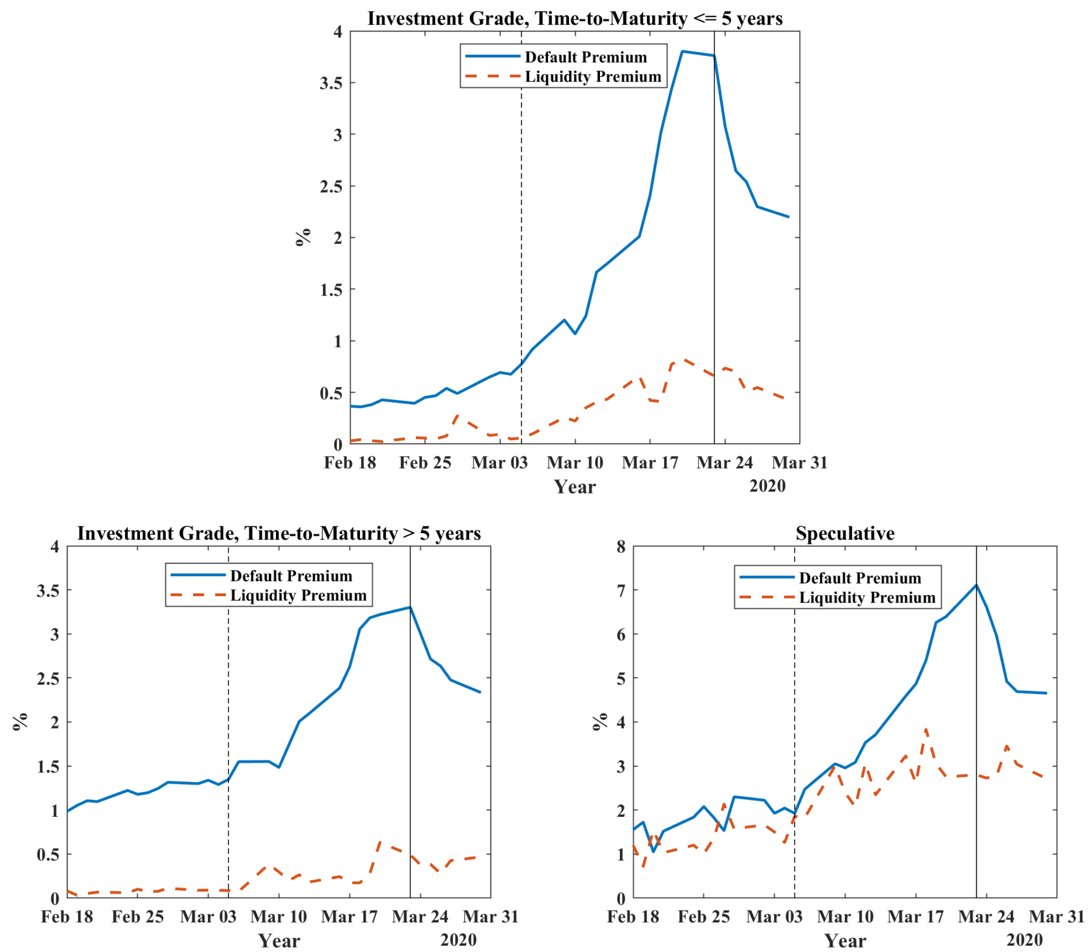
[38] `https://www.federalreserve.gov/newsevents/pressreleases/files/monetary20200409a2.pdf`.

[39] Liquidity premium is $\lambda_t(\text{liq}_{it} - \text{liq}_{1t})$ where liq_{it} is the equally weighted standardized bid-ask spread, Roll and Amihud measures, and liq_{1t} is the 1% quantile. I use this combined measure of corporate bond liquidity because at daily frequency individual measures of liquidity may suffer from missing values and possibly liquidity risk rises 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 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.

years, and the speculative bonds [40]. Clearly the default component of the yield spread has dropped since the Fed intervention, consistent with Nozawa and Qiu (2020). Interestingly, we see that liquidity premium has only dropped for the bonds eligible for Fed's purchases: investment grade bonds with time-to-maturity less than 5 years. Their liquidity premium dropped from 1% to 0.5%. On the other hand, for investment grade bonds with time-to-maturity longer than 5 years, their liquidity premium stays at 0.5% before and after the announcement of SMCCF, and for speculative bonds, their liquidity premium stays at 3%. Liquidity premium therefore offers more direct evidence of the impact of SMCCF on corporate bond liquidity, and 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 speculative bonds

[40] The rating data is from Mergent FISD, which was most recently updated in August 2019. Therefore, the rating information may not be up-to-date.

Figure A1: Liquidity and Default Premia during COVID-19 Pandemic



Notes: This figure plots the liquidity and default premia during the COVID-19 pandemic. 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 month 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.

C.8 Low Bid-Ask Spread vs High Liquidity Premium: A Model

The model largely follows the canonical framework developed in Lagos and Rocheteau (2006), Lagos and Rocheteau (2007) and Lagos and Rocheteau (2009), with slightly twisted interpretations that fit in the corporate bond market. To be specific, time is continuous with discount rate r and there is an asset with fixed supply of A. There are customers with total measure of 1 and dealers with measure v. Customer i with asset holding a has a linear utility function $\epsilon_i a$, where $\epsilon_L < \epsilon_H$. That is, customer H enjoys a higher utility of holding the asset. There is a liquidity shock that happens at the Poisson rate of δ. Conditional on the shock, customer H remains at his type H with probability π_H or switches to the low type L with probability $\pi_L = 1 - \pi_H$. Dealers incur a flow cost k when participating in the market.

As in Lagos and Rocheteau (2006), there is a competitive asset market which dealers have access to. Customers can trade in the market by contacting dealers at the Poisson rate of $\alpha \cdot v$. 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 Poisson rate β. Brokers do not charge intermediation fees. Naturally $\alpha > \beta$, representing greater capability of dealers to provide liquidity[41].

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

$$\begin{aligned} rV_i(a) = \epsilon_i a + \delta\pi_j\big(V_j(a) - V_i(a)\big) &+ \alpha v\big(V_i(a_i) - V_i(a) - p(a_i - a) - \phi_i(a)\big) \\ &+ \beta \max_{a'} \big(V_i(a') - V_i(a) - p(a' - a)\big) \end{aligned} \tag{16}$$

where $j \neq i$. These value functions are intuitive. For customer of type i, he enjoys the flow utility $\epsilon_i a$ each time until a liquidity shock hits him at rate $\delta\pi_j$ in which case he becomes a customer

[41] In the original Duffie, Gârleanu, and Pedersen (2005) and Lagos and Rocheteau (2006) framework, dealers are brokers that do not hold inventory, and customers can trade with each other directly. I twist their interpretations that in the former cases 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 interedaler market, which allows dealers to unwind their inventory positions and all end up with the even position of zero. However, even if dealers in the model end up holding zero positions, they still incur a flow cost k, which can be readily seen as the dealer inventory cost. Similarly, customer-customer trading can be seen 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.

of type j. He contacts a dealer at rate αv upon which he trades $a_i - a$ at price p and pays an intermediation fee $\phi_i(a)$. Alternatively, this customer can trade $a' - a$ in the competitive market via the broker service without paying the intermediation fee at the rate β. Trades with dealers are determined by Nash Bargaining: $(a_i, \phi_i) = \text{argmax}\big[V_i(a_i) - V(a) - p(a_i - a) - \phi_i\big]^{(1-\eta)}\phi_i^{\eta}$. where η is the dealer's bargaining power. This suggests that the optimal asset holding is the same regardless of whether the trade is done with dealers or brokers: $a_i = a'$.

For customer distributions, denote n_{ij} be the measure of customer with asset holding a_i and preference type j. As in Lagos and Rocheteau (2006), the distributions satisfy:

$$\begin{aligned} n_{HL} = n_{LH} &= \frac{\delta \pi_L \pi_H}{\alpha v + \beta + \delta} \\ n_{ii} &= \frac{(\alpha v + \beta)\pi_i + \delta \pi_i^2}{\alpha v + \beta + \delta} \end{aligned} \tag{17}$$

Finally, market clears: $\sum_{i,j} n_{i,j} a_i = A$.

Following routine algebra in this framework, one can solve for price, intermediation fees and asset holdings. The asset price satisfy:

$$p = \frac{1}{r} \frac{(r + \alpha v(1-\eta) + \beta)\epsilon_H + \delta \bar{\epsilon}}{r + \delta + \alpha v(1-\eta) + \beta} \tag{18}$$

where $\bar{\epsilon} = \pi_L \epsilon_L + \pi_H \epsilon_H$. Clearly as trading friction vanishes: $\alpha, \beta \to \infty$, $p \to \frac{\epsilon_H}{r}$. Therefore, the absolute illiquidity discount/liquidity premium (in the price space) is $\frac{\epsilon_H}{r} - p$:

$$LP = \frac{1}{r} \frac{\delta \pi_L (\epsilon_H - \epsilon_L)}{r + \delta + \alpha v(1-\eta) + \beta} \tag{19}$$

The asset positions are $a_L = 0$ and $a_H = \frac{A}{\pi_H}$. The trading fees satisfy $\phi_H(a_L) = 0$, and $\phi_L(a_H) = \frac{\eta(\epsilon_H - \epsilon_L)}{(r + \delta + \alpha v(1-\eta) + \beta)} a_H$. So the dealer bid-ask spread per unit of quantity is just $\frac{\eta(\epsilon_H - \epsilon_L)}{r + \delta + \alpha v(1-\eta) + \beta}$.

Finally, let's look at the dealer's problem. The free-entry of dealers suggest that dealer 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 implies:

$$\alpha \frac{\eta A \delta \pi_L (\epsilon_H - \epsilon_L)}{(r + \delta + \alpha v(1-\eta) + \beta)(\alpha v + \beta + \delta)} = k \tag{20}$$

From the above equation, it is clear that as dealer costs go up, less dealers will enter the market $\frac{\partial v}{\partial k} < 0$. Therefore customers contact dealers less frequently at rate αv as k goes up. As a consequence, the fraction of brokered trades, $\frac{\beta}{\alpha v+\beta}$, will go up, and customers will experience longer execution delays, $\frac{1}{\alpha v+\beta}$, as dealer costs k increase. The bid-ask spread charged by dealers, $\frac{\eta(\epsilon_H-\epsilon_L)}{r+\delta+\alpha v(1-\eta)+\beta}$, will of course go up as dealer costs increase. However, econometricians often times end up measuring the average bid-ask spread as it is hard to distinguish which trades are done by dealers or brokers. The average bid-ask spread, observed by econometricians, therefore is:

$$\text{Bid-Ask} = \frac{\alpha v}{\alpha v+\beta}\frac{\eta(\epsilon_H-\epsilon_L)}{r+\delta+\alpha v(1-\eta)+\beta} + \frac{\beta}{\alpha v+\beta}(p-p) = \Big(\frac{\alpha v}{\alpha v+\beta}\Big)\Big(\frac{\eta(\epsilon_H-\epsilon_L)}{r+\delta+\alpha v(1-\eta)+\beta}\Big) \tag{21}$$

The fraction of dealer trades $\frac{\alpha v}{\alpha v+\beta}$ decreases as dealer costs go up. Therefore the average bid-ask may not increase or even decrease as dealer costs k increase, which is what we have observed in the data. However even if the average bid-ask spread may be low, the illiquidity discount/liquidity premium is high, because customers now experienced longer execution delays than before. Indeed, equation(19) suggests that liquidity premium indisputably increases as dealer costs go up:

$$\frac{\partial LP}{\partial k} = \frac{\partial LP}{\partial v}\frac{\partial v}{\partial k} > 0. \tag{22}$$

Figure 9 shows the model generated statistics as a function of the dealer cost k. As we see, as dealer cost k increases, the fraction of the brokered trades and the execution delay both increase. The bid-ask spread charged by dealers (dashed blue) increases too, empirically supported by Choi and Huh (2019) who look at large trades. However, the average bid-ask spread (solid red) decreases as more trades are just being brokered with lower spreads. Finally the illiquidity discount/liquidity premium increases despite the lower average bid-ask spread. The intuition is simple. As more transactions are being brokered and the bid-ask spread charged by brokers are lower, the average bid-ask spread can be lower. However, a low bid-ask spread does not mean that liquidity premium is low. On the contrary, prices are more heavily discounted because customers spend longer time waiting to execute the trades.

Table A2: Liquidity Regressions: Market Condition Controls

Rating	A and above	BBB	Speculative
Pre-Crisis: Jan 2004 - Jun 2007			
$\lambda_{\text{pre-Crisis}}$	0.132***	0.225***	0.672***
	(6.13)	(15.23)	(9.67)
Crisis: Jul 2007 - Apr 2009			
λ_{Crisis}	0.458***	0.328***	1.073***
	(4.23)	(5.45)	(8.47)
Post-Crisis: May 2009 - May 2012			
$\lambda_{\text{post-Crisis}}$	0.431***	0.426***	0.987***
	(11.50)	(12.73)	(7.82)
Basel II.5: Jun 2012 - Jun 2013			
$\lambda_{\text{Basel II.5}}$	0.388***	0.576***	2.040***
	(10.61)	(26.14)	(17.95)
Basel III: Jul 2013 - Mar 2014			
$\lambda_{\text{Basel III}}$	0.229***	0.484***	2.034***
	(4.84)	(24.64)	(25.22)
Post-Volcker: Apr 2014 - Sep 2019			
$\lambda_{\text{post-Volcker}}$	0.210***	0.487***	2.682***
	(8.96)	(11.48)	(15.55)
Coefficient-Difference			
$\lambda_{\text{Crisis}} - \lambda_{\text{pre-Crisis}}$	0.326***	0.103*	0.401**
	(2.71)	(1.67)	(2.51)
$\lambda_{\text{post-Crisis}} - \lambda_{\text{Crisis}}$	-0.027	0.098	-0.086
	(-0.23)	(1.54)	(-0.50)
$\lambda_{\text{Basel II.5}} - \lambda_{\text{post-Crisis}}$	-0.043	0.150***	1.053***
	(-0.85)	(4.46)	(5.90)
$\lambda_{\text{Basel III}} - \lambda_{\text{Basel II.5}}$	-0.159**	-0.091***	-0.007
	(-2.56)	(-3.57)	(-0.05)
$\lambda_{\text{post-Volcker}} - \lambda_{\text{Basel III}}$	-0.019	0.002	0.649***
	(-0.39)	(0.06)	(3.53)
$\lambda_{\text{post-Volcker}} - \lambda_{\text{pre-Crisis}}$	0.078***	0.262***	2.010***
	(2.70)	(6.03)	(11.41)
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:

$$\lambda_t = \lambda_{\text{pre-Crisis}} \mathbb{1}_{\{t \in \text{pre-Crisis}\}} + \lambda_{\text{Crisis}} \mathbb{1}_{\{t \in \text{Crisis}\}} + \lambda_{\text{post-Crisis}} \mathbb{1}_{\{t \in \text{post-Crisis}\}} + \lambda_{\text{Basel II.5}} \mathbb{1}_{\{t \in \text{Basel II.5}\}} + \lambda_{\text{Basel III}} \mathbb{1}_{\{t \in \text{Basel III}\}} + \lambda_{\text{post-Volcker}} \mathbb{1}_{\{t \in \text{post-Volcker}\}} + \Delta \log(\text{SP500}_{t-1}) + \Delta \log(\text{Barclays}_{t-1}) + \Delta \text{VIX}_{t-1} + \Delta \text{LIBOR}_{t-1} + \epsilon_t.$$

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 4 lags are presented in parentheses. *** (**) [*] denotes statistical significance at 1% (5%) [10%] level.

Table A3: Liquidity Regressions: Accounting 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)
$\lambda_{\text{post-Crisis}} - \lambda_{\text{Crisis}}$	0.082**	0.143**	0.235
	(1.98)	(2.29)	(1.16)
$\lambda_{\text{Basel II.5}} - \lambda_{\text{post-Crisis}}$	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 (13) 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 4 lags are presented in parentheses. *** (**) [*] denotes statistical significance at 1% (5%) [10%] level.

Table A4: Liquidity Regressions: 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)
$\lambda_{\text{post-Crisis}} - \lambda_{\text{Crisis}}$	0.036	0.140**	0.180
	(0.37)	(2.11)	(0.69)
$\lambda_{\text{Basel II.5}} - \lambda_{\text{post-Crisis}}$	-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 (14) where the rating dummies are replaced by the 5-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 4 lags are presented in parentheses. *** (**) [*] denotes statistical significance at 1% (5%) [10%] level.

Table A5: Liquidity Regressions: 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)
$\lambda_{\text{post-Crisis}} - \lambda_{\text{Crisis}}$	-0.052	0.092**	-0.100
	(-0.84)	(2.49)	(-0.63)
$\lambda_{\text{Basel II.5}} - \lambda_{\text{post-Crisis}}$	-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 4 lags are presented in parentheses. *** (**) [*] denotes statistical significance at 1% (5%) [10%] level.

Table A6: Liquidity Regressions: Bid-Ask+Roll+Amihud

Rating	A and above	BBB	Speculative
Pre-Crisis: Jan 2004 - Jun 2007			
$\lambda_{\text{pre-Crisis}}$	0.108***	0.202***	0.718***
	(8.19)	(13.40)	(13.17)
Crisis: Jul 2007 - Apr 2009			
λ_{Crisis}	0.621***	0.530***	1.288***
	(4.56)	(3.68)	(14.43)
Post-Crisis: May 2009 - May 2012			
$\lambda_{\text{post-Crisis}}$	0.515***	0.532***	1.220***
	(14.38)	(10.69)	(8.70)
Basel II.5: Jun 2012 - Jun 2013			
$\lambda_{\text{Basel II.5}}$	0.572***	0.769***	2.285***
	(9.38)	(13.30)	(54.81)
Basel III: Jul 2013 - Mar 2014			
$\lambda_{\text{Basel III}}$	0.341***	0.639***	2.278***
	(5.79)	(48.67)	(24.13)
Post-Volcker: Apr 2014 - Sep 2019			
$\lambda_{\text{post-Volcker}}$	0.298***	0.624***	2.571***
	(10.75)	(9.97)	(22.55)
Coefficient-Difference			
$\lambda_{\text{Crisis}} - \lambda_{\text{pre-Crisis}}$	0.513***	0.328**	0.570***
	(3.75)	(2.27)	(5.50)
$\lambda_{\text{post-Crisis}} - \lambda_{\text{Crisis}}$	-0.106	0.002	-0.068
	(-0.76)	(0.01)	(-0.43)
$\lambda_{\text{Basel II.5}} - \lambda_{\text{post-Crisis}}$	0.057	0.237***	1.064***
	(0.84)	(3.47)	(6.89)
$\lambda_{\text{Basel III}} - \lambda_{\text{Basel II.5}}$	-0.230**	-0.130***	-0.007
	(-2.56)	(-2.15)	(-0.07)
$\lambda_{\text{post-Volcker}} - \lambda_{\text{Basel III}}$	-0.043	-0.015	0.293**
	(-0.69)	(-0.24)	(1.97)
$\lambda_{\text{post-Volcker}} - \lambda_{\text{pre-Crisis}}$	0.190***	0.422***	1.853***
	(6.20)	(6.56)	(14.66)
Observations	287,172	337,053	169,880
Average R-squared	0.434	0.372	0.597

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 replace by 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 4 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 report the results of a principal component analysis of various corporate bond transaction cost and trading activity measures. The reported values are standardized scoring coefficients scaled up by a factor of 100.

Table A8: Liquidity Regressions: PC1

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)
$\lambda_{\text{post-Crisis}} - \lambda_{\text{Crisis}}$	-0.165	-0.081	-0.210
	(-1.13)	(-0.52)	(-1.37)
$\lambda_{\text{Basel II.5}} - \lambda_{\text{post-Crisis}}$	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 (15). 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 4 lags are presented in parentheses. *** (**) [*] denotes statistical significance at 1% (5%) [10%] level.